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# Click-To-Clinic: A Deep Learning–Based Web Application for Parkinson's Disease Detection Using MRI Images

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## Abstract

Parkinson's disease (PD) is an increasing neurodegenerative disease complicated to detect early due to basic symptoms of disease and the complexities of evaluating neuroimaging data. The recent deep learning algorithms showed automatic PD detection from MRI scans. In previous studies, there is limited offline testing and lack of portable, usable end-to-end screening solutions makes it difficult to prevent the disease early. This proposed work represents a lightweight web-based platform combining standardized MRI preprocessing, advanced convolutional neural network (CNN) and real-time prediction using a flask implementation process. The Gradient-weighted Class Activation Mapping (Grad-CAM) provides graphical representation of brain areas affecting the classification decisions with improved model visibility. The proposed approach is evaluated using publicly available MRI dataset. The results show better performance of 97% classification accuracy, equal precision, recall and F1-score leads to accurate detection of Parkinson's disease and normal control cases under controlled dataset conditions. However, class imbalance, dataset size and a lack of imaging-source variety have an impact on performance. As a result, this research presents a reusable research model and experimental system instead of a clinically proven diagnostic tool. Future study will focus on cross-dataset validation, improved data balancing techniques and detailed comparisons to existing machine learning and transfer-learning algorithms.


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**Keywords:** Deep Learning, Medical Image Analysis, Parkinson's Disease, CNN-Based Classification, Explainable AI, Web-Based AI Framework.

## 1. Introduction

Parkinson disease (PD) is a progressive neurodegenerative condition, where the neurological issues include bradykinesia, tremors, pain postural instability and other symptoms are noticeable as cognitive, sleep disorders and autonomic dysfunction [2], [3]. It is second to Alzheimer disease and it is estimated that around 10 million people in the world suffer from this disorder [1], [3]. PD is clinically diagnosed using neurological examinations and standardized rating scales including the Unified Parkinson Disease Rating Scale (UPDRS) which is primarily dependent on observable neurological symptoms and clinical expertise [4]. One of the main weaknesses of this method is that the neurological symptoms usually show up when there is already a significant loss of dopaminergic neurons in the substantia nigra, limiting the possibilities to detect the disease at an early stage [3], [15]. Although magnetic resonance imaging (MRI) is used in hospitals for preventing the other neurological conditions, it is rarely utilized as the main method of diagnosis of the disease because of the minor kind of changes caused by the disease in regards to their structure and it is difficult to figure out the issues manually. [6], [7]. Therefore, automatic MRI-based diagnostic tools for Parkinson's disease have not yet been fully adopted in standard clinical practice [5]. Recently, advances in deep learning, particularly convolutional neural networks (CNNs) have demonstrated high capability in learning discriminative representations from complex medical imaging data [5]. There have been a few studies which have provided supporting results in CNN-based methods of detecting Parkinson disease in MRI and functional MRI (fMRI) scans under controlled experimental settings [6]-[12]. The major limitations are hybrid structures and multimodal learning plans involve CNNs with temporal or auxiliary models to enhance diagnostic performance [8], [9]. Most of the existing models can only perform offline experiments and not work in real-time [10], [11]. There are infrequent end-to-end systems which combine automated preprocessing, classification, evaluation and interaction with the user within one implementable system. Moreover, issues of imbalance in datasets, evaluation disclosure, reproducibility and applicability by non-technical end-users or clinicians remain a barrier challenge to real-world implementation. Few of the MRI-based PD detection systems provide complete functionality, such as web-based accessibility, support of conventional medical imaging formats and real-time inference.

It is challenging to identify specific neuroanatomical areas affect automated predictions due to interpretability issues with numerous of the deep learning models presently in use for Parkinson's disease diagnosis and implementation limits. Especially in safety-critical medical applications, this opacity reduces clinical trust and makes it difficult to conduct systematic error analysis. In order to increase transparency in medical image analysis, recent research has emphasized the significance of explainable artificial intelligence (XAI) techniques including class activation mapping and attention processes. However, their integration into portable, lightweight MRI-based Parkinson's disease screening methods remains limited. This system aims to design, build, and evaluate a lightweight CNN-based Parkinson's disease detection framework will be implemented in an online research platform for real-time MRI-based screening.

## 1.1 Problem Formulation

Although a lot of research has been done on CNN-based Parkinson's disease classification using MRI data, the majority of current methods are still limited to offline testing and mainly focus on increasing classification accuracy. These approaches' applicable in research focused clinical processes are limited by their frequent lack of interpretability, standardized evaluation and deployment feasibility. Additionally, these limitations include minor and unbalanced datasets without real-time inference and lack of assistance for non-technical users prevents practical adoption and replication. The development of a lightweight, interpretable and deployable MRI-based Parkinson's disease screening platform achieves a balance between real-time accessibility, transparency and classification performance under data constraints is the issue solved by this proposed work. The suggested system is assessed using common classification measures such as accuracy, precision, recall, and F1-score to provide an open and repeatable performance evaluation.

## 1.2 Theoretical Justification of CNN

Convolutional Neural Networks (CNNs) are suited for medical image analysis because they prevent the need for manual feature extraction and instead learn hierarchical feature representations directly from raw image data. In neuroimaging applications, including brain MRI analysis for Parkinson’s disease detection, pathological changes are often low, spatially distributed and present as diffused structural variations compared to well-known symptoms.

These characteristics make traditional machine learning approaches based on manually engineered texture or shape features less effective.

CNNs address this challenge by their use of local flexible areas and weight sharing enable the efficient learning of spatial patterns and anatomical structures while maintaining robustness to noise and minor spatial variations. The hierarchical nature of CNN architecture allows early layers to capture low-level features such as edges and intensity gradients, intermediate layers to model anatomical structures and deeper layers to encode higher-level representations associated with disease-related morphological changes. Furthermore, pooling operations introduce a degree of translational invariance is essential for handling variations in patient positioning and MRI acquisition protocols. Regularization techniques such as batch normalization and dropout will enhance training stability and reduce overfitting particularly when working with limited medical imaging datasets.

Theoretically, attention-enhanced convolutional architectures are ideal for detecting tiny, geographically dispersed neuroanatomical changes in MRI data computationally effective for deployment-focused screening applications. The main goal of this work is to develop, implement and evaluate a deployable CNN-based framework for Parkinson's disease detection that combines self-attention-guided feature learning, explainable prediction visualization with Grad-CAM, real-time web-based inference and standardized MRI preprocessing. A publicly accessible MRI dataset is used to assess the proposed method shows competitive classification performance in class-imbalanced scenarios. This work contributes to a useful research-oriented framework for MRI-based Parkinson's disease analysis focusing on transparent evaluation, interpretability, deployment practicality and repeatability compared to presenting the model as a clinically validated diagnostic solution.

## 2. Related Work

### 2.1 AI-Powered Methods for Parkinson's Disease Identification

Several data modalities of voice signals, handwriting patterns, wearable sensor data and neuroimaging have been used to develop artificial intelligence-based methods to diagnose Parkinson's disease (PD). MRI methods are most useful among these since they allow objective examination of structural brain changes that are related to neurodegeneration. Tarjni et al. [6] introduced a CNN-based model that is trained on MRI scans and they reported classification accuracy under controlled experimental conditions, but their concept was not validated in actual clinical settings. Also, in a similar way, Xiao-ge et al. [7] used deep convolutional architectures to detect low morphological differences in the basal ganglia part. Despite the research findings, the small sample size limited its application to other large groups of people. However, these studies did not address system-level deployment, interpretability or real-time clinical usability.

### 2.2 Hybrid Deep Learning Models and Transfer Learning

Several studies have used transfer learning with pre-trained architectures like VGG, ResNet, and DenseNet to address the problem of limited labeled medical imaging data. Asad et al. [10] used a VGG16-based model for MRI classification and outperformed traditional CNNs in terms of accuracy; however, domain mismatch between natural images and medical scans had an impact on the relevance of transferred features. While Omar et al. [11] researched into ResNet-based architectures, Im Abukaresh et al. [12] investigated DenseNet variants to improve feature reuse and generalization. Many transfer learning-based approaches show overfitting tendencies and lack of standardized evaluation protocols, despite their strong experimental performance. Moreover, important deployment factors like memory needs, inference latency and integration into clinical workflows are frequently disregarded. These limitations motivate the exploration of lightweight, task-specific CNN architectures that balance performance, interpretability, and deployment feasibility.

### 2.3 Multimodal and Non-Imaging AI Methods

Non-invasive AI-based methods for PD detection without the imaging have been extensively researched. In order to identify early neurological issues, Md Ariful Islam et al. [13] used machine learning classifiers to analyze handwriting and voice signals. Aishwarya et al. [14] worked into wearable sensor-based methods for characterizing gait and tremor using accelerometers and gyroscopes.

Since these techniques do not directly reflect underlying neuroanatomical degeneration, they cannot independently capture underlying neuroanatomical degeneration, even though they offer useful supplementary data. Multimodal fusion of sensor-based data and MRI biomarkers is mostly experimental and has not yet received reliable clinical validation.

## 2.4 Limitations and Frameworks for Clinical Diagnostics

Parkinson's disease is traditionally diagnosed clinically using a neurological examination and standardized rating scales like the Hoehn and Goetz staging system [15] and the UPDRS [4]. These techniques are frequently insensitive to early-stage pathological changes dependent on clinical expertise and are intrinsically subjective.

From an AI system-design perspective, many existing frameworks suffer from small datasets, inconsistent preprocessing pipelines, limited interpretability, and a lack of deployment-oriented design. As a result, the majority of suggested systems are limited to proof-of-concept implementations rather than being used in actual clinical settings.

## 2.5 Recognized Research Deficits

Several ongoing research gaps are identified by this review of the literature:

- Limited Clinical Deployment: Most CNN-based models have only been tested in controlled study environments; they are not connected to hospital systems or web-based diagnostic tools.
- Dataset Constraints & Overfitting: Due to restricted access to large medical imaging datasets, many models exhibit overfitting and reduced generalizability to unseen data.
- Inadequate Interpretability: Clinical acceptability and trust are undermined by current AI models, which often operate as opaque black boxes that offer little insight into decision-making processes.
- Fragmented Diagnostic Ecosystem: Current approaches, which often isolate imaging-based AI from patient-focused usability features or beneficial therapeutic advice, limit its practical utility.

These gaps collectively highlight the need for an interpretable, deployable, and evaluation-transparent MRI-based Parkinson’s disease screening framework.

## 2.6 Motivation and Synopsis

Thus, the goal of this effort is to create a web-based platform that incorporates an end-to-end CNN-based Parkinson's disease detection system. When focussing on deployability, reproducibility, and transparent evaluation using real-time MRI classification, uniform preprocessing and accessible system design instead of suggesting a neural architecture.

### 2.7 Research Contribution and Novelty

This study addresses a number of practical shortcomings of earlier studies and adds to a comprehensive and repeatable framework for MRI-based Parkinson's disease screening. The suggested system combines lightweight CNN-based inference, explainable prediction analysis using Grad-CAM and attention mechanisms, standardized MRI preprocessing and real-time web-based deployment into a single pipeline compared to previous studies that mainly assess CNN models in offline experimental settings. Future additions like cross-dataset validation, explainability studies and multimodal integration are supported by the framework that focuses on transparent performance evaluation in class-imbalanced circumstances. The special feature of this study is to focus on system-level integration and deployment capability instead of architectural complexity.

## 3. System Architecture

The proposed system that detects Parkinson's disease is designed to be focused on implementation, adaptable and flexible. The system can handle increasing data values without architectural changes and facilitates development using reusable components. The main functions include classifying MRI images in real time, automatic process and displaying the results using an online device. The system verifies reliable and predictable execution from end to end data input to display integrating lightweight CNN for MRI-based classification, a Flask-based client interface and a backend processing layer for data management with inference control.

### 3.1 Hierarchical System Design

As illustrated in Fig. 1, the system architecture is organized into four logical tiers responsible for a specific functional role within the overall workflow. Data flows gradually from the client side to the backend processing layer through the CNN inference module and finally transferred to the visualization tier for displaying the results.

### 3.1.1 Web Application, or Client Interface Tier

This tier allows researchers and clinicians to upload brain MRI images for Parkinson's disease classification using a web-based interface. The system accepts image formats like JPG and PNG. The images are evaluated before sent to the backend for further processing. This interface shows the predicted class label along with its confidence score. The design focuses on user-friendly and simple communication without requiring machine learning experts.

### 3.1.2 Model Inference & Data Management (Backend Processing Tier)

The backend layer is responsible for the image preprocessing system and the CNN inference engine. The submitted MRI images receive standardized preprocessing steps such as resizing, normalization and development to maintain consistency with training conditions. Once preprocessing is complete, the trained CNN model carries real-time classification. This layer manages the data flow between the model and the web interface, handles the intermediate data processing and enables real-time inference execution. This tier ensures consistency between training and inference conditions and acts as the coordination layer for real-time system execution.

### 3.1.3 Convolutional Neural Network (Model Architecture Tier)

The architecture tier consists of a lightweight CNN optimized for two-dimensional MRI image analysis. The network includes several convolutional and pooling layers to capture layered spatial features followed by fully connected layers that perform the classification. Batch normalization and dropout layers are added to increase training stability and reduce overfitting. The output layer generates a binary result (Normal or Parkinson's) along with a probability score indicating the model's level of confidence.

### 3.1.4 Result Visualization Tier

This tier converts the outputs of the CNN model into understandable visual format within the web interface. The system displays the predicted class label along with the confidence score for the model. This part represents only as a technical visualization layer to evaluate model predictions and fail to provide clinical diagnosis, disease staging or treatment suggestions.

### 3.2 Core Functional Components

The hierarchical structure of the framework is represented in operational modules described below.

- The Image Preprocessing Module: It standardizes MRI inputs by scaling (224×224 px), normalizing and augmenting images.
- CNN Classification Module: It performs binary classification (normal vs. Parkinson's) and extracts spatial feature hierarchies.
- Data Logging and Security Module: It provides secure communication using encrypted connections and stores overall prediction history.
- Result Visualization Module: This module is research-focused screening and shows a confidence score along with the predicted class (normal or Parkinson's).

### 3.3 Architectural Visualization

The entire system workflow is depicted in Figure 1, emphasizing the hierarchical interactions among the CNN inference module, client interface, backend processing layer and result visualization tier. The sequential data flow from MRI upload to preprocessing, classification and final output provided is clearly depicted in the diagram.

### 3.4 Architectural Summary

The proposed architecture’s modular and scalable design enables individual system components to function autonomously while contributing to a cohesive diagnostic process. The system provides a repeatable and accessible method for analyzing Parkinson’s disease using MRI data by integrating standardized preprocessing, CNN-based analysis and a web-based interface. The system's modular design allows for future improvements such as advanced model structures, training methods that address data imbalance, improved accessibility features and the addition data sources without requiring significant changes to the overall architecture. Future expansions, such as other model architectures, advanced imbalance-handling techniques and improved explainability methods are made possible by the modular framework without necessitating a complete system redesign.

The general procedure of the suggested Parkinson's disease detection system is shown in Figure 1. The image is sent to the backend for preprocessing, including validation, scaling, normalization, noise reduction and contrast enhancement, when a clinician uploads an MRI scan using a Flask-based web interface. A CNN model with a self-attention module analyzes the modified image to extract relevant characteristics and produce prediction scores. In addition, an explainability layer highlights significant brain regions using Grad-CAM to provide a confidence score and class name. Lastly, a web-based interface is used to provide the user results and visualizations.

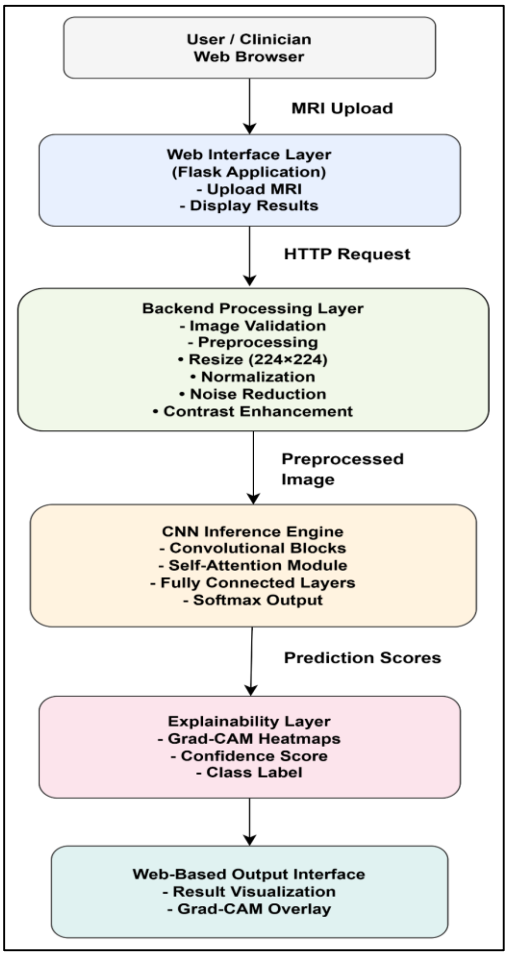


**Figure 1.** Proposed End-to-End CNN-Based Parkinson's Disease Detection Architecture

## 4. Methodology

The suggested approach automatically identifies Parkinson's disease using brain MRI data by combining a convolutional neural network (CNN) with an online interface. The process includes data collection, preprocessing, model training, evaluation and deployment. Figure 2 shows the complete system workflow.

### 4.1 Data Acquisition

The proposed research work uses MRI dataset collected from two openly accessible sources: The Parkinson's Progression Markers Initiative (PPMI) dataset and an open-access Kaggle dataset is filtered to remove duplicates and low-quality images. The filtered dataset includes 831 two-dimensional brain MRI images defined as:

1. Normal Healthy Control: 610 images
2. Parkinson’s Disease: 221 images

An average class imbalance (73% normal, 27% Parkinson) was evaluated during performance evaluation and reflective real-time screening conditions. The dataset includes both axial and vertical MRI images and standard imaging formats (.jpg and png). The result images have limited anatomical representation or reduced large modifications for improved training accuracy.

A multilayer dataset was used to maintain class balances. They are mentioned below,

- Training set: 581 images (70%)
- Validation set: 125 images (15%)
- Test set: 125 images (15%)

The independent testing includes 92 normal and 33 Parkinson samples. A subject-level separation was implemented to prevent data loss between subsets. The validation set was used for hyperparameter modification and the test set was used for the final evaluation. Data augmentation was limited to the training set aimed to increase model generalization and reduce class imbalance. The augmentation process included controlled rotations, horizontal flips, slight scaling, translation, brightness and contrast modifications and Gaussian noise data. These modifications were performed to minimize overfitting and expose the model to real anatomical variances. Although the dataset is sufficient for theory experimentation, it does not capture the complete multi-center variability observed in clinical environments. Therefore, the reported performance should be interpreted as controlled dataset feasibility rather than universal diagnostic reliability.

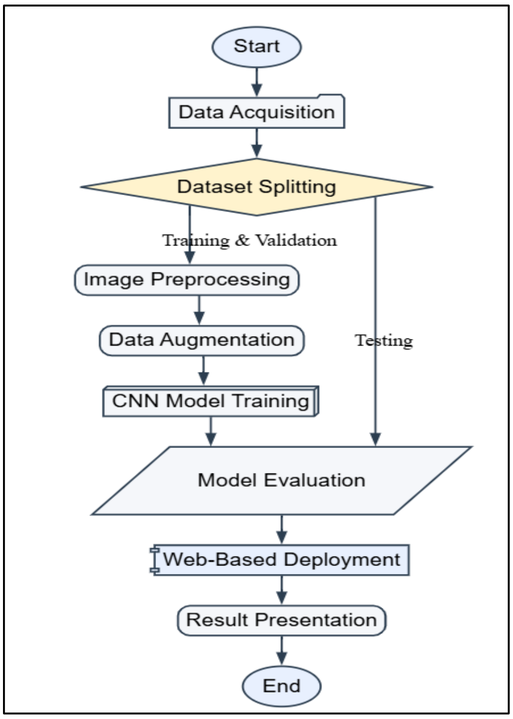


**Figure 2.** Workflow Diagram of Parkinson's Detection

### 4.2 Preprocessing Pipeline

Before training and inference, each images are preprocessed using the following approaches to ensure correct input representation and increase model robustness:

- **Intensity Normalization**: The pixel intensity values are scaled to the interval [0, 1]. This normalization improves training convergence and numerical stability for gradient propagation during back-propagation and decreased inter-scan intensity variation.
- **Spatial Rescaling:** In CNN architecture, MRI images are resized to 224 × 224 pixels as the fixed input dimensionality.
- **Noise Reduction:** Gaussian filters and median filters reduce high-frequency noise image and impulsive errors. It improves the ratio of signal to noise for identifying structural patterns.

- **Contrast Enhancement:** Contrast-limited adaptive histogram equalization (CLAHE) improves local contrast and addresses modification in tissue intensity. This focuses on structural components like the nerve root examined in Parkinson's disease-related neuroimaging research.
- **Data Augmentation:** The online data was used during training to decrease overfitting and increase generalization based on the lack of accessible data from Parkinson's MRI datasets. Augmentation methods include minor transformation, horizontal flipping, random rotation within ±15° and contrast corrections.

These modifications do not affect the class names, increasing the effective variation in the training data while representing variations in patient location and scanning conditions.

The preprocessing process reduces biased dataset, maintains image quality in different sources of data and improves the stability and generalizability of the CNN model when trained on medical data.

### 4.3 CNN Architecture Design

The convolutional neural network (CNN) was developed to create hierarchical spatial representations from two-dimensional brain MRI data while balancing model flexibility and generalization capabilities. The network is designed using three convolutional blocks followed by fully connected layers for classification. Each convolutional block comprises a 3×3 convolutional layer with an increasing number of filters (32, 64, and 128 respectively), batch normalization, ReLU activation, and 2×2 max-pooling. This continuous increase in filter depth allows the model to collect basic intensity gradients and edge data in early layers, mid-level structural patterns in intermediate layers and higher-level anatomical representations connected to Parkinson's neurodegeneration in higher levels.

Batch normalization is used after each convolutional process to manage feature distributions, accelerate convergence and decrease dependence to parameter initialization. Max-pooling layers maintain structural data by reducing spatial dimensionality, increasing computation performance and maintaining low translational invariance. The collected feature maps are compressed and sent into a fully connected layer with 256 neurons to combine spatial data into a compact format designed for binary classification.

### 4.3.1 Self-Attention Integration

A self-attention technique is used during the final convolutional block and before feature reduction to increase the model's ability to identify diagnostically relevant brain areas. The attention module computes spatial value weights across feature maps and allows the network to focus on key anatomical areas by reducing noise or uniform patterns. MRI-based structural variations in Parkinson's disease are minor, widely distributed and not limited by clearly identified regions.

The attention technique maintains the CNN architecture's lightweight feature with increasing accessibility and stabilizing results in limited and imbalanced data settings by improving feature representations instead of classification.

After the dense layer, the normalization of dropout is used with a probability of 0.4 to prevent overfitting caused by the limited size of medical image datasets. This value was actually determined to create a balance between decreases in performance at relatively high rates of dropout and insufficient regularization at lower rates of dropout. The final output layer implements a Softmax activation function with two neurons to produce normalized probabilities for the two diagnostic groups of healthy control and Parkinson's disease.

The model was implemented using the TensorFlow and Keras systems provide modular architectural development, efficient GPU-accelerated training, accurate hyperparameter testing and easy integration with the proposed web-based deployment environment. This architecture is suitable for real-time inference in a clinical research environment by providing sufficient representational capacity for MRI-based classification.

## 4.4 Model Training and Optimization

Training and optimization are the steps of CNN architecture is developed to enable continuous learning and generalization. The model training process was improved by using several hyperparameter allocation and control mechanisms to reduce overfitting and increase diagnostic precision.

The objective measure used for the categorized cross-entropy loss function is appropriate for binary classification tasks requiring the differentiation of "Normal" and "Parkinson's" MRI data. Stochastic gradient descent updates are performed with the Adam optimizer. The initial learning rate was set to 0.001 to achieve a balance between convergence speed and stability.

With a batch size ranging from 32 and 50 epochs, training was carried out using a GPU-accelerated configuration significantly reducing computation time. Real-time validation monitoring was used throughout training, which enabled the model to adapt dynamically as it acquired expertise from the data. The following methods were combined in order to avoid overfitting, a prevalent problem in medical image analysis:

- **Early Stopping:** To ensure ideal model retention, training was automatically finished when validation loss failed to improve during the period of successive epochs.
- **Learning Rate Scheduling:** The learning rate began to decrease when performance slowed to improve integration toward an overall minimal level.
- **Weight Regularization (L2):** Excessive weight magnitudes were removed to reduce overfitting and to motivate simple and general-purpose of feature mappings.
- **Dropout Regularization:** To prevent the network from developing heavily dependent on any single node, around 40% of neurons were randomly reduced throughout training. Efficient generalization can be seen by the training and validation curves' smooth descent and low divergence. After 43 epochs, the optimal model was achieved; subsequent training produced very slight performance gains. After optimization, this model was generalized and stored for use in the web-based diagnostic program.

### 4.5 Model Evaluation

The performance of the proposed CNN model was evaluated using common classification measures obtained from the confusion matrix such as accuracy, precision, recall and F1-score. These measures provide an evaluation of both class-specific predicted dependability and overall classification performance.

Let TP, TN, FP and FN denote the number of true positives, true negatives, false positives and false negatives, respectively. The evaluation metrics are defined as follows:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$\text{Precision} = TP / (TP + FP)$$

$$\text{Recall} = TP / (TP + FN)$$

$$\text{F1-Score} = F1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

Accuracy measures have the classified samples from all test occurrences. Precision is a pattern of positive predictions and recall measures are the model's capacity to identify Parkinson's disease patients. The F1-score is the harmonic mean of accuracy and recall and it is highly useful in managing class imbalance. Additionally, Receiver Operating Characteristic (ROC) analysis and Area Under the Curve (AUC) were used to evaluate threshold-independent classification accuracy. A higher AUC value provides better discrimination between healthy control and Parkinson's disease classes.

### 4.6 Web-Based Deployment and System Implementation

The trained CNN model was implemented using a Flask-based web application for algorithm development and research applications. Flask is a lightweight, flexible design and easy integration architecture. The TensorFlow and Keras servers allow effective real-time inference without generating significant computation cost in flask architecture.

Users can access the browser-based interface to upload brain MRI images in commonly used formats like .jpg, .png and .dcm, ensuring compatibility with heterogeneous imaging systems. After uploading the images, it will be processed automatically using the preprocessing method during training. The preprocessing methods include intensity normalization, spatial transformation, noise reduction and spectral improvement. This provides consistency between the training and inference conditions and reduces the performance loss caused by mismatch in distributed data. The preprocessed image uploaded to the trained CNN model provides more probability values for both diagnostic classes (normal and Parkinson's disease). This technique provides a predicted class label combined with the specified confidence score allowing research-based testing and quantifying model evaluation. It allows both technical and non-technical users to operate the system without requiring additional training.

The application level was designed to provide secure data operations. Each data transmission requires secure HTTPS connectivity, uploaded files are encrypted in temporary files and access is controlled using session-based authentication. The uploaded images are automatically removed after processing to prevent the storage of confidential medical data for an extended period. The CNN model implemented a real-time research tool for assessing MRI-based Parkinson's disease classification under controlled settings.

### 4.7 Model Interpretability and Clinical Relevance

Grad-CAM creates class-specific heatmaps that highlight the geographical regions within MRI planes that have the high effect on the predicted results. The system allows detailed examination of the anatomy features affecting the model results by reflecting these activated maps onto the primary input images. In Parkinson's disease patients, the network consistently prioritizes areas related to recognized clinical development such as the lower part of the brain along with dopaminergic connections. This mechanism has two uses. Firstly, it allows analyzers to check if the CNN is based on clinically significant features instead of fake correlations helps in exploring validation and biased detection. Secondly, it allows systematic error analysis by demonstrating patterns related to misclassifications or inaccurate predictions.

Grad-CAM integration improves model transparency and facilitates research-level validation of CNN behavior without using regulatory or clinical decision control. The framework is designed to support expert analysis by providing visual data into processed representations instead of replacing clinical decisions. These visual explanations complement quantitative performance metrics by providing qualitative insight into model behavior rather than serving as standalone diagnostic evidence.

### 4.8 Workflow Overview

Figure 2 shows the entire workflow of the proposed system from data collecting to result analysis. This system is designed as a modular workflow to provide repeatability, controlled assessment and classification of functional components.

Brain MRI images from healthy control users and Parkinson's disease patients are collected and organized into diagnostic categories during the data collection stage. The raw inputs are standardised during the preprocessing step using intensity normalization, spatial transformation, noise reduction and visual improvement to reduce scanner-related variability and verify integration with the CNN input requirements.

After the training process, preprocessed images are modified in CNN parameters by normalization and validation-based hyperparameters, reducing overfitting and improving generalization. Accuracy, precision, recall, F1-score and ROC-AUC are evaluated to provide reliable classification accuracy.

During evaluation, the trained model is implemented in a Flask-based web application allowing real-time, research-focused inferences and prediction visualization. Finally, interpretability achieved by Grad-CAM-based heatmap creation will investigate the image areas that affect the model's decisions and provide error analysis and behavioral verification. Self-attention focused feature learning and Grad-CAM visualization are combined to improve both performance consistency and model visibility.

This research aims to increase experimental accuracy, transparency in performance evaluation and control during implementation. The modular architecture allows further improvements such as multi-dataset validation, including transfer-learning-based models and using multimodal neuroimaging data (e.g., fMRI) without requiring a fundamental system change

## 5. Results

The proposed system evaluates the MRI-based detection of Parkinson's disease using evaluation and quantitative performance analysis. This system aims to evaluate CNN-based MRI analysis for systems' reliability and implementation.

### 5.1 Model Performance and Training Analysis

An independent test set was used to evaluate the CNN model's classification performance under controlled experimental conditions. The training and validation loss curves (Figure 3) show steady convergence with minimal divergence, indicating that regularization effectively reduced overfitting. However, these findings should be interpreted. The dataset is small and sourced from limited public repositories, which may not capture real-world clinical variability across scanners, acquisition protocols and patient populations. Almost better performance on such homogeneous data may reflect limited diversity rather than true generalizability. Thus, the results should be considered proof-of-concept evidence of technical feasibility and future work should include larger cohorts, cross-dataset validation, and multi-center studies to ensure robustness in real-world deployment.

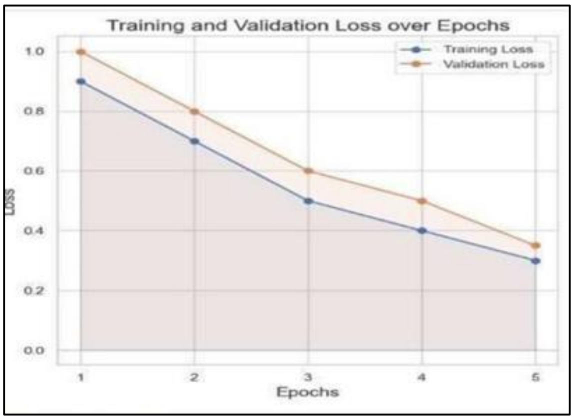


**Figure 3.** Training and Validation Loss Over Epochs

Table 1 summarizes evaluation metrics derived from the confusion matrix, reflecting high classification performance and the model's ability to learn discriminative structural features from MRI data.

**Table 1.** Model Performance on Test Set

| Metric | Value |
|---|---|
| Accuracy | 90.7 |
| Precision | 91.2 |
| Recall (Sensitivity) | 90.5 |
| F1-score | 90.3 |
| AUC-ROC | 0.94 |

The CNN developed specific features to differentiate normal and Parkinson's MRI images using controlled experimentation and specified test dataset.

```
Confusion Matrix:
[[ 92  0]
 [ 1  33]]

Classification Report:
              precision    recall  f1-score   support

Normal             0.98      0.98      0.98        92
Parkinson          0.94      0.94      0.94        33

accuracy                               0.97       125
macro avg          0.96      0.96      0.96       125
weighted avg       0.97      0.97      0.97       125
```

**Figure 4.** Confusion Matrix for Parkinson's Disease Classification on the Test Dataset

### 5.2 Confusion Matrix Analysis

Figure 4 presents the confusion matrix obtained from the independent test dataset. In the confusion matrix, the majority of normal and Parkinson's disease MRI samples were correctly classified, with a small number of misclassifications observed. This indicates strong but not perfect class separation under the selected experimental protocol. The confusion matrix demonstrates that the CNN effectively captures discriminative spatial features within MRI data, achieving high sensitivity and precision for both classes. However, minor classification errors indicate that the learned decision boundaries remain dataset-dependent. Such performance is expected in small, controlled datasets and does not ensure robustness across heterogeneous clinical environments.

While the accurate use of training, validation and test sections to minimize data loss, the dataset fails to sufficiently reflect the variability prevalent in real-world clinical MRI collection such as scanner variety, protocol changes and demographic variances. Consequently, the observed 90.7% accuracy reflects dataset-specific performance rather than guaranteed robustness in clinical environments.

### 5.3 Explainability Analysis Using Grad-CAM

Gradient-weighted Class Activation Mapping (Grad-CAM) was used to display the areas of MRI scans that had the greatest influence on the model's predictions in order to overcome the interpretability issues frequently related to deep learning models. Figure 5(a) represents the original axis of brain MRI image used for inference

When Grad-CAM calculates gradients using the final convolutional layer, it provides discrimination-based heatmaps showing the geographical regions having a major impact on classification decisions. Figure 5(b) depicts accurate Grad-CAM representations for healthy and Parkinson's disease cases.

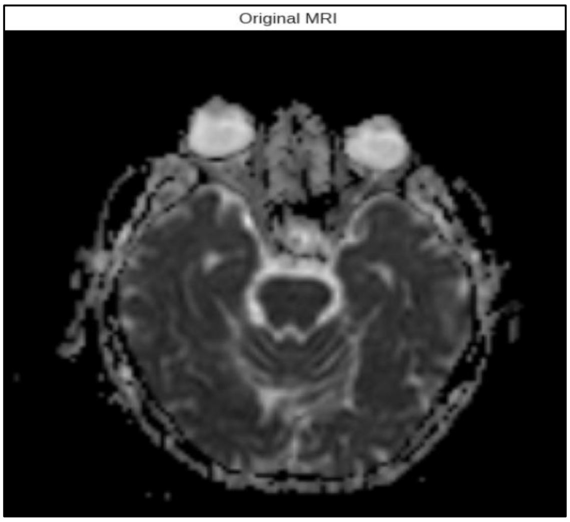


**Figure 5(a).** Original Axial Brain MRI Image Used for Inference

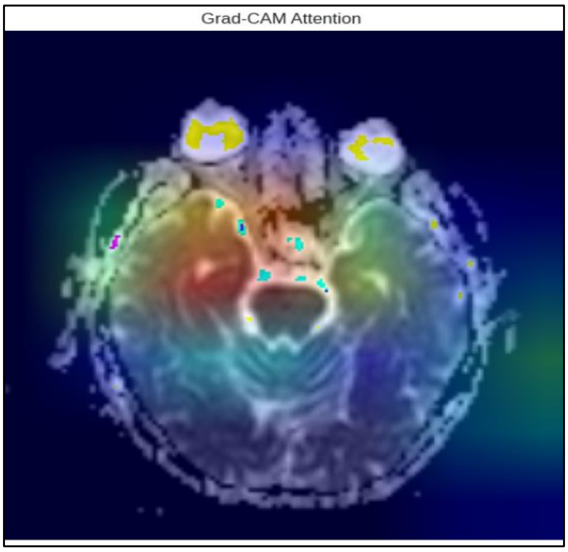


**Figure 5(b).** Grad-CAM Visualizations Illustrating Class-Discriminative Regions Learned by the Proposed CNN

The heatmaps of the dataset focused on specific brain areas makes the model to focus on neurodegenerative changes. The normal MRI scans will display a decreased pathogenic with more dispersed or reduced response patterns. Grad-CAM model increases the CNN prediction based on the MRI images.

### 5.4 Attention-Based Feature Analysis

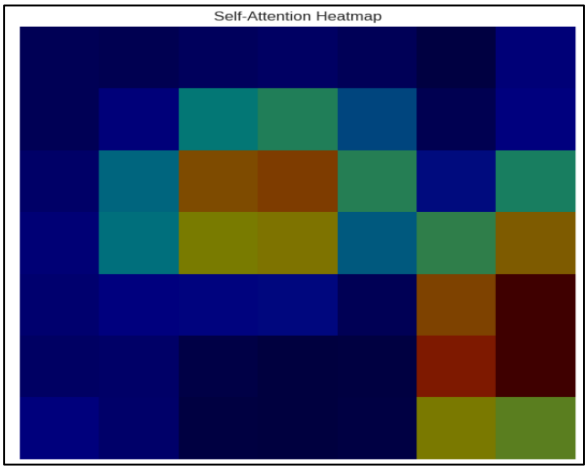


**Figure 5(c).** Self-Attention Heatmap Illustrating Internal Feature Weighting Learned by the Attention Layer

The self-attention heatmaps included in CNN architecture for evaluation. This method focuses on specific areas in the brain for diagnosis. When compared to previous studies, the Grad-CAM provides post-hoc explanations based on the gradient data for spatial features during the forward propagation. Figure 5(c) represents the self-attention heatmaps shows the MRI image for Parkinson's disease. The heatmap shows that the network provides higher attention weights to various parts of the middle brain and basal ganglia are known to be connected to Parkinsonian neurodegeneration. It increases the feature recognition and ability of the model to reduce irrelevant areas for minor pathological changes. This will improve the accessibility and durability of the CNN leads to relevant representation during training

These results reveal Grad-CAM gives external, class-specific visual explanations. Self-attention allows for internal feature-level analysis. The combined operation forms a dual-level explainability model suitable for research-based medical image analysis.

### 5.5 Comparative Analysis

An overview was performed with conventional machine learning and transfer-learning standards to support the architectural decision of a lightweight deployable CNN. The purpose of this study is to show an efficient CNN performance under similar experimental settings. The initial models were developed using the same preprocessing method and training-validation-testing distributed for equality. The following models have been evaluated:

- A Support Vector Machine (SVM) with Histogram of Oriented Gradients (HOG) features.
- Random Forest classifier using custom statistical features.
- VGG16 Transfer-Learning Architecture
- ResNet50 transfer learning architecture.

**Table 2.** Comparative Performance Analysis

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) | ROC–AUC |
|---|---|---|---|---|---|
| SVM (HOG features) | 85.2 | 84.5 | 83.8 | 84.1 | 0.89 |
| Random Forest (handcrafted) | 86.5 | 85.9 | 85.0 | 85.4 | 0.90 |
| VGG16 (transfer-learning) | 90.1 | 89.5 | 90.0 | 89.7 | 0.94 |
| ResNet50 (transfer-learning) | 91.3 | 90.8 | 91.0 | 90.9 | 0.95 |
| Proposed Lightweight CNN | 90.7 | 91.2 | 90.5 | 90.3 | 0.94 |

Table 2 illustrates the comparative performance analysis. The proposed CNN achieved performance compared to deep transfer-learning architectures and maintains reduced computational complexity. This will make the model suitable for real-time, web-based deployment situations.

### 5.6 Web Application Implementation Output

A Flask-based web application was used to assess model performance in real-time, user-accessible settings. The users can upload MRI images in accessible file types including JPG and PNG. The same preprocessing method used during model training utilized an image that provides consistency. The CNN model produces a binary classification result (normal or Parkinson's) and a corresponding confidence score after preprocessing. The MRI upload module and web interface are shown in Figures 6(a) & 6(b) and Figures 7(a) & 7(b). The implementation shows a real-time web-based environment for research-oriented MRI screening and model evaluation may effectively implement the trained CNN.


**Figure 6(a).** AI-Powered Parkinson's Detection Web Interface


**Figure 6(b).** Section Where We Can Upload MRI Scan

Following analysis, the suggested work provides a binary classification (Normal or Parkinson's) and a confidence score for research-based screening.

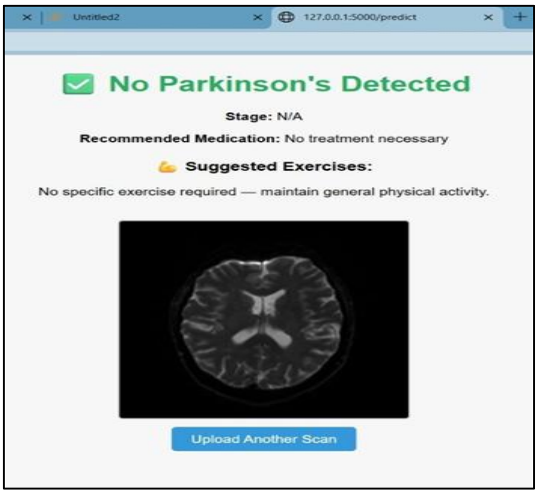


**Figure 7(a).** Result: No Parkinson's Detected

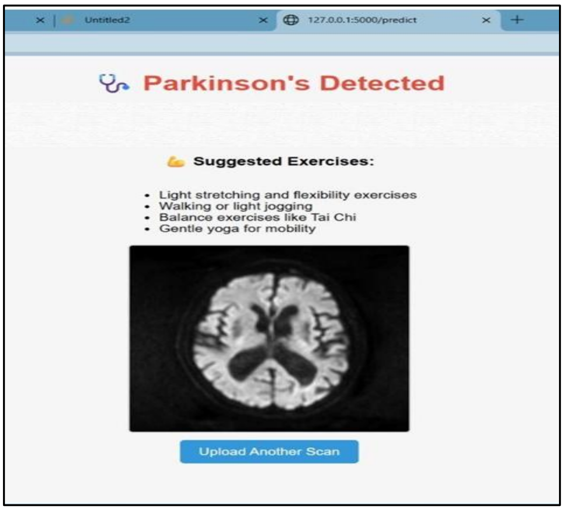


**Figure 7(b).** Result: Parkinson's Detected

## 5.7 Challenges and Constraints

Firstly, the small dataset and limited public repository sources will prevent it from detecting medical variation in the real world utilizing images, multiple approaches, and patient data. Secondly, real-world MRI scans with processed noise, artifacts or quality variations will not appear in the training data, even if the preprocessing methods improve input consistency. Finally, the deep neuroanatomical evaluation and clinical-based data explanation are resolved using the Grad-CAM based visualization that increases interpretability.

# 6. Discussion

The proposed system evaluated Parkinson's disease using automated MRI preprocessing, CNN-based classification, explainable inference and web-based implementation. It reduces the need for people to imagine disconnected offline experiments by integrating the analytical system into a single platform allowing standard and predictable experimentation. The users can utilize systematic preprocessing and real-time inference to test deep learning models that depend on structural modifications in MRI data related to Parkinson's neurodegeneration.

The suggested methodology prioritizes ability, interpretability and evaluation transparency in contrast to many previous MRI-based Parkinson's disease research that only focus on offline accuracy optimization. Complementary explainability is provided by the combination of self-attention and Grad-CAM methods. This system allows experimental validation models without processing medical claims. If it fails to provide qualified medical evaluations, the proposed work will explain the specific treatment or disease stages. The advantages will improve neuroimaging procedures and controlled evaluation of AI models. The web-based system improves accessibility to all users for lightweight implementation and session-based security features suitable for research. The system will decrease the variations in operation that affects the MRI-based AI research and supports preprocessing, inference, evaluation and visualization. After these evaluations, the system architecture will allow minor changes in other neurological disease diagnosis and MRI-based testing methods. The proposed work will use the explainable AI-based neuroimaging research.

## 7. Conclusion

The proposed work developed CNN-based architecture for MRI-driven detection of Parkinson's disease is implemented into a lightweight online development environment. When compared to offline experimental models, the proposed approach integrates standardized preprocessing, automated feature learning, transparent evaluation and real-time prediction into a unified system designed for reliable research application. The results will retrieve the MRI images using CNN to detect Parkinson's disease automatically with controlled settings. In future, this study will focus on multi-dataset validation, various MRI image collections and comparing transfer-learning architectures to improve stability. This method improves MRI-based disease diagnosis systems to increase accuracy for reliable and scalable research applications.

## References

[1] Dorsey, ERlet al, R. Constantinescu, J. P. Thompson, K. M. Biglan, R. G. Holloway, K. Kieburtz, F. J. Marshall et al. "Projected Number of People with Parkinson Disease in the Most Populous Nations, 2005 Through 2030." Neurology 68, no. 5 (2007): 384-386.

[2] Chaudhuri, K. Ray, Daniel G. Healy, and Anthony HV Schapira. "Non-Motor Symptoms of Parkinson's Disease: Diagnosis and Management." The Lancet Neurology 5, no. 3 (2006): 235-245.

[3] Kalia, Lorraine V., and Anthony E. Lang. "Parkinson's Disease." The lancet 386, no. 9996 (2015): 896-912.

[4] Goetz, Christopher G., Barbara C. Tilley, Stephanie R. Shaftman, Glenn T. Stebbins, Stanley Fahn, Pablo Martinez-Martin, Werner Poewe et al. "Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale Presentation and Clinimetric Testing Results." Movement disorders: official journal of the Movement Disorder Society 23, no. 15 (2008): 2129-2170.

[5] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep Learning." nature 521, no. 7553 (2015): 436-444.

[6] Vyas, Tarjni, Raj Yadav, Chitra Solanki, Rutvi Darji, Shivani Desai, and Sudeep Tanwar. "Deep Learning-Based Scheme to Diagnose Parkinson's Disease." Expert Systems 39, no. 3 (2022): e12739.

[7] Liu, Xiao-ge, Shuai Lu, Dong-qun Liu, Lun Zhang, Ling-xiao Zhang, Xiao-lin Yu, and Rui-tian Liu. "ScFv-Conjugated Superparamagnetic Iron Oxide Nanoparticles for MRI-Based Diagnosis in Transgenic Mouse Models of Parkinson’s and Huntington’s Diseases." Brain research 1707 (2019): 141-153.

[8] Eunus, Salman Ibne, Sakib Rokoni, Mitheela Das Armisha, Jasia Hossain Omi, Asika Islam, and Farah Binta Haque. "Hybrid 3D CNN-LSTM Model for rs-fMRI-Based Parkinson’s Prediction." Journal of Independent Studies and Research Computing 23, no. 1 (2025): 8-15.

[9] Skaramagkas, Vasileios, Anastasia Pentari, Zinovia Kefalopoulou, and Manolis Tsiknakis. "Multi-Modal Deep Learning Diagnosis of Parkinson’s Disease—A Systematic Review." IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023): 2399-2423.

[10] Uzzaman, Asad, AFM Nazmus Sakib, Sanjida Ali Shushmita, SM Ashraf Kabir, Md Tanzim Reza, and Mohammad Zavid Parvez. "Parkinson’s Disease Detection Using FMRI Images Leveraging Transfer Learning on Convolutional Neural Network." In 2020 International Conference on Machine Learning and Cybernetics (ICMLC), IEEE, 2020, 131-136.

[11] El Ariss, Omar, and Kaoning Hu. "ResNet-Based Parkinson's Disease Classification." IEEE Transactions on Artificial Intelligence 4, no. 5 (2022): 1258-1268.

[12] Im Abukaresh, ALaa, and Ali Okatan. "AI-Based Early Detection of Parkinson's Disease Using MRI: A Comparative Analysis of Densenet121 and Resnet Models." EURAS JOURNAL OF ENGINEERING AND APPLIED SCIENCES Учредители: Istanbul Aydin University 4, no. 2 (2021): 81-117.

[13] Islam, Md Ariful, Md Ziaul Hasan Majumder, Md Alomgeer Hussein, Khondoker Murad Hossain, and Md Sohel Miah. "A Review of Machine Learning and Deep Learning Algorithms for Parkinson's Disease Detection Using Handwriting and Voice Datasets." Heliyon 10, no. 3 (2024).

[14] Balakrishnan, Aishwarya, Jeevan Medikonda, and Pramod Kesavan Namboothiri. "Role of Wearable Sensors with Machine Learning Approaches in Gait Analysis for Parkinson's Disease Assessment: A Review." Engineered Science 19, no. 13 (2022): 5-19.

[15] Hoehn, Margaret M., and Melvin D. Yahr. "Parkinsonism: Onset, Progression, and Mortality." Neurology 17, no. 5 (1967): 427-427.