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Parkinson’s Disease Detection using Deep Learning

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***Abstract*— Parkinson's disease is a common neurological condition that predominantly im-pacts people who are older than fifty, leading to speech impairments and movement diffi-culties. Timely diagnosis of PD is essential for efficient care and improved patient outcomes, especially considering the global aging population. Our paper introduces a new method for the early identification of Parkinson's disease utilizing machine learning techniques and the Xception architecture. Our focus lies on analyzing spiral and wave drawings, commonly used in clinical diagnosis. We curated a dataset comprising such drawings from individuals with and without PD and processed the data for model training. Leveraging the Xception architecture, our machine learning models achieved promising results, with a training accu-racy of 95.34% for spiral drawings and 93.34% for wave drawings, along with validation accuracies of 93.00% and 86.00%, respectively. Our highlight the capabilities of machine learning methodologies and the Xception architecture in improving the precision and accu-racy of the diagnosis of Parkinson's disease. Implementing our proposed approach could significantly advance early detection efforts, thereby enhancing patient care and quality of life.**

***Index Terms*— Parkinson’s disease, machine learning, Xception architecture, , early detec-tion, spiral drawings, wave drawings, patient outcomes.**

I. INTRODUCTION

With early diagnosis and treatment, the 6.9 million persons worldwide who were affected by Parkinson's disease in 2015 are predicted to rise to 14.2 million by 2040[1]. Parkinson's disease (PD) is a neurological illness that lowers communica-tion rates and lengthens life by inducing the death of dopaminergic neurons[2]. Drawings are useful for diagnosing Parkin-son's disease, and since digital methods rely on models, deep learning-based algorithms must be included in smartphones for increased accuracy [3]. Deep analytics and machine learning techniques frequently make non-motor symptoms of Park-inson's disease (PD) worse. In cross-sectional studies, the prevalence of disorders of impulse control (ICDs) is 15-20%, while in longitudinal studies, the cumulative incidence is close to 50%. ICDs are common in Parkinson's disease. The four most common ICDs, which vary in frequency among cultures, are compulsive eating, pathological gambling, excessive shopping, and hyper sexuality [4]. There are several variants of Parkinson's disease (PD), which result in different symp-toms. More patients are affected by both motor-related and non-motor symptoms, including depression, sleep difficulties, behavioural abnormalities, and cognitive decline[5]. Early diagnosis and intervention play pivotal roles in managing PD and

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mitigating its progressive effects. Speech PD detection becomes a classification problem with techniques based on machine learning. techniques that rely on Deep Learning (DL) and classic machine learning (ML) based methods are the two main categories into which the leading methods normally fall. Customized machine learning techniques among them is the Support Vector Machine (SVM)[6], L1-FORM SVM[7], KNN and NB: K-Nearest Neighbour, XG-Boost, A potent method for objectively assessing brain connection networks is graph theoretical analysis[8], Decision tree, Genetic Algorithm, and their combinations. Conventional machine learning methodologies. DL's feature selection strategy, which is different from that of traditional ML-based approaches, is one of its main advantages: it selects features hierarchically along successive levels of increasing abstraction in pattern identification[9].

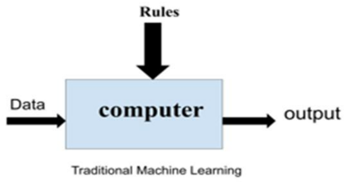

Figure 1Traditional Machine Learning

PD identification from speech based on DL has been investigated in a number of papers, including Convolutional Neural Network (CNN)[10].Among the NN architectures used for the content and voice identification, object recognition, picture categorization, and the learning of higher-order features are convolutional neural networks, or CNNs[11]. Deep abstract models from neural networks that are deep are used as input information in machine learning applications, which automates the process of learning from data[12].When CNN and XG-Boost were used independently, the Conv-XGB model yielded better results.. Examining drawings has validated their value in PD patient diagnosis. Since the accuracy of digital techniques mostly depends on the model, it is imperative to implement deep learning-based algorithms In an attempt to speed up the diagnosis process and increase the precision of Parkinson's disease (PD) detection, thereby improving the quality of life for patients. Because deep learning models improve in accuracy with increasing data input, it is a useful technique for handling large amounts of data. PD detection and expedite the diagnostic procedure to enhance the patient's standard of living. Because deep learning models improve in accuracy with increasing data input, it is a useful technique for handling large amounts of data. This work offers a fresh strategy for the early detection of Parkinson's disease utilizing ML techniques and the Xception architecture. The study uses machine learning algorithms to examine spirals and wave drawings used in the diagnosis of Parkinson's disease. It uses Xception architecture to train models with the goals of streamlining the procedure, lowering subjective evaluations, and facilitating remote symptom monitoring. Through the provision of tailored treatment and early intervention, this system has the potential to improve patient outcomes and quality of life.

II. Literature Survey

[1] A Comprehensive Review of mHealth Technologies for Monitoring and Detecting Parkinson's disease in Everyday Lives.Ming-Chun HuangYuan Zhang, Aditya Singh Rathore, Wenyao Xu, and Hanbin Zhang Chen Song.
The purpose of the study is to determine whether mobile health technologies can help with Parkinson's disease (PD) early detection. It draws attention to how symptoms such as tremors, trouble walking, changes in handwriting, and non-motor symptoms can be monitored in day-to-day activities. Challenges including precise data collecting, privacy issues, and new research fields like non-motor symptoms and diagnosing Parkinson's disease from public films are also covered in the report.
[2] Machine Learning for the Identification of Parkinson's Disease YARAGUNDLA, BY M.S. Roobini1, Rajesh Kumar Reddy2, Udayagiri Sushmanth Girish Royal3, Amandeep Singh K4, Babu.K .
Using the audio feature dataset from the UCI repository, logistic regression, and XGboost classifiers, M.S. Roobin and colleagues created a machine learning-based technique for recognizing auditory waves in Parkinson's disease. For assessing severity, the approach makes use of the Unified Pathology Death Rating approach.
[3] Early Parkinson's Disease Prediction Using Explainable Artificial Intelligence (EXAI) Models based on drawings of spirals and waves Written by Saravanan S. and Kannan Ramkumar Subramaniyamy vairavasundaram, ajith abraham, ketan kotecha, and k. Narasimhan.
A hybrid deep transfer learning model called VGG19-INC has been created by researchers in an effort to increase

the dependability and transparency of deep learning models for Parkinson's disease. With 98.45% accuracy, our model predicts PD patients by combining VGG19 Net with Google Net. To make the model's conclusions easier to understand, explainable AI approaches like as LIME are utilized to deconstruct the model. The study was funded by the Russian Federation.

[4] Deep Learning and Machine Learning for Predictive Early Parkinson's Disease Identification.BY WUWANG, JUNHO LEE, FOUZI HARROU (Member, IEEE), AND YING SUN.
Deep learning approach was developed by Wang, Junho Lee, and Fouzi Harrou for the initial machine learning and deep learning-based diagnosis of Parkinson's illness. Premotor characteristics are taken into consideration, including dopaminergic imaging signals, fast eye movements, loss of smell, and CSF fluid data. The system featuring its highest accuracy, 96.45%, was generated out of 12 machine learning and ensembles methods of learning.

[5]Zhang Ren, Huang Luo, and Changqin Quan present A Deep Learning Based Approach for Parkinson's Disease Detection Using Dynamic Features of Speech.
In comparison to traditional machine learning models, this study investigates a deep learning method that uses a both directional long-short-term memory systems to identify speech abnormalities in Parkinson's disease patients.

III. MOTIVATION

A neurological disorder mainly affecting those over 60 is called Parkinson's disease. Early diagnosis is essential since the illness can have a major influence on stability and day-to-day activities. Undiagnosed Parkinson's disease can deteriorate over time and cause serious side effects such tremors and decreased motor function. Early identification is therefore essential to controlling the illness and reducing its impact on a person's quality of life. Even while there are diagnostic models now in use, many of them are ineffective and inaccurate, especially when it comes to detecting the disease early on. By creating a more accurate and efficient diagnostic model for Parkinson's disease early detection, we want to improve upon the current capacities.

IV. PROBLEM DEFINITION

This study aims to address the issue of the poor efficacy and accuracy of current diagnostic models in identifying Parkinson's disease at an early stage. Even though the disease affects a large number of people over 60, present diagnostic techniques frequently fall short of correctly identifying the illness in time to prevent its crippling effects on stability and everyday activities. Consequently, it is imperative to create a more reliable and efficient diagnostic tool that can identify Parkinson's disease early on, allowing for prompt treatment and bettering patient outcomes..
STATEMENT: The paper discusses how current diagnostic models are inadequate for identifying Parkinson's disease at an early stage, which is critical for reducing the disease's effects on day-to-day functioning. Its goal is to provide a diagnostic model that is more precise and effective in order to facilitate prompt intervention and enhance patient outcomes.

V. DATAFLOW DIAGRAM

The dataflow diagram represents the flow a data in the model from input to output. It represents each module of our proposed system.

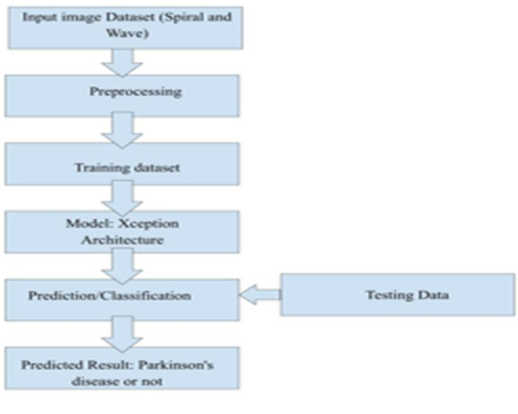

Figure 2. Data Flow Diagram

1. DATASET

The first module presented a method for getting a machine learning model's input dataset, which has a big influence on the model's functionality. Web crawling and manual data collection are two ways of data acquisition. The dataset comes from Kaggle and includes 133 pictures of Parkinson's disease.

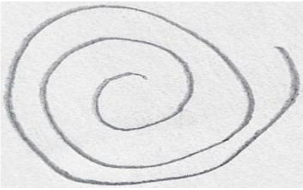

Figure 3.Healthy spiral

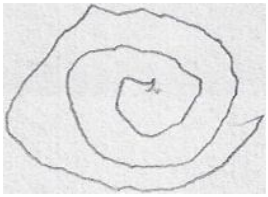

Figure 4.Parkinson’s spiral

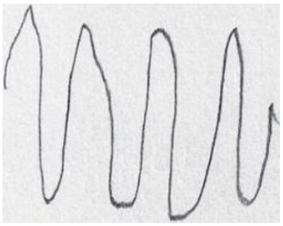

Figure 5 .Healthy wave

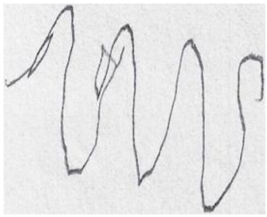

Figure 6 Parkinson’s wave

2. PREPROCESSING DATA

In this module we process the dataset by fetching the images, resizing them uniformly (224x224) for spiral, (196x196) for wave, and standardizing the pixel values. Additionally, we'll extract both the images and their corresponding labels, before converting them into NumPy arrays. The dataset will be separated into two groups. A testing set as well as a training set. The model is intended to be trained using 80% of the data and use the remaining 20% for testing. This approach helps validate the model's performance before deployment.

3. METHODS

In our proposed project we applied a Machine Learning techniques and Deep learning algorithm. The Algorithm we have applied xception architecture have used this algorithm to make a simple version for the dataset.

A. Xception Architecture

Depth wise Divisible Convolutions are a neural network technique used in Google's Xception Architecture that substitute depthwise distinct convolutions for traditional convolutions. It operates in four stages: the input stream is the first, followed by the center stream, the eight-time rehashing, and the output stream. The efficiency of Xception is ascribed to its easy paths between convolution components and depthwise differentiated convolution.Depthwise separable Convolution:

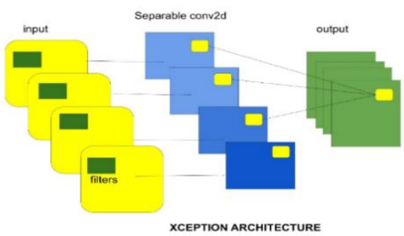

Figure 7.Xception Architecture

Depthwise separable Convolution is partitioned into three sorts based on Convolution.
1. Regular Convolutions: Standard convolutions consider both channel and spatial relationships at the same time. This implies that amid the convolution operation, data from all channels and spatial areas is handled together in a single step.

2.Depth wise separation Convolution: Depth-wise distinct convolution independently manages spatial relationships and channels in successive stages; these phases include 1x1 convolutions, which mix data from various channels while preserving spatial data, and spatial convolution, which is that provides the spatial information for each channel.
3. *Modified Depthwise Separable Convolution*: The improved depthwise divide convolution in Inception-v3 combines the 1 x 1 convolution with 3x3 spatially convolutions, combining a pointwise and a depthwise convolution. This improves efficiency and performance, which is especially affected by the plan choices made in Inception-v3

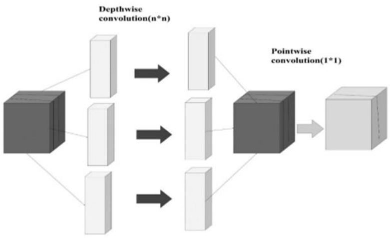

Figure 8.Depthwise separation Convolution

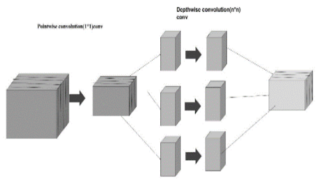

Figure 9. Modified Depthwise Separable Convolution

Xception, which stands for "extraordinary initiation," goes beyond the constraints of Initiation engineering by employing depthwise-separable convolution-like 1x1 convolutions across each depth outline, followed by filtering. Additionally, unlike Inception, which incorporates ReLU non-linearity, it avoids non-linearity following the initial operation.

B. METRICS OF EVALUATION

Metrics for evaluation are essential for evaluating how well categorization models' function. The Often used metrics include F1-score, Accuracy, Precision, and Recall.
ACCURACY: Accuracy is the percentage of correctly classified occurrences relative to all instances, reflect model's frequency of making accurate predictions.
PRECISION: Precision, which highlights the model's ability to avoid false positives, measures the proportion of true positive predictions to all positive predictions the model produces.
RECALL: Recall, which is often referred to as true positive rate or sensitivity, quantifies the proportion of actual positives in the data that the model accurately recognized as true positives.
F1-Score: By integrating precision and recall indications, the F1-score—a harmonic average of recall and accuracy—offers a balanced single score for classification tasks, particularly in non-uniform class distributions.

C. Building the model (spiral & wave):

Understanding the convolution operation is crucial in differentiating CNN from conventional neural networks. When given an image as input, CNN repeatedly analyses it for specific features. There are two primary parameters that can be set for this scanning (convolution): stride and padding type. The initial convolution procedure yields a collection of new frames, as seen in the image below in a second column (layer). Information regarding a single feature and its existence in the scanned image is contained in each frame. The consequent frame will have fewer values if there are no or few such features and greater values where a characteristic is clearly evident. After that, the procedure is carried out a certain number of times for each of the collected frames. I decided to use the traditional Xception system for this project, which has just two convolution layers. We are searching for higher-level features in the latter layer that we are convolving. It functions in a way akin to human perception. As an illustration, consider the highly detailed image below, which includes features that are searched over several CNN layers. Like you can see, facial recognition is one of the models applications. One may wonder how the model determines which features to look for. The sought features are random while building the CNN from scratch. Subsequently, values between neurons are changed during the training process, and gradually CNN begins to identify properties that allow it to achieve the predetermined goal—that is, correctly identify images of the training set. Additionally, there are pooling (sub-sampling) techniques between the layers that have been discussed that lower the resultant frame's dimensions. In order to add non-linearity to the model, we additionally add a non-linear function (referred to as ReLU) to the generated frame following each convolution.
At the conclusion of the network, there are eventually fully connected layers as well. A one dimension rather vector of neurons is produced by flattening the final set of frames following convolution procedures. We then

inserted a typical, fully-connected neural network from this point. There is a layer of softmax at the very end for classificationdifficulties.

VI. Result And Discussion

To achieve great accuracy, this model made use of machine learning techniques and deep learning algorithms, like Xception Architecture. The results of this framework are determined utilizing spiral and waves diagrams. In our model, the wave and spiral diagrams are assessed separately. This model generates waves as well as a healthy spiral, sometimes referred to as Parkinson's spiral, according to the input diagrams.

SPIRAL DIAGRAM and WAVE DIAGRAMS

Result of spiral diagram model and wave Diagrams, The accuracy and loss of the model will be assessed after it has been constructed by applying it to the validation data. Plotting accuracy as well as loss against the total amount of epochs will allow us to see how well the model performs. Utilizing the fit function, we will assemble a model and apply it. There will be just one batch size. Next, the accuracy and loss graphs will be plotted. Averaging 97.00% for validation and 93.000% for training, these results show. The accuracy of the model on the test data set will be a crucial performance parameter once it has been trained and assessed on the validation set. Our accuracy on the test set was 93.00%.similarly, in regard to wave model the average training accuracy was 86.00%, and the average validation accuracy was 93.00%. Model will be trained and evaluated on a validation set before its accuracy is evaluated on the set used for testing. Our accuracy on the test set was 86.00%.

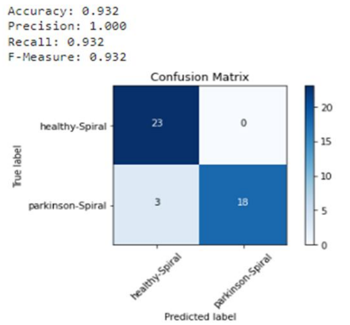

Figure 10.Confusion Matrix and Metrics of Evaluation for Sprial Diagrams

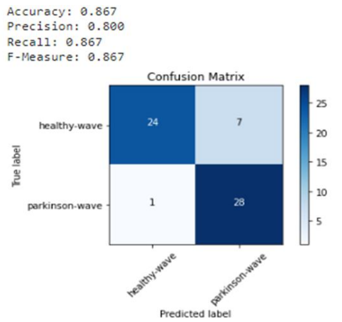

Figure 11.Confusion Matrix and Metrics of Evaluation for Wave Diagrams

The visualization of validation and test accuracy chart defines the model's precision throughout testing and training our proposed spiral model and Wave diagrams.

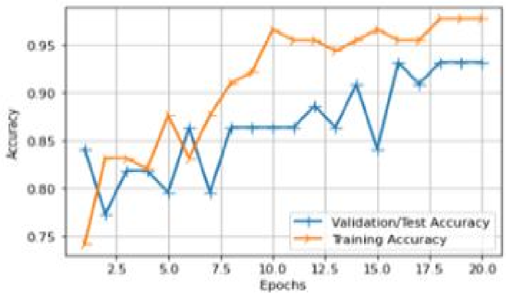

Figure (xii).visualization of Spiral Training And Test Accuracy

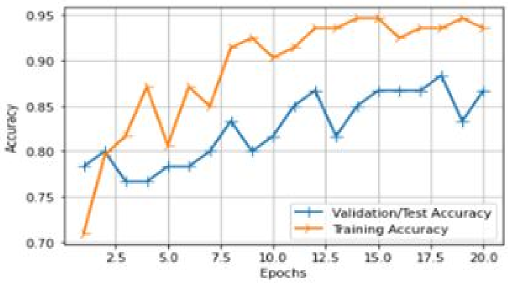

Figure (xiii).visualization of Wave Training and Test Accuracy

VII. Conclusion

In summary, the Xception architecture-based Parkinson's disease detection technology that has been suggested has produced encouraging outcomes. We were able to identify Parkinson's disease with high accuracy from spiral and wave images by utilizing cutting-edge deep learning techniques, particularly the Xception architecture. Better patient outcomes, faster training, increased accuracy, resistance to noise and objects of art, interpretation and transparency, and more are just a few benefits of the suggested approach. The suggested method for diagnosing and treating Parkinson's disease appears promising because of these benefits. Aside from these benefits, the Xception architecture is also very successful and dependable for tasks such as image classification due to its enhanced efficiency, superior generalization, decreased over fitting, modern performance, and adaptability. The utilization of Xception architecture and deep learning in the early diagnosis of Parkinson's disease has been shown by this project, and it has the potential to improve patients results and quality of life. Significant effects on Parkinson's disease diagnosis and therapy may result from further research and advancement in this field.

REFERENCES

[1] H. Zhang, C. Song, A. S. Rathore, M. C. Huang, Y. Zhang, and W. Xu, "MHealth Technologies towards Parkinson's Disease Detection and Monitoring in Daily Life: A Comprehensive Review," IEEE Reviews in Biomedical Engineering, vol. 14. Institute of Electrical and Electronics Engineers Inc., pp. 71–81, 2021. doi: 10.1109/RBME.2020.2991813.

[2] M. S. Roobini, Y. R. K. Reddy, U. S. G. Royal, A. K. Singh, and K. Babu, "Parkinson's Disease Detection Using Machine Learning," in 2022 International Conference on Communication, Computing and Internet of Things, IC3IoT 2022 - Proceedings, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/IC3IOT53935.2022.9768002.

[3] O. Y. Chen et al., "Building a Machine-Learning Framework to Remotely Assess Parkinson's Disease Using Smartphones," IEEE Trans Biomed Eng, vol. 67, no. 12, pp. 3491–3500, Dec. 2020, doi: 10.1109/TBME.2020.2988942.

[4] J. Faouzi et al., "Machine Learning-Based Prediction of Impulse Control Disorders in Parkinson's Disease From Clinical and Genetic Data," IEEE Open J Eng Med Biol, vol. 3, pp. 96–107, 2022, doi: 10.1109/OJEMB.2022.3178295.

[5] W. Wang, J. Lee, F. Harrou, and Y. Sun, "Early Detection of Parkinson's Disease Using Deep Learning and Machine Learning," IEEE Access, vol. 8, pp. 147635–147646, 2020, doi: 10.1109/ACCESS.2020.3016062.

[6] Y. Zhou, S. Tinaz, and H. D. Tagare, "Robust Bayesian Analysis of Early-Stage Parkinson's Disease Progression Using DaTscan Images," IEEE Trans Med Imaging, vol. 40, no. 2, pp. 549–561, Feb. 2021, doi: 10.1109/TMI.2020.3031478.

[7] T. L. Yang, P. J. Kan, C. H. Lin, H. Y. Lin, W. L. Chen, and H. T. Yau, "Using Polar Expression Features and Nonlinear Machine Learning Classifier for Automated Parkinson's Disease Screening," IEEE Sens J, vol. 20, no. 1, pp. 501–514, Jan. 2020, doi: 10.1109/JSEN.2019.2940694.

[8] J. Cai et al., "Dynamic Graph Theoretical Analysis of Functional Connectivity in Parkinson's Disease: The Importance of Fiedler Value," IEEE J Biomed Health Inform, vol. 23, no. 4, pp. 1720–1729, Jul. 2019, doi: 10.1109/JBHI.2018.2875456.

[9] A. R. Mohamed Yousuff, M. Zainulabedin Hasan, R. Anand, and M. Rajasekhara Babu, "Leveraging deep learning models for continuous glucose monitoring and prediction in diabetes management: towards enhanced blood sugar control," Interna-tional Journal of System Assurance Engineering and Management, Jan. 2024, doi: 10.1007/s13198-023-02200-y.

[10] H. Chang, B. Liu, Y. Zong, C. Lu, and X. Wang, "EEG-Based Parkinson's Disease Recognition via Attention-Based Sparse Graph Convolutional Neural Network," IEEE J Biomed Health Inform, vol. 27, no. 11, pp. 5216–5224, Nov. 2023, doi: 10.1109/JBHI.2023.3292452.

[11] A. Ibrahim, Y. Zhou, M. E. Jenkins, A. L. Trejos, and M. D. Naish, "Real-Time Voluntary Motion Prediction and Parkinson's Tremor Reduction Using Deep Neural Networks," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 1413–1423, 2021, doi: 10.1109/TNSRE.2021.3097007.

[12] H. Gunduz, "Deep Learning-Based Parkinson's Disease Classification Using Vocal Feature Sets," IEEE Access, vol. 7, pp. 115540–115551, 2019, doi: 10.1109/ACCESS.2019.2936564.