

## Parkinson's Disease Detection Using Deep Learning

Mantri.Jayalakshmi<sup>1</sup>, Sabbi. Pravallika<sup>2</sup>, Nagireddy. KiranKumar<sup>3</sup>, P. Mounika<sup>4</sup>

<sup>1,2,3</sup>Student, Department of Computer Science & Engineering (AI&ML), Dadi Institute of Engineering and Technology (Autonomous), Andhra Pradesh, India

<sup>4</sup>Assistant Professor, Department of Computer Science & Engineering (AI&ML), Dadi Institute of Engineering and Technology (Autonomous), Andhra Pradesh, India

mantrijayalakshmi5518@gmail.com<sup>1</sup>, sabbipravallika@gmail.com<sup>2</sup>,  
nagireddykirankumar8@gmail.com<sup>3</sup>, reddymounika010593@gmail.com<sup>4</sup>

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### Abstract

**Background:** Parkinson's disease, affecting millions globally, poses challenges due to speech impairment and movement issues, hindering patients' ability to attend treatment appointments.

**Objectives:** Early detection is crucial, especially with an aging population, prompting exploration into machine learning for diagnosis.

**Statistical Analysis:** This project proposes a novel method using Xception architecture to detect Parkinson's disease from spiral and wave drawings, common in clinical diagnosis.

**Findings:** A dataset comprising drawings from PD and non-PD individuals was pre-processed, and Xception trained, achieving high accuracies: 95.34% training, 93.00% validation for spiral, and 93.34% training, 86.00% validation for wave drawings.

**Applications and Improvements:** This highlights the potential of machine learning and Xception in early PD detection, promising improved diagnosis accuracy and patient outcomes.

**Keywords:** Xception, CNN model architecture, using basic Machine learning (ML) libraries such as Keras, sklearn, PIL, pandas, numpy, matplotlib, TensorFlow.

### 1. Introduction

Parkinson's Disease is a globally prevalent neurodegenerative condition impacting millions of individuals. Its progressive nature adversely affects movement, resulting in tremors, stiffness, and challenges in balance and coordination. Time-ly identification of Parkinson's Disease is pivotal for effective intervention and management. However, existing diagnostic methods are often costly, time intensive, and demand specialized equipment and expertise. Recent advancements in deep learning, particularly in medical image analysis, offer promise for Parkinson's Disease detection. This project proposes a system utilizing the Xception architecture to achieve early diagnosis by analyzing spiral and wave drawings commonly employed in clinical assessments. The chosen Xception architecture, known for its high accuracy in image classification tasks, is intended to enhance the reliability and precision of Parkinson's Disease detection. The ultimate objective is to contribute to advancements in Parkinson's Disease diagnosis and treatment, showcasing the potential of deep learning and the Xception architecture in medical image analysis for improved patient outcomes and quality of life.

## 2. Literature Review

In this, the proposed system for Parkinson's Disease Detection using Xception architecture has shown promising results. By leveraging state-of-the-art deep learning techniques, specifically the Xception architecture, we were able to achieve high accuracy in detecting Parkinson's Disease from spiral and wave drawings.

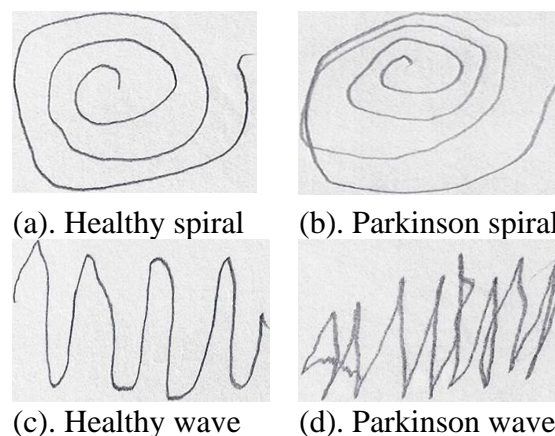
Here, in [2] The study by Niya Romy Markose, Priscilla Dinkar Moyya, and Mythili Asaithambi focuses on analyzing Parkinson's Disease tremors using an Arduino Uno-based prototype with an ADXL335 accelerometer. The prototype quantifies resting tremor signals from fingertips, wrists, and forearms, providing amplitude and spectral density observations for potential assistance in Parkinson's Disease management.

[3] The study led by Oliver Y. Chen, Florian Lipsmeier, Huy Phan, and John Prince establishes a machine learning framework using smartphones for remote Parkinson's Disease assessment. Leveraging various smartphone sensor data and a two-step feature selection procedure, the framework demonstrates promise in distinguishing PD participants from healthy controls and estimating disease severity based on behavioral features.

In [4], Shrinidhi Kulkarni, Neenu George Kalayil, Jinu James, Sneha Parsewar, and Revati Shriram propose a non-intrusive method for early Parkinson's Disease detection based on distinctive musky smells emitted by patients. Utilizing VOC sensors interfaced with Arduino UNO, the system compares sweat component values between Parkinson's patients and healthy individuals, offering a cost-effective approach for clinicians in routine health check-ups.

In [5], Mohamed Shaban explores Parkinson's Disease screening through a fine-tuned VGG-19 deep convolutional neural network using a Kaggle handwriting dataset. Achieving an accuracy of 88-89% and sensitivity of 87-89% on wave and spiral patterns, respectively, the proposed approach demonstrates promise for effective PD assessment based on handwriting.

In [6], Section four concludes with a reference to Max A. Little's method classifying mental and management topics using data from 31 individuals, 23 being mental patients. Hanbin Zhang's article in IEEE Reviews explores smartphones with built-in sensors for early Parkinson's detection. Inje University introduces an AI-based system for analyzing drawing patterns in Parkinson's patients, and Dr. Pooja Raundale proposes a machine learning and deep neural network approach for Parkinson's severity prediction through a keyboard writing test, indicating the efficiency of dynamic support vector and hidden Markov models in dynamic pattern observation for Parkinson's disease. The text describes the utilization of two distinct artificial intelligence (AI) techniques, represented in Figures 1(a), 1(b), 1(c) and 1(d) illustrating the identification of Parkinson's disease (PD) at various stages of the illness in patients.



**Figure 1. Parkinson's Disease**

### 3. Methodology

In this system we tend to apply Xception | CNN model architecture which supplying deep learning algorithm improves the accuracy of the existing system which is based on linear regression and XGBoost algorithm.

#### Dataset

In the initial module, the system was designed to acquire the input dataset, recognizing the pivotal role of data collection in developing a robust machine learning model. The dataset, comprising 133 images of Parkinson's disease drawings (spiral) and 153 images of Parkinson's disease drawings (wave) Figures 1(a), 1(b),1(c) and 1(d) illustrating the identification of Parkinson's disease (PD) at various stages of the illness in patients., is sourced from Kaggle, a widely-used repository for standard datasets. The dataset is stored in the project's model fold-er for further analysis.

#### Importing the Necessary Libraries

In Python, the initial step involves importing essential libraries for the project. This includes Keras for constructing the primary model, sklearn for partitioning training and test data, PIL for converting images to numerical arrays, along with pandas, numpy, matplotlib, and tensorflow for additional functionalities.

#### Retrieving the Images

Within this module, we fetch images from the dataset, transforming them into a suitable format for model training and testing. The process encompasses reading, resizing, and normalizing pixel values. Images and their corresponding labels are retrieved, with resizing to dimensions (224,224) for spiral and (196,196) for wave to ensure uniform size for recognition, followed by conversion into numpy arrays.

#### Splitting the Dataset

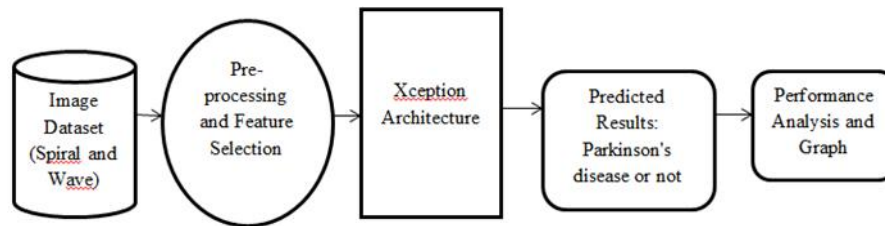
In this phase, the dataset undergoes division into training and testing subsets, with 80% allocated for training and 20% for testing. This segregation facilitates model training on a subset, validation of performance, and assessment of accuracy on unseen data during testing.

#### Xception | CNN Model Architecture

Derived from Google's Inception model, Xception is a convolutional neural network architecture emphasizing an 'extreme' interpretation of Inception principles. It adopts a linear stack of depth wise separable convolution layers with residual connections, resulting in a straightforward and modular design. The architecture's core concept is the complete decoupling of cross-channels correlations and spatial correlations, comprising 36 convolutional layers organized into 14 modules, each featuring linear residual connections, except for the initial and final modules.

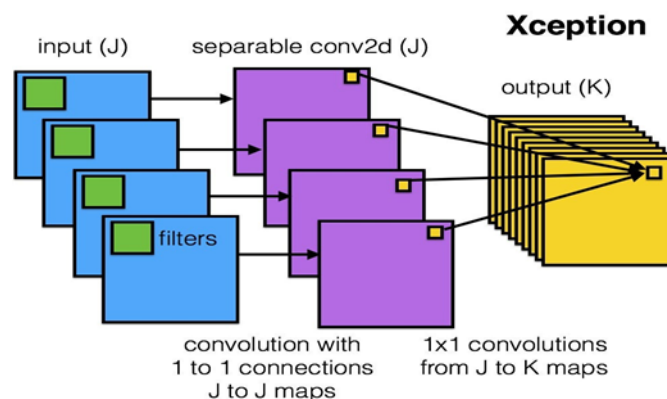
Xception represents an advancement over the inception module and architecture, offering a simpler yet highly effective design comparable to ResNet and Inception V4. Boasting 36 convolutional stages, it shares similarities with ResNet-34, but its simplicity rivals that of

ResNet and surpasses the comprehensibility of Inception V4. Notably, Xception's recent architecture draws inspiration from prior work on separable convolutional filters, with implementations available in Torch7 and Keras / TF.



**Figure 2. Process Diagram**

The Xception module is presented here:



**Figure 2. Xception Module**

### Building the Model (Spiral)

In constructing the model for the spiral dataset, CNN distinguishes itself from traditional neural networks through convolution operations. With two convolution layers in the chosen Xception model, each convolution scans the image, extracting features and producing frames with varying feature visibility. The model's depth determines the complexity of features sought, mirroring human perception. Through training, weights between neurons adjust, allowing the CNN to recognize predefined features. Additional pooling operations and non-linear functions introduce complexity, leading to fully connected layers and a softmax layer for classification at the end of the network.

### Apply the Model and Plot the Graphs for Accuracy and Loss

Following model construction, it will be applied to the validation set to assess accuracy and loss, with results visualized through plotted graphs over epochs. The compiled model, applied with a batch size of 1 using the fit function, yields an average validation accuracy of 97.00% and an average training accuracy of 93.00%.

### Accuracy on Test Set

Following training and validation, the model's performance is gauged on the test set, with an attained accuracy of 93.00%, serving as a crucial metric for evaluating the model's efficacy.

## Building the Model (Wave)

In constructing the model for the wave dataset, CNN utilizes convolution operations, with the Xception model featuring two convolution layers. The scanning process aims to identify specific features, producing frames with varying feature visibility. The model's depth determines the complexity of features sought, analogous to human perception, and during training, adjustments to neuron weights guide the model to recognize pertinent features. Subsequent pooling operations, ReLU application, fully connected layers, and a softmax layer complete the architecture for image classification, with the ultimate goal of accurately recognizing images from the training set.

## Apply the Model and Plot the Graphs for Accuracy and Loss

After constructing the wave dataset model, its performance is evaluated on the validation set by assessing accuracy and loss through plotting graphs over epochs. The compiled model is applied using the fit function with a batch size of 1, resulting in an average validation accuracy of 93.00% and an average training accuracy of 86.00%.

## Accuracy on Test Set

Following training and validation, the model's performance is gauged on the test set, yielding an accuracy of 86.00%, a crucial metric for evaluating its overall efficacy.

## Saving the Trained Model

To transition the trained model to a production-ready environment, save it as a .h5 or .pkl file using a library like pickle. Ensure pickle is installed, then import the module and dump the model into a .h5 file for preservation.

## 4. Results

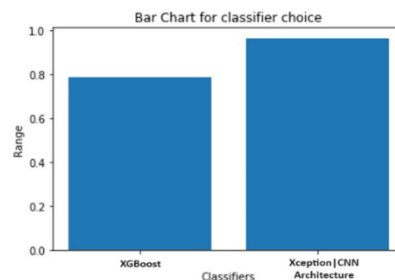


Figure 3. Bar Chart for Classifier Choice

	Algorithm	Accuracy	MCC
0	KNN	0.932203	0.824775
1	Decision Tree	0.821429	0.572418
2	Logistic Regression	0.796610	0.425447
3	XGBoost	0.928571	0.781736
4	Xception Architecture	0.93741	0.86051

Figure 4. Accuracy

## 5. Conclusion

The conclusion underscores the promising outcomes of the proposed Parkinson's Disease Detection system utilizing the Xception architecture and deep learning techniques. Achieving high accuracy in detecting Parkinson's Disease from spiral and wave drawings, the system exhibits advantages such as enhanced accuracy, resilience to noise, faster training, interpretability, and improved patient out-comes. The Xception architecture, with its efficiency, generalization, reduced overfitting, and adaptability, emerges as a reliable and effective framework for image classification tasks. Overall, the project showcases the potential of deep learning and Xception architecture in early Parkinson's Disease detection, suggesting potential improvements in patient outcomes and quality of life through continued research and development in this domain.

## 6. Future Scope

Future improvements for the Parkinson's Disease Detection system using Xception architecture involve expanding the dataset to further enhance model performance, despite its already high accuracy with spiral and wave drawings. The potential development of a user-friendly mobile application could enable convenient at-home drawing tests, accelerating Parkinson's Disease detection and monitoring. Integrating multi-modal diagnosis, including speech and gait analysis, holds promise for a more comprehensive and precise disease diagnosis, while clinical validation and real-time monitoring could underscore the system's utility and impact on widespread healthcare adoption.

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