An Ensembling PLMRI: Alzheimer Detection Via Magnetic Resonance Imaging with Prompt Learning Model

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Abstract— Introduces an end-to-end framework for detecting and classifying stages of Alzheimer's disease using Magnetic Resonance Imaging (MRI) data. The system leverages Convolutional Neural Networks (CNN) to analyze 6,400 pre-processed sagittal plane MRI slices sourced from Hugging Face. Images are categorized into four clinically relevant classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The methodology follows a structured pipeline beginning with comprehensive preprocessing, including pixel normalization, label encoding, and data augmentation techniques to improve convergence and mitigate overfitting. The CNN architecture comprises three convolutional layers with 32, 64, and 128 filters, each activated by Re-LU, followed by max-pooling operations. A dropout-regulated dense layer ensures robust feature extraction, capturing structural brain changes such as atrophy. To enhance interpretability and diagnostic transparency, Gradient-weighted Class Activation Mapping (Grad-CAM) is integrated, generating heatmaps that highlight critical brain regions influencing predictions, particularly the hippocampus. This visualization bridges the gap between automated classification and clinical validation, offering insights into the model's decision-making process. Overall, the proposed system demonstrates the potential of deep learning in medical imaging, providing a scalable and transparent approach for early-stage Alzheimer's detection and supporting clinical decision-making in neurodegenerative diagnostics.

Keywords— MRI, CNN, Re-LU Activation Mapping, Class Activation Mapping.

1. Introduction

Alzheimer's disease is a progressive neurodegenerative disorder that poses significant challenges for early detection and clinical management, and this project addresses those challenges by presenting a comprehensive full-stack medical imaging application that leverages deep learning to classify the stages of Alzheimer's disease using MRI scans, thereby bridging the gap between computational intelligence and practical healthcare deployment; the system is built upon a structured pipeline that begins with dataset management, specifically the retrieval and utilization of the Falah/Alzheimer MRI dataset from Hugging Face, which contains 6,400 grayscale sagittal plane images of 128x128 pixels, and continues with preprocessing steps such as pixel normalization, one-hot label encoding, and image augmentation to enhance model robustness and reduce overfitting; the core of the system is a Convolutional Neural Network (CNN) architecture featuring three convolutional layers with 32, 64, and 128 filters activated by Re-LU, followed by max-pooling operations and a dropout-regulated dense layer, enabling hierarchical feature extraction that captures structural brain changes such as atrophy; classification is performed across four clinically relevant categories Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented providing automated diagnostic assistance that reduces manual effort and increases consistency; to ensure transparency and interpretability, the system integrates Grad-CAM (Gradient-weighted Class Activation Mapping), which generates heatmaps highlighting critical brain regions such as the hippocampus that influence predictions, thereby offering clinicians visual evidence of the model's decision-making process; inference reporting further enhances usability by providing confidence percentages for predictions and automated comparison carousels that allow users to validate outputs against representative samples; the software architecture is designed for end-to-end integration, with a Python-based backend implemented using Flask or Fast-API to handle image uploads, execute model inference, and return JSON-formatted diagnostic data, while a React-based frontend provides a responsive interface for uploading MRI scans and visualizing outputs such as

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heatmaps and confidence metrics, all connected through asynchronous API calls to ensure seamless communication and real-time feedback; performance validation is conducted using standard classification metrics including Accuracy, Precision, Recall, F1-Score, and ROC-AUC curves, ensuring reliability across all disease stages and addressing dataset imbalances through augmentation techniques to improve classification of rarer stages such as Moderate Demented; ultimately, the purpose of this project is to deliver a scalable, transparent, and clinically relevant diagnostic tool that automates Alzheimer's stage detection, enhances diagnostic transparency through explainable AI, improves operational efficiency via standardized pipelines, and provides full-stack accessibility through a user-friendly web interface, thereby demonstrating how deep learning, explainable AI, and modern software engineering can converge to create impactful solutions for neurodegenerative disease diagnostics.

2. Existing Method

Alzheimer's disease detection mainly rely on conventional clinical assessments and basic machine learning techniques. Traditionally, neurologists diagnose Alzheimer's disease using cognitive tests such as the Mini-Mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA), and a detailed patient medical history. These clinical evaluations are often supported by neuroimaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET). These imaging techniques help physicians observe structural and functional changes in the brain, including hippocampal shrinkage, cortical atrophy, and reduced brain metabolism. Although these methods are widely used in hospitals, they require specialized equipment, expert interpretation, and significant time, which may delay early diagnosis.

In recent years, machine learning techniques have been introduced to improve the accuracy and speed of Alzheimer's disease detection. Many existing systems utilize traditional classification algorithms such as Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbours (KNN), and Decision Trees. These algorithms are trained using extracted features from MRI brain images or clinical datasets. Feature extraction methods such as Principal Component Analysis (PCA), texture analysis, and statistical feature selection are commonly used to identify relevant brain characteristics associated with Alzheimer's disease. Once the features are extracted, the machine learning classifier predicts whether the patient belongs to a normal, mild cognitive impairment (MCI), or Alzheimer's category. However, most of the existing systems rely heavily on manual feature engineering, in which domain experts must identify and select relevant features from medical images. This process is time-consuming and may introduce human bias, which can affect prediction accuracy. Additionally, traditional machine learning models often struggle with large and complex medical image datasets because they cannot automatically learn hierarchical patterns present in high-dimensional data.

Some studies have attempted to use deep learning models, such as Convolutional Neural Networks (CNNs), to learn features from brain images automatically. Although these models show improved performance compared with traditional techniques, many existing implementations still face limitations, including insufficient training data, overfitting, and high computational requirements. Furthermore, many systems are designed only for offline analysis and are not integrated into user-friendly applications that allow real-time predictions.

Another limitation of current approaches is the lack of accessible web-based platforms for early screening. Most research models remain experimental and are not deployed as practical tools that doctors or caregivers can easily use. As a result, the potential benefits of artificial intelligence for early detection of Alzheimer's disease are not fully realized in real-world clinical settings, while existing methods provide useful insights into Alzheimer's disease detection, they still face challenges related to accuracy, scalability, automation, and practical deployment. These limitations highlight the need for a more advanced system that integrates deep learning models with an efficient web-based interface for faster, reliable, and accessible Alzheimer's stage detection.

3. System Analysis

The system architecture of the Alzheimer Stage Detection Web Application is designed to provide a robust, modular, and scalable framework that seamlessly integrates advanced deep learning techniques with modern web technologies to support automated medical image analysis. The architecture

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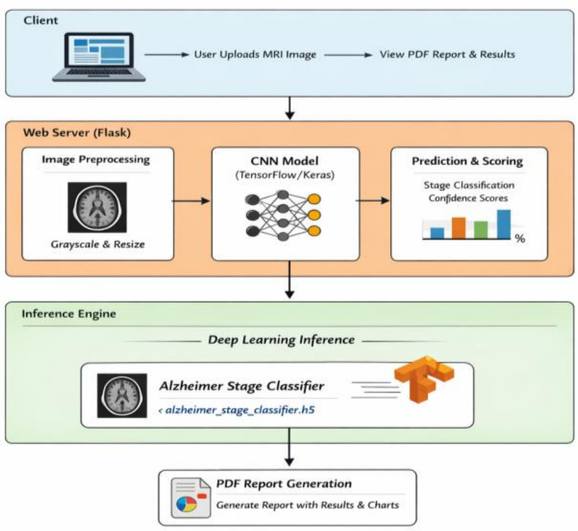
follows a layered client–server paradigm combined with a machine learning inference pipeline to ensure efficient data processing, maintainability, and extensibility. At a high level, the system consists of two principal subsystems: a Deep Learning Inference Engine responsible for predictive intelligence, and a Web Application Layer implemented with the Flask framework that manages user interaction, request processing, and application workflow. The inference engine is built using TensorFlow and Keras, enabling efficient neural network execution and optimized model inference for medical image classification tasks. Within this architecture, the client layer comprises a browser-based graphical interface through which medical professionals, such as doctors, researchers, or healthcare staff, can upload brain MRI images and visualize diagnostic predictions. When an image is submitted, the request is transmitted to the server layer via HTTP protocols, where the Flask application performs input validation, file management, and orchestration of backend processes. The uploaded MRI image is then passed through an image preprocessing pipeline, where libraries such as Pillow and NumPy are used to convert the image to grayscale, resize it to a standardized dimension of 128 × 128 pixels, normalize pixel intensity values between 0 and 1, and reshape the data into a four-dimensional tensor structure compatible with deep learning model input requirements. After preprocessing, the prepared tensor is forwarded to the Convolutional Neural Network (CNN) model, which has been previously trained on labeled brain MRI datasets to recognize structural abnormalities associated with different stages of Alzheimer's disease. The CNN architecture consists of multiple hierarchical convolutional layers designed to automatically learn spatial feature representations from MRI scans. Specifically, three convolutional blocks with increasing filter sizes (32, 64, and 128) extract progressively complex visual features ranging from low-level edges and textures to higher-level anatomical patterns such as cortical atrophy or ventricular enlargement. Each convolutional layer is followed by Max-Pooling operations that reduce spatial dimensionality while preserving salient features, thereby improving computational efficiency and reducing overfitting risk. The extracted feature maps are subsequently flattened into a one-dimensional feature vector and passed through a fully connected dense layer containing 128 neurons with ReLU activation, enabling nonlinear decision boundary learning.

A Dropout regularization layer with a probability of 0.5 is incorporated to prevent model overfitting during training by randomly disabling neurons and encouraging generalization. The final classification stage consists of an output layer with four neurons using Softmax activation, which produces a normalized probability distribution corresponding to the four Alzheimer disease stages predicted by the system. Once inference is completed, the predicted class label is determined using an argmax operation on the probability vector, and the results are returned to the Flask server for presentation to the user. To enhance interpretability and reporting, the system generates a confidence visualization chart using Matplotlib, illustrating the probability scores for each disease stage. Furthermore, a dynamic reporting module implemented with the FPDF library automatically compiles a structured diagnostic report containing the predicted stage, probability values, timestamp, uploaded MRI image, and graphical analysis. This report can be downloaded by the user as a portable PDF document, providing a concise summary suitable for clinical reference or research documentation.

The overall architecture emphasizes clear separation of concerns, where the web interface, preprocessing logic, inference engine, and reporting module operate as loosely coupled components coordinated by the Flask controller. This modular design facilitates independent model updates, supports scalability through deployment technologies such as Gunicorn and Nginx, and allows future integration with cloud infrastructure, medical databases, explainable AI techniques, or advanced 3D CNN architectures for volumetric MRI analysis, thereby establishing a flexible and extensible platform for AI-assisted Alzheimer disease stage detection.



4. Proposed Method

The proposed method aims to develop an efficient Alzheimer Stage Detection System using deep learning techniques applied to brain MRI images. The primary objective of this method is to automatically classify the stages of Alzheimer's disease by analyzing structural patterns present in MRI scans. The proposed system integrates image preprocessing, deep learning–based feature extraction, classification, and result reporting within a web-based framework. By combining medical image analysis with artificial intelligence, the system assists healthcare professionals in identifying Alzheimer's disease stages quickly and accurately.

The first stage of the proposed method involves data acquisition and image preprocessing. Brain MRI images collected from medical datasets are used as input for the model. Since raw medical images may vary in size, format, and intensity values, preprocessing is required to standardize the data before feeding it into the neural network. In this step, the MRI images are converted to grayscale format to reduce computational complexity while preserving essential structural information. Each image is then resized to a fixed resolution of 128 × 128 pixels, ensuring consistency across the dataset and compatibility with the input layer of the deep learning model. After resizing, pixel intensity values are normalized to a range between 0 and 1, which improves the training stability and convergence speed of the neural network.

The second stage involves feature extraction using a Convolutional Neural Network (CNN). CNNs are highly effective for image classification tasks because they automatically learn spatial hierarchies of features from raw images. The proposed CNN architecture consists of multiple convolutional layers that apply filters to extract meaningful visual patterns such as edges, textures, and structural shapes from MRI images. These convolutional layers are followed by Max-Pooling layers and Average pooling from Figure 1: which reduce the spatial dimensions of feature maps while retaining the most significant features. This process reduces computational cost and helps the model focus on important anatomical patterns associated with Alzheimer's disease progression.

Figure 1: Max-Pooling layers and Average pooling.

After the convolution and pooling operations, the extracted feature maps are flattened into a one-dimensional feature vector. This vector is then passed through fully connected dense layers that learn complex nonlinear relationships between extracted features and disease categories. A Dropout layer is incorporated during training to reduce overfitting by randomly disabling a fraction of neurons, which improves the model's generalization capability when encountering unseen MRI scans.

The final stage of the CNN architecture is the classification layer, which uses a Soft-max activation function to generate probability scores for each Alzheimer stage category. In the proposed system, the model predicts four possible classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The class with the highest probability value is selected as the final prediction result. This probabilistic output provides additional interpretability by showing the confidence level of the prediction. Once the model generates the prediction, the result is integrated into a Flask-based web application that serves as the user interface of the system. Medical professionals can upload MRI images through the web interface from Figure 2: after which the system performs preprocessing, executes the CNN model for prediction, and displays the predicted Alzheimer stage along with probability scores. Additionally, the system generates a confidence visualization chart and a downloadable PDF diagnostic report that summarizes the prediction results and analysis, the proposed method

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provides a systematic pipeline for automated Alzheimer stage detection, combining medical image processing, deep learning classification, and web-based deployment. This approach not only improves diagnostic efficiency but also offers a scalable platform that can be further enhanced with larger datasets, advanced neural network architectures, and explainable artificial intelligence techniques in the future.

Figure 2: Medical professionals can upload MRI images through the web interface

5. Conclusion

The Alzheimer Stage Detection Web Application represents a significant step forward in applying deep learning to clinical decision-support systems. By leveraging a specialized Convolutional Neural Network (CNN) trained on structured MRI datasets, the system automates the traditionally complex and subjective process of neuroimaging analysis. This reduces diagnostic variability and improves consistency in identifying stages such as Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia. Deployment through the Flask framework ensures accessibility, allowing healthcare professionals to upload MRI scans and receive structured diagnostic outputs in real time without requiring expertise in machine learning. Interpretability is enhanced through dynamic visualizations with Matplotlib, which present probability-based confidence scores for each classification. Usability is strengthened by automated PDF report generation via FPDF, enabling seamless documentation and integration into clinical workflows. Importantly, the system emphasizes transparency by presenting statistical reasoning behind predictions rather than categorical outputs alone. Positioned as an intelligent assistant or "second opinion" tool, the application supports timely interventions, improved disease management strategies, and enhanced patient monitoring, ultimately contributing to better quality of life for individuals affected by Alzheimer's disease.

6. Future Work

In order to guarantee adaptability among a range of the patient sample sizes, authors intend to test the predictive algorithm in additional analyses leveraging greater in size, more diverse medical information and conduct multi-data set analysis. The suggested structure's dependability and practicality will be strengthened by using k-fold cross-validation and experimentation on separate databases.

7. References

[1] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.

[2] Jack, C. R., et al. (2018). NIA-AA Research Framework: Toward a biological definition of Alzheimer's disease. Alzheimer's & Dementia, 14(4), 535–562.

[3] Litjens, G., et al. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60–88.

[4] Abadi, M., et al. (2015). TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems.

[5] Chollet, F., et al. (2015). Keras.

[6] Grinberg, M. (2018). Flask Web Development: Developing Web Applications with Python. O'Reilly Media.

[7] Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. Computing in Science & Engineering, 9(3), 90–95.