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Detection of Parkinson's Disease Using Convolutional Neural Networks

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***Abstract*—**Parkinson's Disease (PD) is a progressive neurological disorder that primarily affects the motor system, leading to symptoms such as tremors, rigidity, and impaired movement. Accurate early diagnosis remains challenging because PD shares clinical characteristics with several other neurological conditions, contributing to an estimated 25% inaccuracy rate in manual diagnosis. This paper presents a Convolutional Neural Network (CNN)-based automated system designed to classify PD patients from healthy controls (HC) using T2-weighted Magnetic Resonance Imaging (MRI) data sourced from the Parkinson's Progression Markers Initiative (PPMI). Mid-brain slices from 500 MRI scans are selected and spatially aligned via image registration. The system pipeline includes grayscale conversion, noise removal, feature extraction, and CNN-based classification. Performance evaluation using accuracy, sensitivity, specificity, and AUC demonstrates that the proposed CNN model outperforms existing techniques by 3%–9% across all metrics. The system provides a reliable, automated decision-support tool to assist neurologists in early and consistent diagnosis.

***Keywords*—**Parkinson's Disease; Convolutional Neural Network; Deep Learning; MRI; Medical Image Analysis; Early Diagnosis

I. INTRODUCTION

Parkinson's Disease is a neurodegenerative disorder affecting millions of individuals worldwide. It predominantly impacts the motor system, producing hallmark symptoms such as resting tremors, bradykinesia, muscle rigidity, and postural instability. Early-stage diagnosis is essential because timely intervention significantly slows symptom progression and improves quality of life for patients.

Conventional diagnosis relies on clinical observation and neurological assessments performed by specialists. This approach is inherently subjective and often fails to detect the disease during its early phase, when physical manifestations are subtle and overlap with other conditions. Pereira et al. reported that hand-drawn exams of both healthy individuals and early-stage PD patients appear similar, highlighting the difficulty of early detection

Advances in deep learning, particularly Convolutional Neural Networks, have demonstrated strong performance across a range of medical image classification tasks

This research proposes a CNN-based automated system that processes T2-weighted MRI images to classify subjects as either PD-affected or healthy. The system integrates preprocessing, feature extraction, and deep learning-based classification into a unified pipeline, with the aim of providing a consistent and scalable diagnostic aid.

II. PROBLEM DEFINITION

Detecting Parkinson's Disease, especially at an early stage, involves several practical difficulties:

- **Early-stage ambiguity:** Motor symptoms in PD's initial stages closely resemble those of other neurological conditions. Hand-drawn diagnostic exams from healthy and early-stage PD patients are often indistinguishable
- **Limited and biased datasets:** MRI datasets specific to PD graphic diversity of the patient population, making general- isation of trained models a persistent challenge.
- **Cost of at-home monitoring:** Continuous patient monitoring outside clinical settings requires specialised and expensive hardware, limiting long-term follow-up
- **Subjectivity in manual diagnosis:** Clinician-based assessment introduces variability, contributing to the approximately 25% misdiagnosis rate reported in the literature.

An automated system that can reliably analyse MRI scans and distinguish PD-affected patients from healthy individuals addresses each of these challenges by reducing subjectivity and scaling to large datasets.

III. EXISTING SYSTEM

Current approaches to Parkinson's Disease diagnosis include:

Clinical Observation: Neurologists assess motor symptoms such as tremors and gait disturbances. While practical, this method is subjective and dependent on the clinician's experience.

Manual MRI Analysis: Radiologists inspect brain scans for structural abnormalities. This process is time-consuming and prone to inter-observer variability, particularly for subtle early-stage changes.

Traditional Machine Learning: Earlier computational approaches applied Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Naive Bayes classifiers to engineered feature sets. These methods require domain-specific feature extraction and do not generalise well to varied imaging conditions

Imaging Modalities: Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) offer valuable biomarker information but involve radioactive tracers and higher costs, limiting their routine use. Structural MRI has historically played a limited role; how-

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potential for detecting PD-related brain changes

IV. PROPOSED SYSTEM

The proposed system applies a deep CNN architecture to T2-weighted MRI images to automate the classification of Parkinson's Disease. Key advantages of this approach include:

Automated Feature Learning: The CNN learns discriminative spatial features from raw MRI data through stacked convolutional and pooling layers, removing the need for manual feature engineering.

Contextual Spatial Understanding: Convolutional operations capture local neighbourhood relationships in brain images, enabling the model to detect subtle structural changes associated with PD that are imperceptible to the human eye.

Standardised Pipeline: The system applies a consistent preprocessing routine—including noise removal, grayscale conversion, and image registration—ensuring uniformity across different patient scans before classification.

Quantitative Evaluation: Model outputs are evaluated using accuracy, sensitivity, specificity, and the Area Under the ROC Curve (AUC), providing a comprehensive picture of diagnostic performance beyond simple accuracy metrics.

V. OBJECTIVE

The specific objectives of this project are:

- To collect T2-weighted MRI brain images of PD patients and healthy individuals from the PPMI public dataset.
- To preprocess MRI data through grayscale conversion, median filtering for noise removal, and image registration for spatial alignment of mid-brain slices.
- To implement a CNN-based classification model that distinguishes PD-affected subjects from healthy controls.
- To evaluate model performance using accuracy, sensitivity, specificity, and AUC metrics.
- To compare the deep learning model's performance against traditional machine learning approaches.

VI. LITERATURE SURVEY

A growing body of research has applied machine learning and deep learning techniques to Parkinson's Disease detec- tion across multiple data modalities.

Bhan and Kapoor proposed a deep learning model for classifying PD from MRI scans, demonstrating that automated approaches substantially reduce diagnostic time while improving accuracy over manual methods

Qiu et al. introduced a multiscale convolutional prototype network for PD detection using EEG signals, leveraging multiscale feature extraction to achieve robust cross-subject generalisation

Rizvi et al. proposed UEN-PDNet, a deep neural network for classifying PD from resting-state EEG, capturing discriminative temporal-spatial signal patterns with strong accuracy

Zhang et al. analysed EEG-based brain functional networks for early-stage PD detection, constructing connectivity graphs and applying machine learning classifiers to network-level features

Dai et al. conducted a comprehensive review of data-driven PD diagnostic systems across gait, voice, and imaging modalisons

Demir et al. presented an LSTM-based framework that maps speech features to capture temporal dysarthric patterns, demonstrating that voice recordings serve as reliable non-invasive PD biomarkers

Talitckii et al. identified optimal wearable sensor exercises for PD detection using machine learning, contributing to evidence-based data-collection protocol design

Chauhan and Ghosal introduced a hybrid CNN-BiLSTM model that combines spatial feature extraction with tempo- ral sequence learning on multimodal inputs including gait, speech, and handwriting data

Santos et al. converted EEG data into graph representations and applied residual neural networks for PD classification, capturing spatial-topological electrode relationships

Malekroodi et al. utilised large self-supervised speech models fine-tuned for PD detection, representing a recent shift toward foundation-model-based medical diagnostics

VII. SOFTWARE REQUIREMENTS

- **Operating System:** Windows 10/11 or Linux
- **Programming Language:** Python 3.8 or higher
- **Libraries:** OpenCV, TensorFlow/Keras, NumPy, Pandas, Matplotlib, Scikit-learn, Seaborn
- **IDE:** Jupyter Notebook / Visual Studio Code
- **Toolbox:** Image Processing Toolbox (OpenCV)

VIII. HARDWARE REQUIREMENTS

- **Processor:** Intel Core i3/i5 at 2.4 GHz or better
- **RAM:** 4 GB minimum (8 GB recommended)
- **Storage:** 500 GB hard disk
- **GPU:** NVIDIA GPU recommended for model training; CPU sufficient for inference

IX. METHODOLOGY

The proposed methodology is structured as a sequential image processing and classification pipeline:

Image Collection: T2-weighted MRI scans of 500 subjects are obtained from the PPMI public dataset, comprising both PD-affected patients and healthy controls.

Image Preprocessing:

- *Grayscale Conversion:* RGB MRI images are converted to 8-bit grayscale, reducing memory requirements by approximately 33% and simplifying downstream feature computation.
- *Noise Removal:* A non-linear median filter is applied using a sliding window of odd length. Each sample within the window is sorted by magnitude and replaced by the me- dian value, preserving edge information while suppressing random pixel noise.
- *Image Enhancement:* Global thresholding removes background regions and retains structures of diagnostic interest. A high-pass filter amplifies fine spatial details, sharpening structural boundaries within the mid-brain.

Image Segmentation: The processed image is partitioned into meaningful regions using a mean-shift clustering algorithm. This sliding-window approach iteratively converges toward high-density pixel clusters, isolating brain structures from surrounding tissue.

(HOG) descriptors are computed from preprocessed images. For each pixel, the horizontal and vertical gradient components (G_x and G_y) are calculated, from which gradient magnitude and orientation angle are derived. Orientation frequencies are binned into histograms that constitute the feature vector fed into the classifier.

CNN-Based Classification: The preprocessed image is passed directly through the CNN, which performs its own internal feature learning via stacked convolutional, rectification, and pooling layers. A SoftMax output layer produces class probability scores for the PD and HC categories.

Evaluation: Model performance is assessed using accuracy, sensitivity, specificity, and AUC to provide a multidimensional view of diagnostic reliability.

X. SYSTEM DESIGN

The overall system architecture processes MRI data through a sequence of well-defined modules:

1. Image Collection — acquisition of T2-weighted MRI scans.
2. Image Preprocessing — grayscale conversion, noise removal, and image enhancement.
3. Image Segmentation — region-of-interest extraction using mean-shift clustering.
4. Feature Extraction — HOG descriptor computation.
5. Training — CNN model training on labelled MRI slices.
6. Classification — prediction of PD or healthy status.

A. CNN Architecture

The network consists of alternating convolutional and pooling layers followed by fully connected layers and a SoftMax output. The convolutional layer applies learnable filters across the input image to generate feature maps. The pooling layer performs max-pooling to downsample spatial dimensions and retain dominant activations. The fully connected layer flattens the feature maps into a single vector, which is then mapped to class probabilities by the output layer

B. MVC Architecture

The application follows a Model-View-Controller pattern. The *Model* encapsulates the CNN inference logic. The *View* is the Python Tkinter GUI, which accepts MRI image input from the user and displays the classification result. The *Controller* coordinates data flow between the interface and the deep learning backend.

XI. SYSTEM TESTING

Testing was carried out on a Windows 10 machine with an Intel Core i5 processor and 8 GB RAM, using Python with OpenCV and TensorFlow libraries. The GUI was validated using the Python Tkinter framework.

Unit Testing: Individual functions—including grayscale conversion, median filtering, and CNN inference—were tested in isolation to verify that each module produces correct outputs independently. This phase ensured that foundational components were defect-free before system integration.

Integration Testing: The communication between the Tkinter frontend and the CNN backend was validated to confirm that selected MRI images are correctly forwarded to the inference engine and that classification results are returned and displayed without format mismatches. Both bottom-up and top-down integration strategies were applied.

System Testing: The complete application was evaluated as a unified system against all specified functional and non-functional requirements. Testing verified OS compatibility across Windows XP and Windows 10, confirming that performance is best on Windows 10. Latency measurements confirmed that the system delivers predictions within an acceptable response time for practical clinical use.

XII. RESULT

Experimental evaluation demonstrates that the CNN-based model outperforms traditional machine learning classifiers across all metrics. The system accurately distinguishes PD-affected MRI scans from healthy controls, particularly in cases where early-stage structural differences are subtle.

Table 1. Model Performance Comparison

Method	Accuracy (%)	AUC
SVM (Traditional)	87	0.85
KNN	83	0.81
CNN (Proposed)	**95**	**0.97**

The proposed CNN model achieved an improvement of 3%–9% over existing techniques in terms of accuracy, sensitivity, specificity, and AUC, consistent with findings reported in the literature for deep learning-based PD detection

XIII. CONCLUSION

This paper presented a CNN-based automated system for the early detection of Parkinson's Disease using T2-weighted MRI brain images. The proposed pipeline integrates grayscale conversion, median filtering, global thresholding, HOG-based feature extraction, and deep CNN classification into a cohesive diagnostic framework.

Experimental results confirm that the CNN model significantly outperforms conventional machine learning approaches by capturing spatial feature hierarchies that man- ual methods miss. The system reduces diagnostic subjectiv- ity, scales to large imaging datasets, and provides quantitative confidence scores to support clinical decision-making.

Future work will focus on training the model on larger and more diverse patient cohorts to improve generalisation. Integration of complementary modalities—including EEG signals, speech biomarkers, and gait data—can further enhance diagnostic robustness. Incorporating explainable AI techniques such as Grad-CAM will improve clinical interpretability, and deployment as a cloud-based web application will support remote patient monitoring.

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