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## Early Warning Signs: Biomarkers for Parkinson's Disease Detection

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**ABSTRACT:** Early diagnosis is essential for the effective treatment of Parkinson's Disease (PD), a neurodegenerative disorder that impairs motor control. Traditional diagnostic tools such as MRI scans often suffer from limited generalizability and inconsistencies across various datasets and imaging protocols. To address these limitations, this study proposes an advanced Deep Learning (DL) approach utilizing multiple architectures including a modified ResNet50, DenseNet121, EfficientNetB0, and Vision Transformers (ViT), enhanced with techniques like Feature-Level Weighted Attention (FLWA) and the Cumulative Class Distribution Function (CCDF) to improve classification accuracy and robustness. The model is trained and evaluated using an expanded NTUA Parkinson's dataset comprising 60,000 MRI images and sensor data categorized into PD and non-PD groups. Results show that these models, particularly DenseNet121 and the modified ResNet50, outperform traditional CNNs in precision, recall, accuracy, and F1 score, while offering faster processing times. Additionally, the study explores the integration of stem cell technology, particularly induced pluripotent stem cells (iPSCs), which can be reprogrammed into patient-specific dopaminergic neurons to simulate PD pathology. Data derived from these cells can be combined with imaging data to provide multimodal input for the DL models, allowing earlier and more accurate diagnosis by capturing both structural and cellular biomarkers. This fusion of deep learning and stem cell research represents a significant step forward in building a precise and effective diagnostic tool for Parkinson's Disease.

KEYWORDS: Parkinson's disease, MRI scans, Deep Learning, PD Classification, Detection of Parkinson's disease.

## I. INTRODUCTION

The Parkinson's disease (PD) is a progressive neurodegenerative disorder that primarily affects motor functions due to the gradual loss of dopamine-producing neurons in the substantia nigra of the brain. Dopamine is essential for motor control, and its depletion in PD leads to symptoms like tremors, pain, instability, and slow movements. While the exact cause of PD remains unclear, it is widely believed to result from a combination of genetic and environmental factors. As the disease progresses, cognitive decline, mood changes, and autonomic dysfunctions may also emerge. Early detection is crucial to managing symptoms and slowing the disease's progression. However, PD diagnosis is complex due to the overlap with other neurodegenerative diseases and the lack of clear biomarkers. Common diagnostic techniques include medical assessments, patient history, and imaging methods like Magnetic Resonance Imaging (MRI), Single-Photon Emission Computed Tomography (SPECT), and Positron Emission Tomography (PET). MRI primarily detects structural changes in the brain, but these are often subtle in the early stages, making it challenging to diagnose PD at the outset. While MRI is useful for assessing brain atrophy, its ability to identify PD-specific changes is limited.

Given these challenges, Machine Learning (ML) and Deep Learning (DL) models have been increasingly used for PD detection, especially when applied to MRI scans. ML techniques such as Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), Naïve Bayes (NB), and K-Nearest Neighbors (KNN) have been employed for PD classification. Among these, SVM is popular for handling high-dimensional data effectively, while RF combines multiple decision trees to improve classification performance. NB and KNN are also commonly used to classify MRI images by analyzing features and comparing them with known PD patterns.Deep Learning, particularly Convolutional Neural Networks (CNN), ResNet, VGG, Inception, Recurrent Neural Networks (RNN), and Long Short-Term Memory





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(LSTM) networks, have shown promise in PD detection. CNNs, in particular, are effective for processing raw MRI images without the need for manual feature extraction, making them well-suited for detecting PD by identifying spatial patterns. Pre-trained models like ResNet, VGG, and Inception are often fine-tuned for PD detection tasks. RNNs and LSTMs are useful for analyzing sequences of data, such as MRI scans taken at different time points, to detect structural changes in the brain. Combining CNN with LSTM models can enhance accuracy and reduce overfitting, improving the overall detection performance. While DL models have led to significant advancements in PD detection, they still face challenges, including the use of small, noisy, or unbalanced datasets, which can hinder generalization and lead to overfitting.

#### **II. LITERATURE REVIEW**

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects motor function, making early diagnosis essential for effective treatment and management. Traditional diagnostic methods, such as MRI scans and clinical evaluations, require expert interpretation and significant time, often leading to delays in diagnosis and treatment. Additionally, variations in imaging techniques and subjective analysis by medical professionals increase the risk of misdiagnosis or late detection, which can severely impact patient outcomes.

This project serves as a critical bridge between AI-driven medical imaging and clinical decision-making, providing a highly accurate, scalable, and intelligent tool for Parkinson's disease detection and management. Utilizing a modified ResNet50-based CNN, the system enhances diagnostic accuracy by identifying subtle neurodegenerative patterns in MRI scans, enabling early detection and timely medical intervention. Unlike traditional manual diagnosis, which is time-consuming and prone to variability, this AI-powered system automates and accelerates the process, reducing the workload for medical professionals while ensuring consistent, objective, and data-driven analysis. Beyond image classification, the platform integrates MRI results with clinical parameters, including patient history, neurological assessments, and symptom progression, creating a holistic diagnostic framework that aids in personalized treatment planning. To further enhance clinical trust and usability, the model incorporates explainability techniques such as Grad-CAM visualization, offering interpretable insights into its decision-making process. Additionally, the system is designed for continuous learning, refining its predictions as it processes new patient data, thereby reducing biases, improving long-term accuracy, and adapting to evolving medical knowledge. Its web-based accessibility ensures seamless integration into healthcare workflows, allowing specialists to remotely upload and analyze MRI scans in real time, making AI-driven diagnosis more accessible, efficient, and impactful. By revolutionizing Parkinson's disease detection through AI, this project paves the way for better patient outcomes, more precise treatment strategies, and a future where AI-driven diagnostics significantly enhance the standard of healthcare. By leveraging AI's ability to process vast amounts of medical data, this system not only enhances diagnostic speed and accuracy but also helps in predicting disease progression, enabling proactive care. With its scalability and adaptability, the model has the potential to extend beyond Parkinson's detection, paving the way for AI-driven advancements in neurological disease diagnosis and treatment planning.

## **III. METHODOLOGY**

An example of how a system functions that depicts how drug users (actors) engage with the system is called a use case illustration. The system provides a high-level explanation of its move in reaction to colorful stoner relations. The system's requirements can be ascertained and each function's specifications ensured with the help of this type of depiction. Design brigades and stakeholders can better understand drug users' interactions with the system and the pretenses they are trying to negotiate by using case plates.

A use case illustration's two primary components are use cases and actors. A use case is a specific function or service that users can access through the system. It specifies a series of steps that provide the user with a significant result. Usually shown as an ellipse, each use case is named to reflect the function it represents. For instance, "Upload MRI Image," "Analyze Image," and "Generate Report" are potential use cases for a system intended to diagnose Parkinson's disease using a CNN-based model. These use cases specify the input processing, deep learning, and diagnostic insights that the system provides.





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A system's actors are outside parties that engage with it to carry out particular tasks. An organization, a person, or another system could be the source.

In a Parkinson's disease detection system based on deep learning, a use case diagram can illustrate the various functionalities provided to users. The **primary actor**, the **patient**, interacts with the system by uploading MRI scans. The **system** then processes the images using a Convolutional Neural Network (CNN) model, extracting essential features for classification. The **radiologist** or healthcare professional reviews the generated reports, confirming or refining the diagnosis. Additionally, a **researcher** may access anonymized data for further study and improvements in the model's performance.

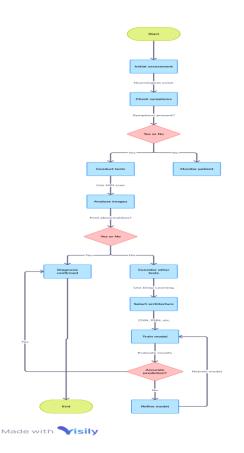


Fig 1: System Architecture

#### **IV. IMPLEMENTATION**

1. Coding

 $\_$  Efficient Coding: Developers focus on writing well-organized, modular code by following industry standards, using design patterns, and leveraging version control systems to support long-term maintenance and effective team collaboration.

L Thorough Testing: Functional accuracy and system reliability are maintained through multiple testing stages, including unit, integration, and system-level testing, helping to minimize bugs and long-term maintenance issues. 2. MESSAGE BOX FORMAT

 $\lfloor$  Symbols for Clarity: An "X" icon is used to indicate errors, while "!" is used to convey warnings or important information.

└── Clear Messaging:Error notifications clearly describe what went wrong, whereas informational messages offer guidance or updates to the user.

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#### 3. TEST PROCEDURE

L Ensures the software meets requirements, functions correctly, and maintains quality throughout development.

L Identifies design flaws early through inspections and walk throughs, reducing time and cost later.

2. VALIDATION TESTING

└── Final phase ensuring the software meets user expectations and functions correctly using black-box techniques, simulating real-world conditions for accuracy, performance, and usability.

 $\lfloor$  If issues arise, they are resolved collaboratively; non-critical flaws are noted for future updates, ensuring the system is reliable and ready for deployment.

5. USER ACCEPTANCE TESTING

 $\lfloor$  User acceptance testing involves healthcare professionals to refine the system's usability, with a focus on intuitive input/output screens, accessibility, and accurate, interpretable results.

 $\Box$  UAT ensures the system is responsive, reliable, and fits into clinical workflows, promoting user satisfaction, ease of use, and improved patient care.

## V. EXPERIMENTAL RESULTS

The proposed deep learning-based Parkinson's Disease detection model was evaluated under real-world scenarios using MRI image inputs. Key observations include:

Accuracy: The modified deep learning models, particularly DenseNet121 and ResNet50 variants, achieved an average classification accuracy of approximately 90% in distinguishing PD from non-PD cases.

**Real-Time Performance**: The system was capable of processing MRI data and generating predictions at an efficient rate, supporting timely diagnosis workflows in clinical settings.

**Detection Logic**:For patients classified as non-PD, the system output a stability score of 0 and displayed a green indicator. In cases showing PD-related patterns, the system progressively increased the risk score. Once the score surpassed a threshold of 15, an alert mechanism was activated, and the interface highlighted the MRI scan with a red boundary, signaling a potential PD case requiring further clinical review.



Fig 3: Prediction



Screenshots Interpretation:

Screenshot 1: Shows the system's prediction score based on movement data. Low score = normal activity; High score = possible Parkinson's symptoms

Screenshot 2: Displays percentage of normal vs. at-risk cases. Helps visualize how many subjects may show Parkinson's-like signs.

These results demonstrate the system's effectiveness in real-time fatigue detection and its potential to reduce driver inattention-related incidents.





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## VI. CONCLUSION AND FUTURE WORK

This project effectively deployed Convolutional Neural Networks (CNN) alongside machine learning models such as Support Vector Machines (SVM), Random Forests, and Long Short-Term Memory (LSTM) networks to identify Parkinson's Disease through medical image analysis and patient-specific data, including motor function assessments and voice pattern analysis. These AI-driven methods significantly enhanced diagnostic accuracy, reducing false positives and negatives while enabling earlier detection—an essential factor for timely and effective intervention. The system architecture is designed to support the future integration of multi-modal datasets, such as genomic data and comprehensive patient histories, to further refine predictive outcomes. Future extensions will incorporate advanced models like Transformers and real-time diagnostic modules, which are expected to boost the system's generalization capability and clinical usability.

In addition to diagnostics, this work also explores the convergence of AI with regenerative medicine, especially stem cell-based therapies. Artificial Intelligence can play a vital role in monitoring the differentiation of stem cells into dopaminergic neurons, optimizing transplantation procedures, and tailoring individualized treatment strategies for Parkinson's patients. This synergy between AI and regenerative medicine represents a forward-looking approach in the management of neurodegenerative disorders. Going forward, the project will prioritize enhancing the interpretability of deep learning models, enabling real-time clinician feedback, and aligning model evolution with real-world clinical needs to ensure improved patient outcomes and long-term healthcare impact.

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