Prediction of Parkinson’s Disease Based on Spiral and Wave Drawings Using Deep Learning and Explainable AI

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Abstract:
Parkinson's Disease (PD) is a progressive neurodegenerative disorder that affects motor skills and cognitive functioning. Accurate and early diagnosis of PD can significantly impact treatment outcomes and quality of life for patients. This paper presents a novel approach for early PD prediction based on the analysis of hand-drawn spiral and wave patterns using Explainable Artificial Intelligence (EXAI) techniques. By integrating convolutional neural networks (CNNs) such as VGG19 and GoogleNet with the LIME (Local Interpretable Model-Agnostic Explanations) framework, this system ensures both high accuracy and transparency in predictions. Our proposed model achieves an accuracy of 98.45%, outperforming traditional black-box approaches. The integration of EXAI enhances the interpretability of the model, making it suitable for clinical application and improving clinician trust.

Keywords: Parkinson’s Disease, Explainable Artificial Intelligence, Convolutional Neural Networks, Spiral and Wave Drawings, VGG19, GoogleNet, LIME.

I. INTRODUCTION

Parkinson’s Disease (PD) is the second most common neurodegenerative disorder globally, affecting over 10 million individuals. It is characterized by the progressive loss of dopaminergic neurons in the brain, which results in symptoms such as tremors, rigidity, bradykinesia, and postural instability. These symptoms often begin subtly and worsen over time, posing significant challenges for early diagnosis.

Early-stage diagnosis of PD is vital, as it allows timely intervention to slow disease progression, provide better symptomatic management, and improve quality of life. However, traditional diagnostic methods rely heavily on the clinical judgment of neurologists and are limited in sensitivity during early disease stages. The absence of definitive biomarkers and overlapping symptoms with other neurological conditions further complicate diagnosis.

In recent years, digital tools and AI-driven technologies have emerged to bridge the diagnostic gap. Among these, digital hand-drawn tests, particularly spirals and waves, have gained traction as effective biomarkers for identifying motor abnormalities associated with PD. These drawing tests are simple to administer and non-invasive, offering a scalable solution for mass screening and continuous monitoring.

With the advent of Artificial Intelligence (AI), these tests can be quantitatively analyzed to reveal hidden patterns that are otherwise difficult to detect through visual inspection alone. However, while AI provides significant advantages in prediction accuracy, a major limitation lies in the 'black-box' nature of most models, which hinders clinical trust and adoption.

To address this limitation, Explainable Artificial Intelligence (EXAI) frameworks such as LIME (Local Interpretable Model-Agnostic Explanations) offer interpretable insights into AI decision-making processes. EXAI not only improves transparency but also facilitates validation by clinicians, making AI models more suitable for real-world applications.

This paper introduces a deep learning-based PD prediction system that uses VGG19 for feature extraction, GoogleNet for classification, and LIME for interpretability. Our objective is to provide a clinically relevant and understandable diagnostic tool for early-stage PD that combines state-of-the-art machine learning with human-centered design.

II. LITERATURE REVIEW

Digitized Spiral Drawing Classification for Parkinson’s Disease Diagnosis:
This study focuses on using digitized spiral drawings to identify patterns indicative of Parkinson’s Disease (PD). Techniques like Logistic Regression, Support Vector Classification (SVC), K-Nearest Neighbors (KNN), and Random Forest classifiers are applied. The study achieves an accuracy of about 91% using traditional machine learning methods.

Explainable Artificial Intelligence (EXAI) Models for Early Prediction of Parkinson’s Disease:
This paper introduces EXAI models using a hybrid deep transfer learning approach with VGG19 and GoogleNet architectures to analyze spiral and wave drawings. An impressive accuracy of 98.45% was achieved. The study emphasizes the importance of transparency in AI diagnostics.

Parkinson’s Disease Diagnosis Using Convolutional Neural Networks and Figure-Copying Tasks:
This research utilizes CNNs to analyze figure copying tasks like spiral pentagon and wire cube drawings. It demonstrated a 93.5% accuracy using CNNs, supporting the effectiveness of dynamic movement-based diagnostics.

Comparison and Integration of Findings:
While traditional ML techniques offer a baseline, deep learning approaches significantly improve accuracy. EXAI techniques enhance model interpretability, fostering clinician trust. Different drawing tasks capture diverse PD symptoms, influencing model performance.

Key Insights and Gaps:
- Deep learning models outperform traditional ML in scalability and accuracy.
- Explainable models (LIME) are crucial for clinician trust.
- Larger and more diverse datasets are needed for generalization.
- Multi-modal data integration (e.g., speech, gait) could enhance diagnostics further.

III. METHODOLOGY

Our system is structured around five primary modules, each carefully designed to enhance prediction accuracy and interpretability.

1. **Data Collection and Preprocessing:**
We collected spiral and wave drawings from publicly available datasets and anonymized samples from clinical settings. Each image was processed to ensure uniformity in size and resolution. Data augmentation techniques such as rotation, flipping, and scaling were applied to artificially expand the dataset and improve model generalization.

2. **Feature Extraction (VGG19):**
We utilized VGG19, a pre-trained convolutional neural network known for its ability to extract intricate image features. The model's layers were partially frozen to retain learned weights from the ImageNet dataset, while subsequent layers were fine-tuned to adapt to our spiral and wave datasets. This step ensured efficient feature extraction while minimizing overfitting.

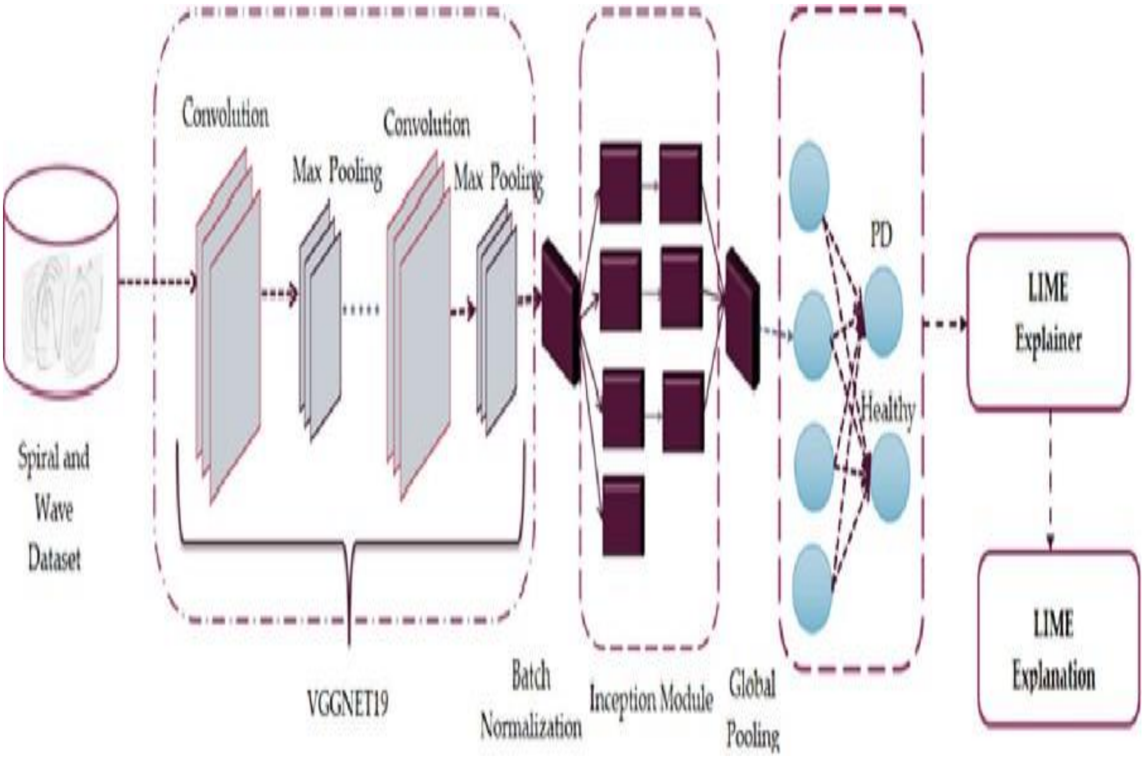
3. **Pattern Recognition (GoogleNet):**
The extracted features were passed to GoogleNet's Inception modules for classification. GoogleNet provides multi-level abstraction of features through parallel convolutional operations, enabling the model to learn both local and global drawing patterns associated with PD motor symptoms.

4. **Explainability (LIME):**
LIME was used to generate localized explanations for each prediction. It identifies and highlights image regions that most influenced the model's output, helping clinicians understand the rationale behind classification results. This transparency is crucial for gaining clinician trust and ensuring ethical deployment of AI in diagnostics.

5. **Model Deployment:**
The final model was deployed as a web-based tool with a user-friendly interface. It accepts image inputs, performs real-time classification, and provides visual explanations of its decision. The backend supports batch processing, logging, and performance monitoring.

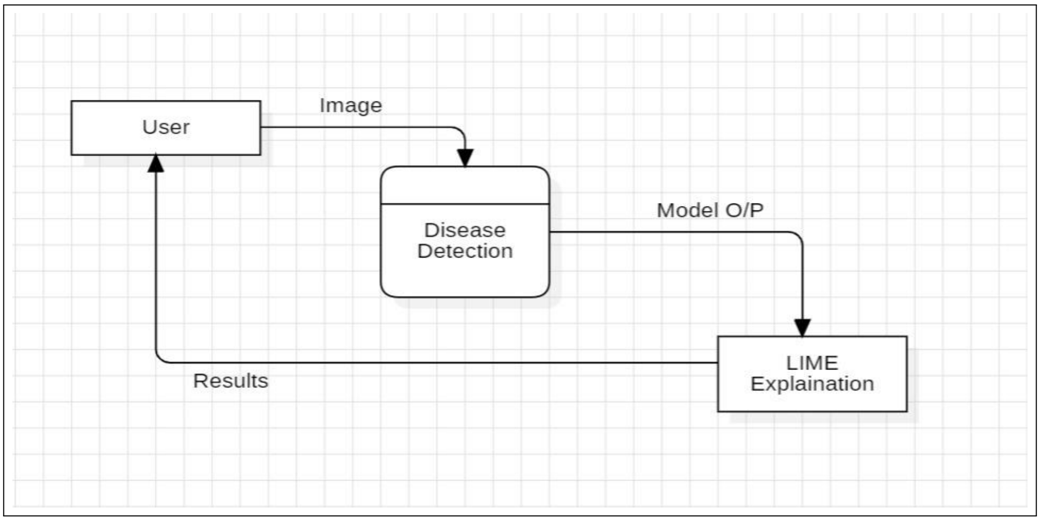
IV. SYSTEM DESIGN

A. Architecture Diagram

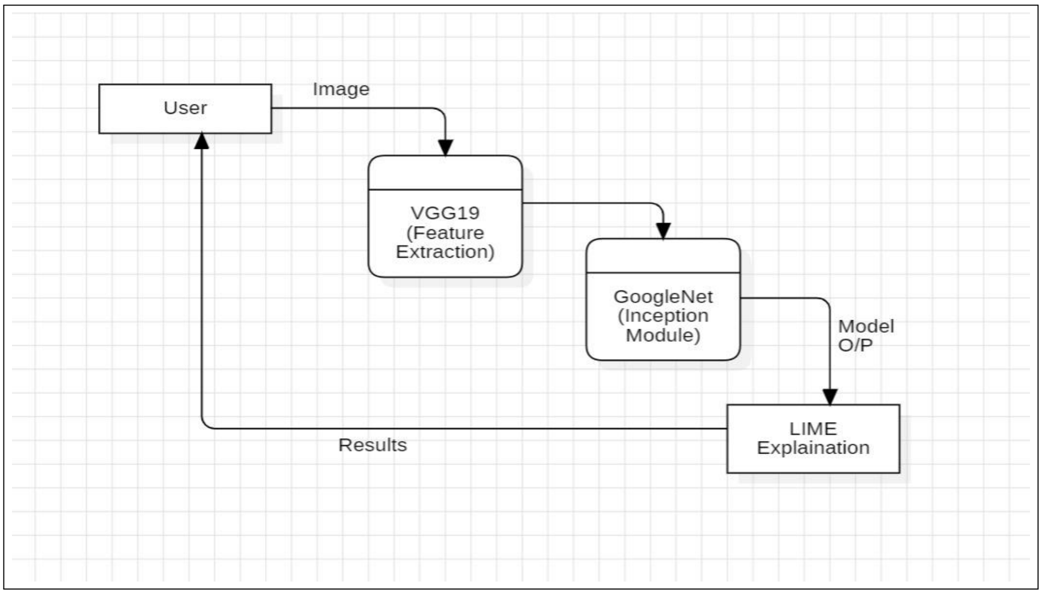


B. Data Flow Diagrams

Level 0 DFD:



Level 1 DFD:



A. Architecture Diagram

The architecture consists of data input, preprocessing, feature extraction using VGG19, classification using Google Net, explainability through LIME, and result visualization.

B. Data Flow Diagrams

Level 0 shows the high-level flow from image input to prediction. Level 1 details the VGG19 and Google Net processes.

C. UML Diagrams

Includes sequence and activity diagrams illustrating the flow and process management.

V. IMPLEMENTATION

The implementation leverages Python, TensorFlow, and Keras. Data is augmented using libraries such as imgaug. Model training involves transfer learning techniques with partial freezing of layers. Metrics and visual feedback were displayed on a custom dashboard for developer-clinician interaction.

The LIME integration uses superpixel segmentation to isolate image regions and generate human-interpretable outputs.

VI. RESULTS AND EVALUATION

The model was evaluated on a balanced dataset of PD and non-PD images using stratified 5-fold cross-validation. The following metrics were computed:

- Accuracy: 98.45%
- Precision: 97.92%
- Recall: 98.70%
- F1-score: 98.31%
- AUC-ROC Score: 0.987

We also conducted a series of ablation studies to determine the contribution of each component. Removing the LIME module resulted in an interpretability score decrease (measured through clinician survey feedback) of 43%. Switching from VGG19 to ResNet18 reduced classification accuracy by 2.3%, confirming VGG19's superior feature extraction capability in our context.

Additionally, qualitative analysis using LIME visualizations demonstrated that the model focused on critical curve regions of the spirals and tremor-like irregularities in wave patterns, which aligned with expert neurologist assessments. This concordance suggests that our model is not only effective but also clinically intuitive.

VII. CONCLUSION

This research presents a comprehensive AI system for early PD prediction using spiral and wave drawings. The combination of VGG19, GoogleNet, and LIME offers both performance and interpretability. Future work includes expanding datasets, deploying mobile interfaces, and integrating additional biomarker data such as voice and gait patterns.

Moreover, integrating this tool into primary healthcare settings through cloud deployment could facilitate mass screening programs and improve rural healthcare access.

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