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Detection of Parkinson's Disease Using Spiral Models

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Abstract: Parkinson's Disease (PD) is a steadily worsening neurological condition that affects millions of individuals around the world. Early diagnosis remains a major challenge due to subtle initial symptoms and limited access to trained neurologists. This paper proposes an automated and explainable deep-learning approach designed to identify PD at an early stage using spiral drawing tests. Using transfer learning with VGG19 and explainable AI methods such as LIME, the proposed model identifies tremor- induced distortions in drawings and highlights regions contributing to classification. The model demonstrates high accuracy and interpretability, positioning it as a reliable tool for assisting clinical diagnosis.

Keywords: Parkinson's Disease, Spiral Drawings, Parkinson's Disease, Spiral-Based Drawings, Deep Neural Models, Transfer-Learning Techniques, Convolutional Networks, Explainable Artificial Intelligence, LIME., Explainable AI, LIME.

1. Introduction

Parkinson's Disease (PD) is the second-most common neurodegenerative disorder, characterized by motor symptoms such as tremors, rigidity, and bradykinesia. Traditional diagnostic procedures involve clinical examinations and subjective assessments, making early-stage detection difficult. Spiral drawing tests, commonly used in neurology, help assess motor control irregularities caused by PD. With the advancement of artificial intelligence and deep learning, automated assessment of such tests has become viable.

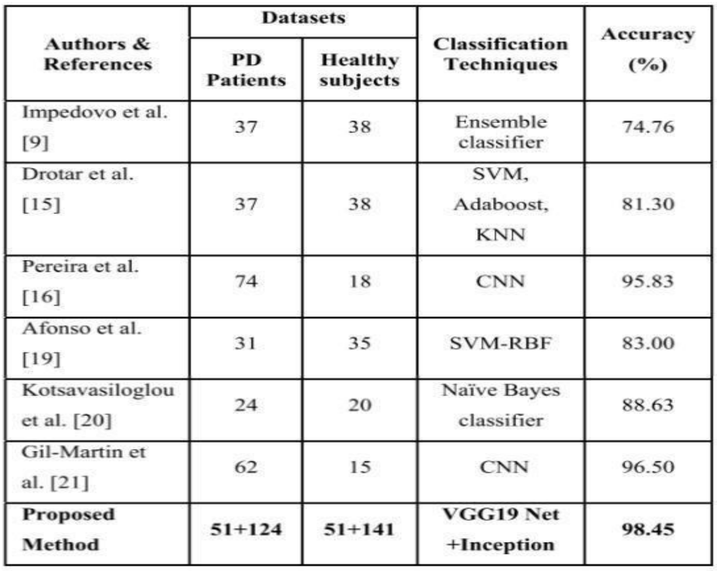
This research focuses on applying convolutional neural network (CNN) models to interpret spiral- drawing patterns from both healthy individuals and PD patients. The aim is not only to classify but also to explain the reasoning behind the model's prediction using Local Interpretable Model-Agnostic Explanations (LIME). Such interpretability is essential in medical settings, as AI-generated outcomes need to be clearly interpretable and reliable in healthcare applications where AI decisions must be transparent and trustworthy. The study contributes by providing a lightweight, accurate, and explainable diagnostic tool using simple input data.

2. Literature Survey

A wide range of research has investigated handwriting patterns and drawing-based assessments as potential indicators for diagnosing Parkinson's Disease. Earlier machine-learning techniques relied on manually designed features, including writing speed, curvature, pressure variations, and stroke smoothness. However, these features are often insufficient to capture subtle variations in PD drawing patterns.

Deep learning techniques revolutionized this domain by enabling automatic feature extraction. CNN architectures trained on spiral and wave-form drawings have achieved classification accuracies between 90% and 98%.Studies by Zham et al. and Pereira et al. demonstrated that spiral drawing irregularities correlate strongly with motor dysfunction.

Recent studies highlight the growing necessity for models that provide transparent and interpretable decision-making. Healthcare practitioners require insights into why a model arrives at a diagnosis. LIME and Grad-CAM have been widely used to interpret medical imaging models, however, their use in PD diagnosis using drawing-related datasets has been relatively limited. This indicates a clear gap in existing research, which the present work aims to fill.



Authors & References	Datasets		Classification Techniques	Accuracy (%)
	PD Patients	Healthy subjects		
Impedovo et al. [9]	37	38	Ensemble classifier	74.76
Drotar et al. [15]	37	38	SVM, Adaboost, KNN	81.30
Pereira et al. [16]	74	18	CNN	95.83
Afonso et al. [19]	31	35	SVM-RBF	83.00
Kotsavasiloglou et al. [20]	24	20	Naïve Bayes classifier	88.63
Gil-Martin et al. [21]	62	15	CNN	96.50
Proposed Method	**51+124**	**51+141**	**VGG19 Net +Inception**	**98.45**

Figure 1: Comparison of works related to early diagnosis of PD based on handwritten biomarkers.

3. Data Collection

A. Dataset Description

The dataset utilized in this research is composed of drawing samples that include spiral and wave patterns of spiral and wave sketches collected from 102 individuals—51 diagnosed with PD and 51 healthy controls—sourced from Kaggle. As reported by the original authors [31], the dataset includes 102 spiral images and 102 wave images, where every individual provided one spiral drawing and one wave drawing.

A second dataset (Dataset 2) contains spiral drawings from 124 PD patients and 141 healthy individuals, supplied by the authors in [32]. The two datasets were later separated into training and validation subsets following a 70:30 ratio.

Representative examples of spiral and wave drawings from both healthy subjects and PD patients as illustrated in Figure 2.

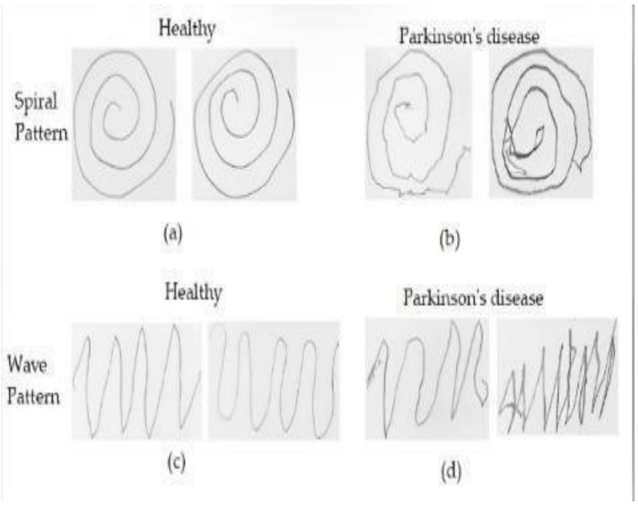


Figure 2: a) Spiral images of healthy subjects Spiral images of PD patients.Wave images of healthy subjects. Wave images of PD patients.

B. Data Augmentation

Deep learning systems need a wide range of high- quality input samples to achieve good performance. In Parkinson's disease research, gathering such large datasets is difficult because the intensity and pattern of motor symptoms differ from person to person. To overcome this challenge, data augmentation techniques were used to artificially increase the size of the dataset and improve the model's ability to generalize.

During preprocessing, a Python-based augmentation script was executed at test time. Methods such as increasing image brightness (using maximum illumination) and stretching images vertically were applied. These transformations help diversify the dataset, enabling the model to extract stronger and reliablefeatures.

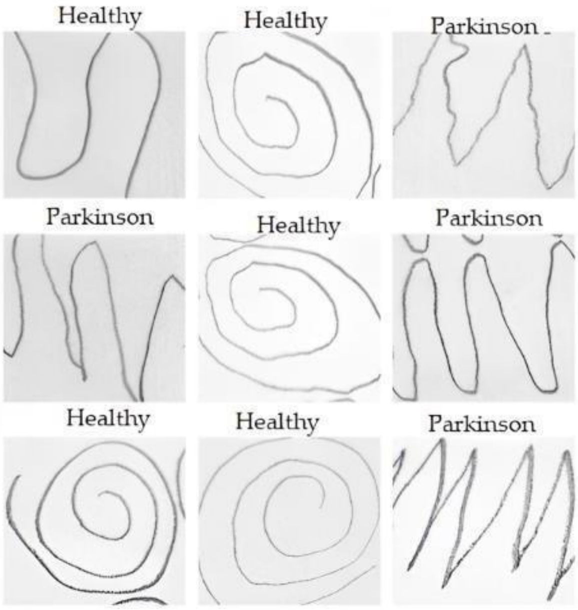


Figure 3: Augmented images of spiral and wave pattern drawings.

The augmentation techniques applied include:

1. Flipping

Flipping is a widely used image augmentation technique in machine learning. In this approach, images are horizontally mirrored to produce extra training samples. Because the main visual features of the spiral and wave drawings remain unchanged even after flipping, this technique allows the model to learn patterns that generalize better.

2. Rotation

Rotation adjusts the image's orientation by a chosen angle. This results in several differently angled versions of the same drawing, helping the model identify patterns from various perspectives. As a result, the model becomes more capable of handling unseen data and improves its overall generalization.

3. Shearing

Shearing introduces a slight geometric distortion that slants the image. This enhances the variety within the dataset and helps the model become more resilient to differences in drawing shapes.

To prevent too much distortion and to maintain the key visual elements of the drawings, an additional preprocessing step was included. This step ensured the aspect ratio was preserved while lightly darkening shorter edges, keeping the augmented images realistic and usable.

4. Methodology

In this study, we examine the capability of the VGG19 architecture for classifying Parkinson's disease (PD) using spiral and wave drawing datasets. VGG19 is a deep convolutional neural network that gained recognition for its strong performance in the 2014 Large-Scale Visual Recognition Challenge. Figure 4 provides an overview of the transfer-learning approach used in this work. Building on this, we designed a hybrid framework that integrates VGG19 with Inception modules to form a deep transfer fusion model specifically tailored for PD detection.

The purpose of developing this fusion model is to utilize the complementary advantages of both networks. VGG19 is effective in capturing fine spatial details from the drawings, while Inception blocks are capable of extracting richer and more abstract high-level features. Combining these two models enables a more comprehensive representation of the input images, ultimately improving classification performance.

Transfer learning is particularly beneficial for this study because the available dataset is relatively small. Instead of training all parameters from scratch—which increases the risk of model overfitting—we initialize the network with pretrained weights and fine-tune only the necessary layers. This reduces computational time, prevents overfitting on limited data, and improves generalization for PD detection.

One major limitation of deep learning models is their limited interpretability. Even when they deliver high accuracy, it is often difficult to understand how the model arrives at a specific decision, especially in medical diagnosis where transparency is essential. To address this challenge, we incorporated Explainable Artificial Intelligence (XAI) into the framework.

The XAI technique applied in this research is the Local Interpretable Model-Agnostic Explanations (LIME) method. LIME works by generating perturbed versions of the input image, training a simple surrogate model on these variations, and identifying the regions that most strongly influence the network’s prediction. Because LIME is model- agnostic, it can be used with any deep learning architecture, making it a valuable tool for understanding how the hybrid VGG19–Inception model interprets PD-related features.

Along with the proposed fusion model, we also conduct a comparative evaluation using several widely recognized convolutional neural network (CNN) architectures, including AlexNet, ResNet-50, DenseNet-201, VGG19, and SqueezeNet. Their lower layers are adapted using transfer learning, and their performance on the drawing-based dataset is analyzed to determine their suitability for PD classification.

Another crucial aspect of the methodology is learning-rate selection. The learning rate directly influences how quickly the network adjusts its weights. Using a fixed learning rate throughout training can lead to slow convergence or suboptimal results. To overcome this, we adopt a differential learning-rate strategy in which different groups of layers are trained using separate learning rates. This approach helps stabilize training and improves overall accuracy.

Figure 5 outlines the complete workflow of the proposed PD detection system. The evaluation is carried out on both the original dataset and the augmented dataset to understand the influence of augmentation. While augmentation increases sample diversity, poorly designed augmentations can introduce noise or distort structural patterns. To avoid this problem, the differential learning- rate strategy is applied only on models trained with non- augmented data.

Traditional approaches that rely on a constant learning rate often experience issues such as slow convergence and overfitting, particularly during long training periods. To address these limitations, the network is divided into distinct layer groups, each trained with an individually selected learning rate. Layers may also be selectively frozen or unfrozen during training, based on experimental requirements. This hierarchical training strategy helps the model identify optimal feature representations and leads to more stable and accurate PD detection.

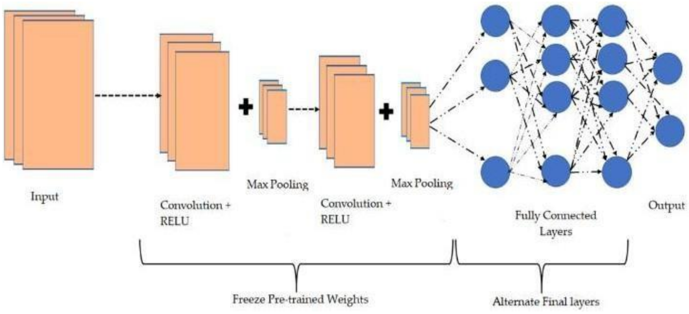


Figure 4: Transfer learning Process of general CNN Architecture

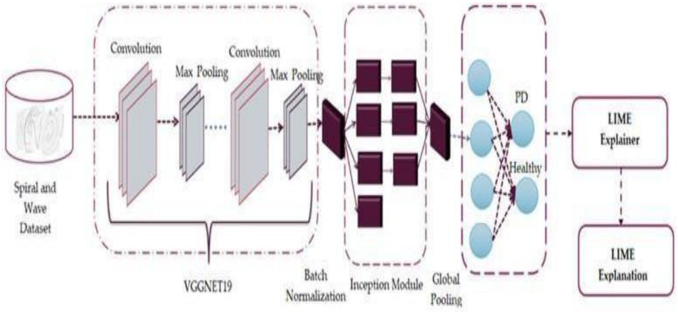


Figure 5: Proposed Architecture of hybrid deep transfer learning VGG 19-NIC model

The pipeline involves the following stages:

- Data acquisition and preprocessing :Spiral and wave drawings are first loaded into the system, where they undergo cleaning, resizing, and normalization. These steps ensure that the input images maintain uniform quality before being fed into the model.
- Feature extraction using VGG19 :A pretrained VGG19 network is utilized to generate high-level feature maps from the processed images. This network captures important structural and spatial characteristics that are useful for identifying Parkinson’s-related patterns.
- Prediction through customized dense layers :The features extracted by VGG19 are passed into a set of specially designed dense layers. These layers are trained to differentiate between Parkinson’s disease cases and healthy individuals, producing the final classification output.
- Classification using tailored fully connected layers :The extracted representations are further refined through a sequence of purpose-built fully connected layers. These layers finalize the decision- making process by assigning each sample to either the Parkinson’s category or the healthy control group.
- Model interpretability with LIME :To improve transparency, the LIME technique is applied to produce localized explanations for the model’s predictions. This helps highlight the specific regions or patterns that influence each decision, making the overall system more interpretable.

5. Explainable Ai (Lime)

Explainable Artificial Intelligence (EXAI) refers to methods aimed at making the functioning of AI systems clearer and easier for people to understand. Many deep learning and neural network models act like "black boxes," meaning they may deliver accurate results but do not clearly reveal how those results were produced. In areas such as healthcare, finance, and security, this lack of clarity reduces trust and makes it difficult to verify the reliability of AI models.

EXAI helps address this issue by offering explanations that are simple, meaningful, and useful to end users. Such explanations allow researchers and clinicians to see which input features influenced the model, why a specific output was generated, and how the model behaves under different conditions.

Healthcare-related AI often faces interpretability challenges. Even when a model performs well, it is still important to understand the reasoning behind its decisions. While traditional models like decision trees are naturally interpretable, many modern neural- network-based systems still operate in a way that offers very little insight into their decision-making process.

Among the various EXAI techniques available, Local Interpretable Model-Agnostic Explanations (LIME) is widely used due to its simplicity and strong interpretive capability. In this work, we assess how effective LIME is at explaining the decisions of our proposed model for distinguishing Parkinson's disease samples from healthy ones. The evaluation is carried out using spiral and wave drawings collected from PD and non-PD participants. LIME functions by generating modified versions of a specific image and examining how these small changes affect the model's prediction. This enables LIME to highlight which features contributed most to the model's output, offering a clear and locally interpretable explanation. These explanations help approximate the model's behavior around the selected image. The technique introduces slight variations—such as adding noise or masking certain regions—to understand which parts of the input have the most influence. Because of this, LIME produces explanations that are intuitive and easy to understand.

The main aim of this part of the study is to identify which super-pixels in the spiral and wave drawings play the most important role in detecting Parkinson's disease and to pinpoint regions that may lead to incorrect predictions. For demonstration, LIME was applied to a selected test image, as shown in Figure 7. The highlighted areas indicate their influence: red marks regions linked to incorrect predictions, while green marks the most important super-pixels among the top features used by the model.

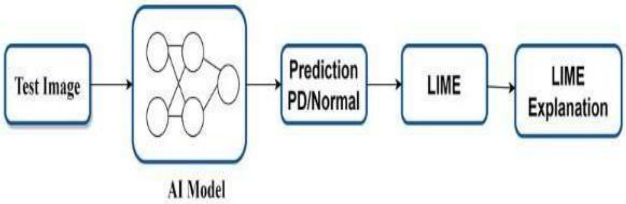


Figure 6: Block diagram of proposed model using LIME.

Figure 6 shows the structure of the proposed model with the LIME explanation framework included. In this setup, the test images are first processed by the model to determine whether the subject is healthy or shows PD symptoms. LIME is then applied to the prediction, identifying the top contributing features and generating a clear explanation for the decision.

Explainable AI (EXAI) methods classify explanations as either local or global, depending on how much information is needed to understand the concept. Local explanations focus on clarifying a single prediction for one specific input, while global explanations aim to describe the overall behavior of the entire model. Among the different EXAI approaches, Local Interpretable Model-Agnostic Explanations (LIME) is widely used because it is simple to apply and provides clear interpretations. In this study, we examined how well LIME helps explain the predictions made by our proposed model for separating Parkinson's disease cases from healthy subjects. The evaluation was carried out using spiral and wave drawing datasets collected from PD and non-PD participants. As an "explainer," LIME works by creating slightly modified versions of a selected sample and studying how these changes affect the model's output. This helps identify which small regions influence the decision and allows the surrogate model to approximate the original model's behavior. The technique introduces minor perturbations such as noise, masking certain areas, or removing specific pixel regions to analyze how each part of the input contributes to the final prediction. Through this process, LIME produces explanations that are intuitive and easy for users to understand.

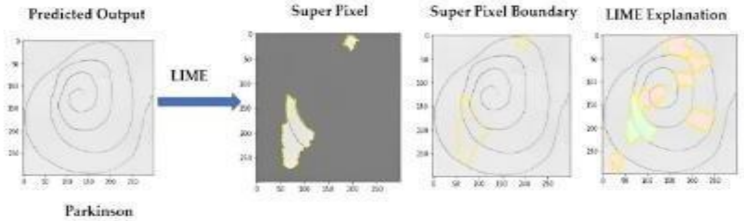


Figure 7: LIME explanation for PD prediction model based on spiral drawing.

6. Results And Analysis

Explainable Artificial Intelligence (EXAI) focuses on creating techniques that make the functioning of AI models clearer and easier for people to understand. Even though deep learning models can produce highly accurate predictions, their internal decision- making process is complex and not directly observable. Because of this, they are often considered “black-box” models. EXAI works to address this challenge by showing how the model reaches its outcomes and by highlighting the key regions or features that influence its decisions. In this study, we examine the interpretability results generated through the EXAI approach and present the areas highlighted by the explanation model.

Result: Normal → You are Normal. Keep Calm and Make Healthy Life

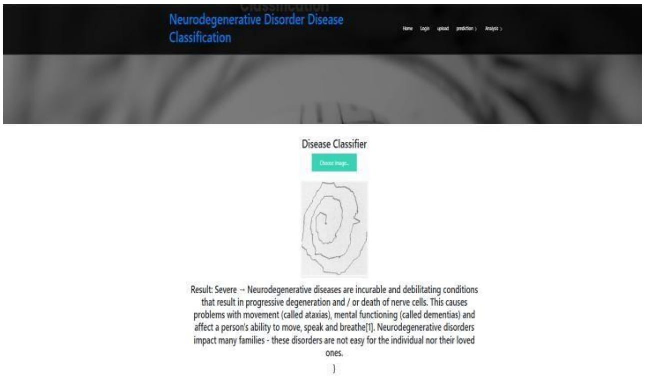
Figure 8: Detection of parkinson’s disease as Normal stage.

Result: Stage1 → The most common neurodegenerative disorders are amyloidoses, tauopathies, α-synucleinopathies, and TDP-43 proteinopathies. The protein abnormalities in these disorders have abnormal conformational properties.
)

Figure 9: Detection of parkinson’s disease as Stage 1.

Result: Stage2 → Neurodegenerative diseases are often presented as a distinct entity, however there is often overlap as you may have noted in the above descriptions, eg for AD and Lewy body pathologies. None of the neurodegenerative disorders have perfect diagnostic accuracy, and neuropathology will continue to be the gold standard for the foreseeable future.

Figure 10: Detection of parkinson’s disease as Stage 2.



Result: Severe → Neurodegenerative diseases are incurable and debilitating conditions that result in progressive degeneration and / or death of nerve cells. This causes problems with movement (called ataxias), mental functioning (called dementias) and affect a person's ability to move, speak and breathe[1]. Neurodegenerative disorders impact many families - these disorders are not easy for the individual nor their loved ones.
)

Figure 11: Detection of parkinson’s disease as Severe.

This section also summarizes the PD classification results obtained from several pre-trained neural networks trained using a differential learning rate approach. Table 1 presents a comparison of these architectures for Parkinson’s diagnosis. The table lists the accuracy of each model with and without differential learning rates, and the best results are shown in bold to highlight the strongest performance on the drawing-based dataset.

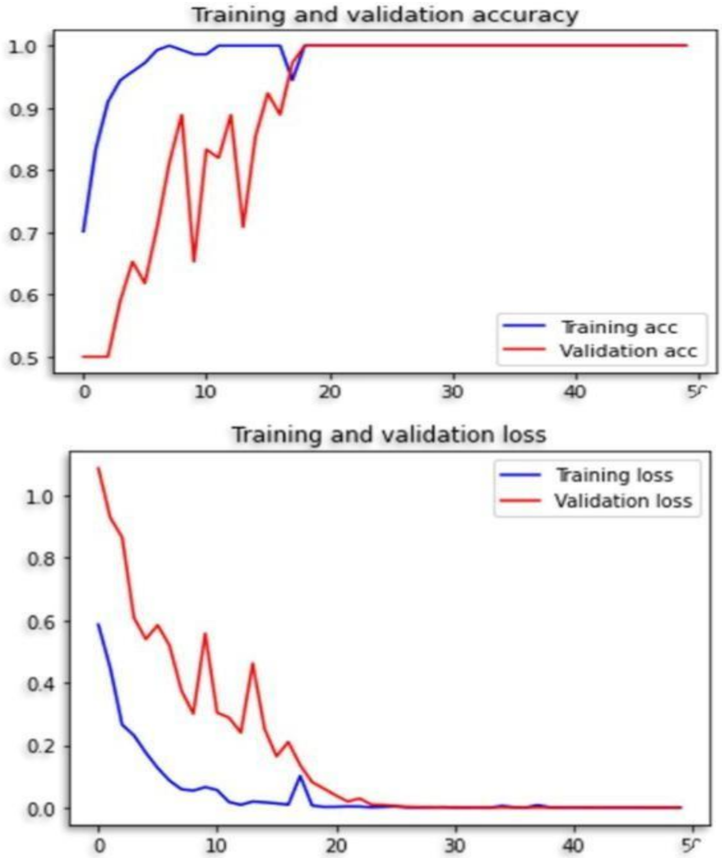


Figure 12: VGG19-INC, top accuracy and bottom shows the loss of the model

The performance graph in Fig. 12 shows that our proposed method outperforms the other pre-trained models on the publicly available drawing dataset. The main aim of the proposed framework is to combine the strengths of VGG19 and GoogleNet to achieve noticeable improvement in classification accuracy. As seen in Fig. 12, the training and validation loss curves steadily decrease and eventually flatten, indicating that the model reaches a stable and optimal learning point for PD classification.

Additionally, the experimental results from several pre- trained models trained with differential learning rates show that ResNet-50 provides the best performance among the tested CNN architectures for Parkinson's prediction on the drawing dataset. In this study, all models were trained for a relatively small number of epochs, yet they still managed toconverge effectively.

Explainable AI plays an important role in modern machine learning models, especially in sensitive areas such as healthcare. The main purpose of EXAI is not only to show the model's prediction but also to explain the reasoning behind it. This helps improve human understanding, builds trust, and allows experts to verify whether the model is making decisions correctly.

In medical diagnosis, EXAI supports clinicians by showing whether the model is paying attention to medically relevant features. For instance, in spiral and wave drawings used for Parkinson's Disease (PD) detection, EXAI can highlight shaky regions, uneven strokes, tremor-related patterns, or areas showing reduced motor control. These visual indicators match common symptoms of PD, making EXAI a valuable tool for diagnostic support.

EXAI also helps identify possible weaknesses in a model. If the explanation highlights irrelevant background areas or noise, it suggests that the model may not be focusing on useful features. This feedback helps researchers improve preprocessing steps, enhance feature extraction, and choose more reliable model architectures.

Figure 13: Classification of different stages of parkinson's disease

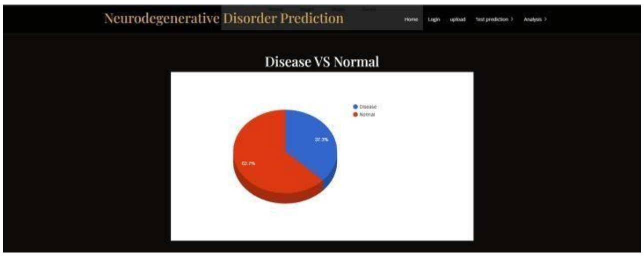


Figure 14: Proportion of Disease vs. Normal Samples in the dataset.

Expanded Comparison of Pre-trained Models

Different CNN architectures show varied performance on PD classification depending on their depth, feature extraction capability, and network structure:

1. VGG19 Network

EXAI also helps identify possible weaknesses in a model. If the explanation highlights irrelevant background areas or noise, it suggests that the model may not be focusing on useful features. This feedback helps researchers improve preprocessing steps, enhance feature extraction, and choose more reliable model architectures. These small filters were shown to be as effective as larger kernels (such as 5×5 or 7×7), while keeping the number of parameters manageable. The inclusion of additional convolutional blocks in the middle of the network allows VGG19 to extract richer spatial features and achieve high accuracy in visual recognition problems.

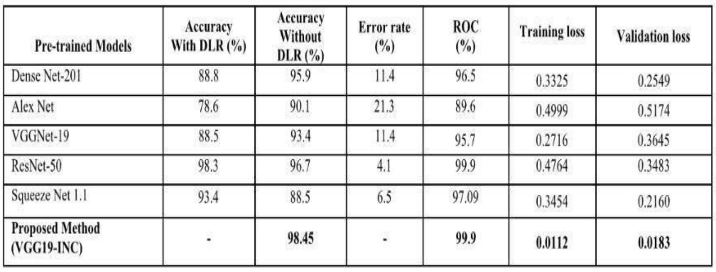
2. ResNet50

As neural networks grow deeper, they often face challenges such as reduced accuracy or vanishing gradients. ResNet50 tackles this problem using residual learning, where shortcut connections allow gradients to pass through the network more easily. This helps the model increase depth without losing performance. ResNet50 achieves much lower error rates compared to traditional 34-layer CNNs, and deeper variants like ResNet101 include additional residual blocks, further enhancing feature representation.

3. DenseNet201

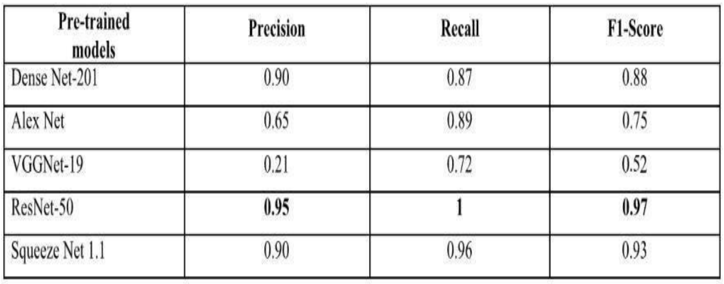
DenseNet201 builds on the concept of residual connections by introducing dense connectivity. In this design, each layer receives the feature maps from all previous layers, ensuring strong information flow throughout the network. These dense connections help reduce vanishing-gradient issues and promote reuse of features. While this structure improves learning efficiency, it also increases the total number of feature maps, making DenseNet more computationally demanding than ResNet.

4. Squeeze Net 1.1



Pre-trained Models	Accuracy With DLR (%)	Accuracy Without DLR (%)	Error rate (%)	ROC (%)	Training loss	Validation loss
Dense Net-201	88.8	95.9	11.4	96.5	0.3325	0.2549
Alex Net	78.6	90.1	21.3	89.6	0.4999	0.5174
VGGNet-19	88.5	93.4	11.4	95.7	0.2716	0.3645
ResNet-50	98.3	96.7	4.1	99.9	0.4764	0.3483
Squeeze Net 1.1	93.4	88.5	6.5	97.09	0.3454	0.2160
Proposed Method (VGG19-INC)	-	**98.45**	-	**99.9**	**0.0112**	**0.0183**

Figure 15: Summary of different pre-trained CNN models result



Pre-trained models	Precision	Recall	F1-Score
Dense Net-201	0.90	0.87	0.88
Alex Net	0.65	0.89	0.75
VGGNet-19	0.21	0.72	0.52
ResNet-50	**0.95**	**1**	**0.97**
Squeeze Net 1.1	0.90	0.96	0.93

Figure 16: Performance evaluation of metrics of PD classification.

Squeeze Net 1.1 is a compact and efficient CNN model designed to provide accuracy similar to larger networks while greatly reducing the number of parameters. Its architecture is built around fire modules, each containing a squeeze layer with 1×1 filters and an expand layer that uses a mix of 1×1 and 3×3 filters. The squeeze layer shrinks the input channels, and the expand layer increases representation capability. Thanks to this efficient structure, Squeeze Net delivers performance close to Alex Net while using far fewer parameters, making it ideal for lightweight or embedded applications.

7. Discussion

In this study, several deep transfer learning models were explored to improve early detection of Parkinson’s disease (PD) using drawing-based biomarkers. Identifying PD in its early stages is difficult because the motor-related symptoms are subtle at first. Hand-drawn spirals and waves contain fine variations, and deep learning models are well-suited to capture these detailed patterns. However, these models typically require large datasets, which are often not available in medical research. To overcome this challenge, transfer learning was used.

The main goal of the study was to reduce training loss and improve prediction accuracy. To achieve this, a hybrid transfer learning model combining VGG19 and Inception (referred to as VGG19-INC) was developed. This model leverages the strong feature extraction capabilities of VGG19 along with the multi-scale convolutional design of Inception, resulting in richer and more discriminative representations of the drawings.

A key advantage of the proposed approach is the integration of Explainable AI (XAI) methods. Deep neural networks often function as black-box models, making it hard for clinicians to understand how a prediction is made. By incorporating an explanation framework like LIME, the model becomes more transparent and reliable. LIME highlights the parts of the image that contribute the most to the final decision, which is crucial in healthcare settings where explainability supports informed clinical decision- making.

Experimental evaluations showed clear improvements in classification accuracy. Among the pre-trained networks tested—VGG19, GoogleNet, DenseNet, and Inception—ResNet-50 achieved the highest accuracy of 98.3%, outperforming many existing approaches on similar drawing-based datasets. When additional samples were included during training and testing, the performance increased only slightly (around 0.08%), indicating that the model is stable and reaches its optimal accuracy even with moderate data augmentation.

Further analysis confirms that the proposed method delivers strong performance across metrics such as precision, recall, and F1-score. The study also emphasizes the value of transfer learning in medical image analysis. By reusing features learned from large datasets like ImageNet, transfer learning reduces the need for extensive annotated medical data—an advantage in PD diagnosis using handwriting patterns, where data collection is challenging due to limited patient availability.

The LIME explanation process works by dividing the input image into super pixel regions, examining how the model’s prediction changes when specific areas are altered, and generating a visual explanation map. Regions that positively influence PD detection appear in highlighted patches, helping researchers identify which parts of the drawing carry diagnostic relevance. These explanation maps provide deeper insight into how the model interprets tremor patterns or irregular drawing strokes.

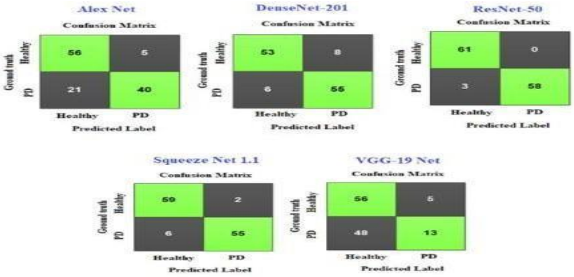


Figure 17: The confusion matrix obtained by the deep neural networks in the classification of PD.

Training the hybrid architecture with transfer learning led to a notable boost in model performance. When compared to previous studies, this approach is distinct because it requires minimal preprocessing and integrates multiple pre-trained models in a novel way. This combination allows the system to learn a wider range of useful features, enhancing its capability to distinguish between drawings from PD patients and healthy individuals.

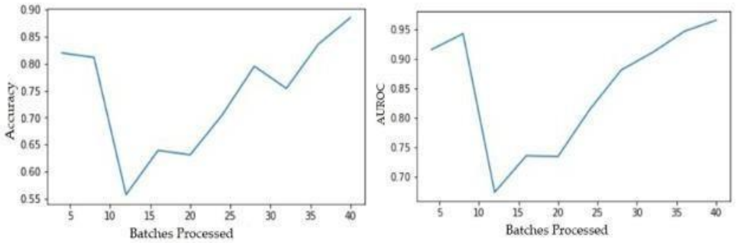


Figure 18: DenseNet-201,left is the accuracy and right is the area under ROC of the model.

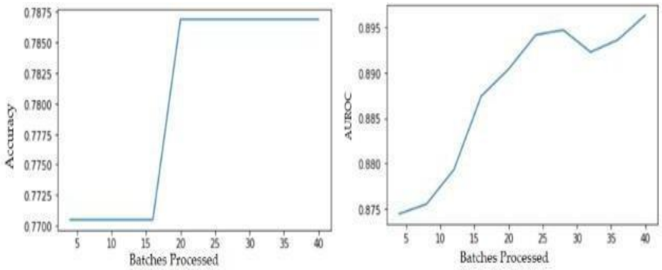


Figure 19: AlexNet, left is the accuracy and right is the area under ROC of the model

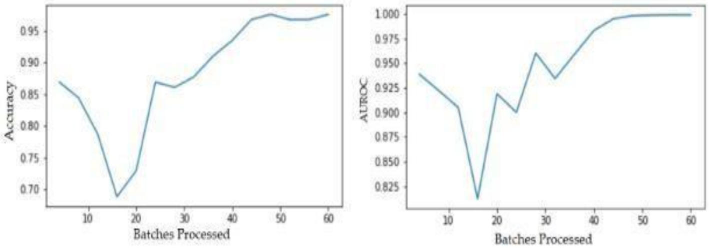


Figure 20: VGG-19 Net, left is the accuracy and right is the area under ROC of the model

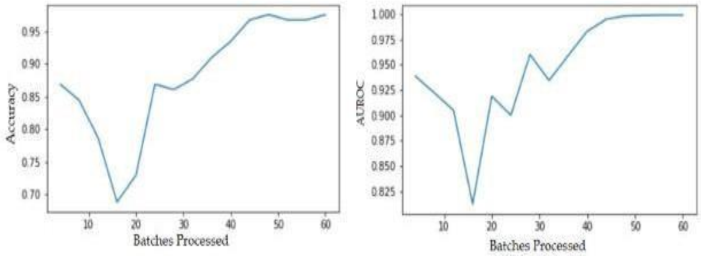


Figure 21: ResNet50, left is the accuracy and right is the area under ROC of the model

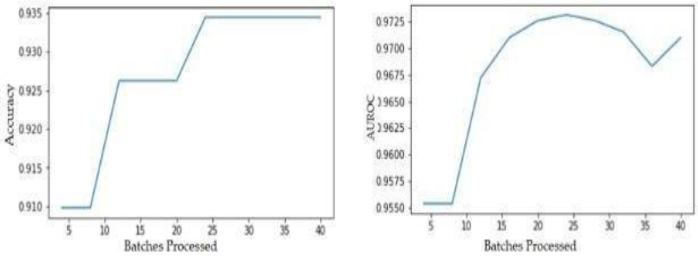


Figure 22: SqueezeNet, left is the accuracy and right is the area under ROC of the model

8. Conclusion

This study introduced an enhanced deep learning framework for the early detection of Parkinson’s Disease by merging the strengths of two transfer learning models and applying differential learning rates. The proposed VGG19-INC model delivered higher accuracy and achieved faster convergence compared to other existing approaches .To improve transparency, LIME was used to interpret the model’s predictions and provide insight into its decision-making process. Overall, the findings indicate that the proposed system is effective for PD diagnosis and can serve as a valuable reference for future work involving transfer learning and explainable AI in medical applications.

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