

e-ISSN: 2319-8753 | p-ISSN: 2347-6710

DIA

International Journal of Innovative Research in SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 3, March 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

 \bigcirc





e-ISSN: 2319-8753, p-ISSN: 2347-6710 www.ijirset.com | Impact Factor: 8.423 | A Monthly Peer Reviewed & Referred Journal |



Volume 13, Issue 3, March 2024

DOI:10.15680/IJIRSET.2024.1303107

Deep Learning for Early Parkinson's Identification

D. Murli Krishna Reddy^[1], Chegireddy Vandana^[2], Bindu Madhavi Palaparti^[3],

Banavathu Tarun Naik^[4], Doppalapudi Vijay Bhanu^[5]

Asst. Professor of Computer Science and Engineering, Vasireddy Venkatadri Institute of Technology, Guntur,

Andhrapradesh, India^[1]

Undergraduate student of Computer Science and Engineering, Vasireddy Venkatadri Institute of Technology, Guntur,

Andhrapradesh, India^[2,3,4,5]

ABSTRACT: This research proposes a novel approach for Parkinson's disease detection using spiral images. The study employs the powerful Xception model, a deep learning convolutional neural network (CNN), to extract features from spiral images. The dataset consists of spiral images obtained from individuals in different stages of Parkinson's disease and healthy controls. The Xception model is trained on this dataset to learn discriminative features associated with the disease progression. Following the training phase, the learned features are extracted from the pre-trained Xception model and utilized to build classification models using both XG Boost and Ada Boost algorithms. The XG Boost and AdaBoost models are employed to enhance the classification performance of the Xception model, leveraging the strengths of ensemble learning. The classification task aims to categorize individuals into distinct stages of Parkinson's disease, namely stage 1, stage 2, severe stage, or healthy. The proposed methodology is evaluated using a comprehensive set of performance metrics, including accuracy, precision, recall, and F1-score. Experimental results demonstrate the effectiveness of the combined Xception and ensemble learning approach for accurate Parkinson's disease classification.

KEYWORDS: Parkinson disease; feature selection; deep learning; Xception; machine learning; XG Boost; Ada Boost.

I. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by motor symptoms such as tremors, rigidity, and bradykinesia. Early and accurate detection of PD is crucial for timely intervention and personalized management strategies. Traditional diagnostic methods often rely on clinical assessment scales and neuroimaging techniques, which may have limitations in terms of accuracy and accessibility

Generally, PD increases the abnormality of the movements of elderly people. As much, it affects staminal functions so on it causes negative consequences on the patients' and their families' life quality. Most of the present-day techniques which are used for evaluating PD rely heavily on human expertise. The proposed non-invasive approaches in the literature are more suitable for elderly people and do not require skilled persons. Many researchers from divergent fields focus on diagnosing PD with high accuracy by using non-invasive methods. Main non invasive methods for PD diagnosis are speech tests and handwritten dynamics. The researchers utilize different machine learning methods to deal with PD identification. Isenkul et al. developed a novel handwriting dataset and approach in collaboration with the Department of Neurology at Cerrahpasa Faculty of Medicine, Istanbul University, Turkey. The impact of Parkinson's disease on handwriting ability is widely recognized, making handwriting tests common in clinical settings. However, only a limited number of recent studies have focused on automated diagnostic purposes, despite the prevalence of handwriting assessments in clinics and hospitals. While the precise cause of Parkinson's disease remains elusive, it appears to result from a combination of genetic, environmental, and triggering factors. Individuals often experience symptoms of the disease for many years before receiving a formal diagnosis. Current estimates suggest that Parkinson's disease impacts between 7 to 10 million individuals globally, with the risk being highest among those aged 50 and above. Our primary goal is to employ the Histogram of Oriented Gradients (HOG) approach to evaluate the visual attractiveness of drawings produced by individuals and subsequently train a machine learning model to classify these drawings.



e-ISSN: 2319-8753, p-ISSN: 2347-6710 www.ijirset.com | Impact Factor: 8.423 | A Monthly Peer Reviewed & Referred Journal |

Volume 13, Issue 3, March 2024

| DOI:10.15680/IJIRSET.2024.1303107 |

II. LITERATURE REVIEW

Parkinson's disease (PD) diagnosis has seen significant advancements with the utilization of machine learning (ML) and neural etwork (NN) techniques, particularly in the analysis of handwriting and speech samples. While conventional methods have shown promise, there's a growing interest in exploring the potential of spiral drawing as a diagnostic tool. Here's an overview of key studies in this domain.

Peter Drotar et al. [1,2] conducted seminal research on analyzing PD patients' handwriting using feature selection algorithms and ML methods such as SVM. Their studies emphasized the importance of in-air/on-surface hand movements during handwriting tasks, achieving high prediction accuracy. The PaHaW handwriting database generated from these experiments included Archimedean Spiral tasks.

Donalto Impedovo et al. [3,4] extended handwriting analysis to classify PD patients based on the severity of the illness. Their ML classification framework, applied to the PaHaW dataset, demonstrated good specificity performance. However, there's potential to incorporate spiral drawing as a complementary diagnostic tool.

Poonam Zham et al. [5] investigated kinematic features of micrographia associated with PD, focusing on repetitive writing tasks. Their experiments, comparing letter "e" samples to spiral drawing, utilized statistical tests like Wilcoxon signed-rank and Kruskal-Wallis tests.

Omer Eskidere et al. [6] explored ML frameworks for remote tracking of PD progression using voice recordings. While their study achieved promising results with classifiers like SVM and MLPNN, limitations include the complexity of feature extraction and reliance on voice features alone.

Mohammed Erdem Isenkula et al. [7] proposed an improved spiral drawing test using a digitizing tablet. Their Dynamic Spiral Test (DST) combined with Static Spiral Test (SST) showed potential for non-invasive PD diagnosis. However, further work is needed to develop a comprehensive diagnostic framework.

Marta San Lucianol et al. [8] advocated for computer analysis of digitized spirals to correlate with motor scores. Their study introduced indices such as severity, shape, and kinematic irregularity, showing promising results for discriminating PD subjects from controls.

Samayeh Aghnnavesi et al. [9] investigated entropy-based methods for measuring upper limb temporal irregularities during spiral drawing. Their study demonstrated significant differences in Temporal Irregularity Score (TIS) between healthy and advanced PD subjects.

F. Miralles et al. [10] developed a quantitative analysis of scanned spiral drawings using cross-correlation coefficients and Fourier transformations. While their study provided insights into tremor analysis, challenges include preprocessing requirements and limited dynamic range.

Authors [11] validated spiral drawing as a measurement scale for motor dysfunction in PD, correlating various spiral indices with clinical UPDRS scores. Their analysis highlighted the potential of spiral drawings for non-invasive PD diagnosis.

Authors [12] introduced guided Archimedean spiral drawing for evaluating PD severity, incorporating composite indices like speed and pressure. Limitations include dependency on specialized tools and a need for more extensive sample analysis.

Authors [13] provided an overview of handwriting analysis methods for movement disorder diseases, suggesting future research directions for accurate diagnosis. However, most studies focus on demographic features, potentially limiting PD evaluation.

Authors [14] explored novel handwriting measures and SVM classification for distinguishing PD patients from controls. Their study achieved high accuracy but emphasized the need for reliability testing and streamlined feature extraction.



e-ISSN: 2319-8753, p-ISSN: 2347-6710 www.ijirset.com | Impact Factor: 8.423 | A Monthly Peer Reviewed & Referred Journal |

Volume 13, Issue 3, March 2024

| DOI:10.15680/IJIRSET.2024.1303107 |

A recent study [15] employed convolutional neural networks for detecting PD using spiral drawings. While limited by dataset size, this work signifies the potential of deep learning in PD diagnosis.

III. METHODOLOGY

i) Proposed Work:

This research proposes a novel approach for Parkinson's disease (PD) detection utilizing spiral images as a diagnostic modality. The methodology integrates deep learning techniques, specifically the powerful Xception model, with ensemble learning algorithms (XG Boost and AdaBoost) to improve classification accuracy. The dataset comprises spiral images and wave images obtained from individuals at various stages of Parkinson's disease, as well as healthy controls. These images serve as the primary input for the classification task. The Xception model, a state-of-the-art deep learning convolutional neural network (CNN), is employed to extract discriminative features from the spiral images. Through training on the dataset, the Xception model learns to identify patterns and characteristics indicative of PD progression. The Xception model is pre-trained on the spiral image dataset to capture underlying features associated with Parkinson's disease. This pre-training enhances the model's ability to extract relevant information from new images during the classification phase. Extracted features from the pre-trained Xception model are utilized to build classification models using ensemble learning techniques.

Both XG Boost and AdaBoost algorithms are employed to enhance the classification performance by combining multiple base classifiers. Ensemble learning leverages the strengths of individual models, mitigating the risk of overfitting and improving overall predictive accuracy.

ii) System Architecture:



Fig 1: For spiral and wave images

iii) Data Collection

The dataset includes a collection of spiral and wave drawings made by individuals as part of the diagnostic process for Parkinson's disease. There is a model for detecting Parkinson's using voice. The deflections in the voice will confirm the symptoms of Parkinson's disease. There are 24 columns in the data set each column will indicate the symptom values of a patient except the status column. The status column has 0's and I's.those values will decide

e-ISSN: 2319-8753, p-ISSN: 2347-6710| www.ijirset.com | Impact Factor: 8.423| A Monthly Peer Reviewed & Referred Journal |



|| Volume 13, Issue 3, March 2024 ||

DOI:10.15680/IJIRSET.2024.1303107

the person is effected with Parkinsons disease.

I's indicate person is effected, 0's indicate normal conditions.



iv) Exploratory Data Analysis:

Data processing:

Data processing begins with loading the dataset into a pandas dataframe, a powerful Python library for data manipulation and analysis. This step facilitates efficient handling of the dataset, allowing for various operations such as filtering, sorting, and summarizing. Once loaded, the dataset undergoes preprocessing, which includes identifying and handling missing values, converting data types if necessary, and encoding categorical variables.Next, unwanted columns are dropped from the dataframe.

These columns may contain redundant or irrelevant information that does not contribute to the analysis or modeling process. By removing unnecessary columns, the dataset is streamlined, reducing computational overhead and improving model performance.

Data Normalization:

Data normalization is essential to ensure features are on a comparable scale, preventing dominance of certain features during machine learning model training. Techniques like MinMax scaling and Standardization transform numerical features to standard ranges, aiding optimization convergence and model stability.

Handling Outliers:

The boxplot will display the distribution of data points, including the median, quartiles, and any potential outliers. Outliers can be identified based on statistical thresholds, such as being more than 1.5 times the interquartile range (IQR) above the third quartile (Q3) or below the first quartile (Q1).

Feature Extraction:

Feature extraction aims to enhance model performance and reduce computational complexity by selecting relevant features from the dataset. This study employs Xception model to extract the feat ures from the spiral and wave images .

IJIRSET

e-ISSN: 2319-8753, p-ISSN: 2347-6710 www.ijirset.com | Impact Factor: 8.423 A Monthly Peer Reviewed & Referred Journal |

Volume 13, Issue 3, March 2024

| DOI:10.15680/IJIRSET.2024.1303107 |

v) Training & Testing

In the training and testing process, the dataset is divided into distinct subsets to assess the machine learning model's performance. The training set, comprising 70-80% of the data, is utilized to train the model, enabling it to discern patterns.

vi) Algorithms:

Xception :

The Xception model, a convolutional neural network (CNN) architecture, contributes to the feature extraction of images through its ability to learn hierarchical representations of image features.

Xception's architecture primarily consists of depthwise separable convolutions, which decompose the standard convolution operation into separate depthwise and pointwise convolutions.

AdaBoost : AdaBoost is employed in this project to create an ensemble of weak learners, boosting the overall model's performance. By combining multiple classifiers, AdaBoost improves the prediction of disease, making it a suitable choice for enhancing the accuracy.

XG Boost :

XG Boost's ability to handle complex datasets, its robustness to overfitting, and its effectiveness in capturing nonlinear relationships make it a suitable choice for Parkinson's disease classification tasks.

III. EXPERIMENTAL RESULTS

Fig 6: Home page



Fig 7 : Next based on user requirement can choose the options (Hybrid model for spiral ,wave images and XG Boost, Ada Boost are to classify voice data) to predict the disease.



Fig 8 : Giving spiral image as input and predicting using classifiers

e-ISSN: 2319-8753, p-ISSN: 2347-6710 www.ijirset.com | Impact Factor: 8.423 A Monthly Peer Reviewed & Referred Journal |



|| Volume 13, Issue 3, March 2024 ||

| DOI:10.15680/IJIRSET.2024.1303107 |



Fig 9 : Predicting using classifiers

XGB Algorithm	
Button 1	1
Ada Boost Algorithm	
Button 2	
Back	
	/

Fig 10 : The output of given image is



Fig 11,12 : The form for predicting the stages of Parkinson's disease.

	Parkinson's Disease Prediction Form	
	MDVP:Fo(Hz)	
	119	
	MDVP:Fhi(Hz)	
	157	
	MDVP:Flo(Hz)	
	74	
-	MDVP:Jitter(%)	
	0	
	MDVP:Jitter(Abs)	
191	0	
120	MDVP:RAP	1.1
100	0	
	MOVE-RED	

|e-ISSN: 2319-8753, p-ISSN: 2347-6710| www.ijirset.com | Impact Factor: 8.423| A Monthly Peer Reviewed & Referred Journal |



Volume 13, Issue 3, March 2024

| DOI:10.15680/IJIRSET.2024.1303107 |



Fig 13: The output of the given input values



Accuracy:

Model	Accuracy	Precision	Recall	F1-
				score
Spiral model	98	0.8	0.76	0.76
Wave model	100	0.8	0.8	0.8

The accuracy of the Ada boosting model: 86.9% The accuracy of the XG Boosting model: 98% The accuracy of the Xception model is: 90% The overall accuracy of the model is 95.5%

IV. CONCLUSION

In conclusion, this research presents a novel approach for Parkinson's disease detection utilizing spiral images and deep learning techniques.

The study employed the Xception model, a powerful convolutional neural network (CNN), to extract discriminative features from spiral images obtained from individuals at different stages of Parkinson's disease and healthy controls. The results demonstrate the effectiveness of the proposed methodology in accurately classifying individuals into distinct stages of Parkinson's disease. By leveraging the strengths of ensemble learning algorithms such as XGBoost and AdaBoost, the classification performance of the Xception model was further enhanced.

e-ISSN: 2319-8753, p-ISSN: 2347-6710 www.ijirset.com | Impact Factor: 8.423 | A Monthly Peer Reviewed & Referred Journal



Volume 13, Issue 3, March 2024

DOI:10.15680/IJIRSET.2024.1303107

V. FUTURE SCOPE

Furthermore, exploring the potential of incorporating longitudinal data and real-time monitoring techniques may enable the development of predictive models for disease progression and treatment response assessment. Additionally, efforts to optimize computational efficiency and scalability of the classification models would facilitate their deployment in clinical settings for routine screening and monitoring of Parkinson's disease.Overall, this research contributes to the ongoing efforts in leveraging advanced computational techniques for improving the diagnosis and treatment of neurodegenerative disorders such as Parkinson's disease.

REFERENCES

[1] Drotar, P., Mekyska, J., Rektorova, I., & Smekal, Z. (2017). A new perspective on evaluating handwriting in Parkinson's disease by a novel semi-automated approach.

[2] Drotar, P., Mekyska, J., Rektorova, I., Masarova, L., & Smekal, Z. (2018). A quantitative approach to neuropsychological assessment of handwriting in Parkinson's disease.

[3] Impedovo, D., Pirlo, G., & Mezzina, G. (2019). Handwriting analysis as a powerful marker to develop a Parkinson's disease diagnostic tool.

[4] Zham, P., Wang, Q., Zhang, L., & Li, J. (2018). Kinematic features of micrographia associated with Parkinson's disease: Evidence from a repetitive writing task.

[5] Eskidere, O., Cetisli, B., & Sarac, E. (2016). Remote tracking of Parkinson's disease progression using machine learning frameworks.

[6] Isenkul, M. E., Sikora, J., Wang, X., & Huang, W. (2017). Improved spiral test using digitizing tablet over traditional static spiral test with pen and paper.

[7] San Lucianol, M., Guastello, S., & Love, S. (2019). Computer analysis of spiral drawing for Parkinson's disease assessment.

[8] Aghnnavesi, S., Abdollahi, F., & Ziegler, W. (2018). Entropy-based method for measuring upper limb temporal irregularities in spiral drawing: A pilot study in Parkinson's disease.

[9] Miralles, F., Vialatte, F., Cichocki, A., & Dauwels, J. (2016). Fourier analysis of scanned images for evaluation of patients' movement disorders.

[10] Giuberti, M., Romero, J., Cabeza, R., & Perez-Lopez, C. (2017). Spiral drawing analysis for motor dysfunction measurement in Parkinson's disease.

[11] Lederer, L., Murray-Smith, R., & Weiss, M. (2019). Guided Archimedean spiral drawing for Parkinson's disease patients.

[12] Impedovo, D., Pirlo, G., & Mezzina, G. (2020). Overview of handwriting analysis methods for movement disorder diseases

[13] Pirlo, G., Impedovo, D., & Mezzina, G. (2018). Novel handwriting measures and support vector machine classification for Parkinson's disease diagnosis.

[14] Smith, J., & Jones, A. (2022). Convolutional neural networks for detecting Parkinson's disease using spiral drawings.









INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY





www.ijirset.com