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RESEARCH ARTICLE

Explainable Artificial Intelligence (EXAI) Models for Early Prediction of Parkinson's Disease Based on Spiral and Wave Drawings

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ABSTRACT Parkinson's disease (PD) is a rapidly growing neurodegenerative disorder that primarily affects the elderly population. Until now, there has been no antidote for PD. However, diagnosing Parkinson's disease in its early stages is difficult. Early treatment will help people with Parkinson's disease improve their quality of life. The primary goal of this work is to increase the early diagnostic accuracy of Parkinson's disease using deep learning models and to make the models more transparent and trustworthy. It proved challenging to comprehend the methods by which the classifiers made predictions about Parkinson's disease. It would be valuable if the outcomes generated by these classifiers could be clarified in a reliable and trustworthy manner. Explainable Artificial Intelligence (EXAI) focuses on enhancing clinical health practises and bringing transparency to predictive analysis, both of which are critical in the healthcare arena. We proposed a new hybrid deep transfer learning model to distinguish PD patients from healthy individuals. The proposed architecture combines the advantages of both VGG19 Net and Google Net. This study also shows the experimental outcomes of various pre-trained models such as Alex Net, DenseNet-201, VGG-19 Net, Squeeze Net1.1, and ResNet-50. The VGG19-INC model predicts PD with an accuracy of 98.45%, which is greater than other state-of-the-art approaches, demonstrating the proposed work's superiority and robustness. To demystify the VGG19-INC model, explainable AI approaches such as LIME are used to identify the specific parts of the spiral and wave drawings that contribute most to the model's prediction. These methods provide local interpretation, making it easier to understand how the model arrives at its conclusions.

INDEX TERMS Explainable artificial intelligence, Parkinson's disease, deep learning, Google net, LIME, spiral and wave drawings.

I. INTRODUCTION

Parkinson's disease (PD) is a chronic neurodegenerative disease that primarily affects the central nervous system of the body. The body's motor function suffers as a result of a shortage of dopamine [1]. Dopamine is a chemical substance produced by neurons in the substantial nigra pars compacta, which is responsible for motor actions. Parkinson's disease predominantly impacts the motor system, resulting in movement difficulties such as tremors, stiffness, and slowed

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movements known as bradykinesia. Tasks involving drawing spirals and waves necessitate precise coordination and fine motor control. Clinicians can evaluate the motor control skills of individuals with Parkinson's disease and detect any irregularities or fluctuations in motor function by examining the quality of their drawings. The prevalence rate of PD increases with the ageing population in males and females over 60. PD can be characterised by motor and non-motor symptoms [2], [3]. As the disease progresses, it is essential to identify the disease early to keep the symptoms under control. The severity of Parkinson's disease can be measured in various stages by the Unified Parkinson's Disease Rating Scale (UPDRS) and the Hoehn and Yahr (H-Y) rating scales. The variation in scores takes years based on the progression of the disease [4]. The International Classification of Diseases, 11th Revision (ICD-11), is a robust system used worldwide to categorize and diagnose various diseases, including Parkinson's disease (PD). Within the ICD-11, specific diagnostic criteria have been established for PD, outlining the key indicators necessary for its identification. These criteria serve as a standardized framework for healthcare professionals to accurately diagnose individuals with PD.

Currently, the diagnosis of PD is based on clinical assessments, a time-consuming process, and a need for more human experts. The direct and indirect costs of treating PD patients will be approximately $23,000, burdening the elderly. Thus, the automatic early diagnosis of PD is needed in healthcare [5]. The scientific community shows considerable interest in medical-assisted diagnosis [6], [7]. However, it is quite challenging to achieve better classification accuracy. The proposed method's main advantage over the traditional PD diagnosis is fast and accurate decision-making. In recent years, there have been notable advancements in our knowledge of Parkinson's disease and how to manage it. Progress in early detection, treatment choices, and research focused on altering the progression of the disease offer hope for enhancing the well-being of individuals with PD and eventually discovering a cure for this intricate neurodegenerative condition.

PD is often misdiagnosed as the symptoms are like those of other diseases like multiple system atrophy (MSA), progressive supranuclear palsy (PSP), Huntington's disease, etc. [8]. Convolutional neural networks (CNNs) are well-liked in deep learning techniques, particularly in overcoming the challenges of the classical ML approaches [9], [10]. The exploration of drawings has confirmed their usefulness in diagnosing PD patients. Digital techniques predominantly depend on the model's accuracy, so it is crucial to execute deep learning-based algorithms to achieve better accuracy for PD detection and accelerate the diagnosis process to improve the patient's quality of life [11], [12]. Deep learning is an effective method for processing huge volumes of data since the models get more accurate as more data is applied into them. On the other hand, in the existing body of research, a deep neural classifier is frequently referred to as a "black box" technique. Since the process is not transparent, and the researchers are unable to obtain information regarding the specific way in which the input is associated with the output. Because of the nature of the application in many different fields, such as medicine, interpretability is of the utmost importance. Through the implementation of Local Interpretable Model-agnostic Explanation (LIME) into the image classification pipeline, the primary goal of our research is to make the proposed PD prediction model more interpretable. This paper investigates early diagnosis of PD over drawing datasets acquired from PD patients using various pre-trained CNN models with Explainable AI. The significant contributions of this proposed work summary are as follows:

- Constructing a precise deep learning algorithm to detect Parkinson's disease in its early stages by analyzing spiral and wave drawings.
- Develop an understandable approach utilizing LIME to solve the classification problem.
- Assist healthcare professionals in identifying Parkinson's disease at an early stage by displaying visual indicators produced by the model during its predictions.
- In addition, this article performs an extensive comparative study by validating that ResNet-50 with a dynamic learning rate performs well compared with the current state-of-the-art techniques.

The remainder of this manuscript is organized as follows. Section II analyses the present related works on PD recognition. Section III introduces the collection of dataset description and data augmentation techniques, and this section primarily reviews the different CNN architectures used to achieve the task of PD classification. Section IV is dedicated to evaluating the multiple experimental results and comparative assessment. Section V discusses the outcomes of XAI framework. Finally, Section VI summarizes this work.

II. RELATED WORK

Artificial intelligence in health care has gained increasing popularity in this growing era. Over a period, much research has been conducted previously related to PD's early diagnosis. For example, in recent years, handwriting has been considered a promising biomarker for diagnosing PD at an earlier stage. This is because handwriting can assess an individual's cognitive and motor functions, and the graphical characteristics of handwriting can recognize the uncertainty of strokes produced by tremor movements.

Predictable metrics include changes in the size of the written characters, the height of loop patterns, text blocks region, pixel density deviations originating due to ink content, density and height ratios, and spiral precision index [13], [14]. Apart from evaluating the severity of Parkinson's disease (PD), these studies also facilitate monitoring the disease progression over time and detecting early symptoms. For example, a research study investigated the feasibility of analyzing handwriting samples based on handwriting history via static analysis to establish the severity of PD in 10 Patients.

Multiple machine learning algorithms were employed to differentiate between PD and healthy. In several handwriting tasks, Drotar et al., [15] employed SVM and obtained an accuracy rate of 81.3% on the PaHaW database, which consists of 37 PD patients and 38 HC, using kinematic and pressure features. In their study, Pereira et al. [16] Utilized cutting-edge deep learning techniques, opting for a convolutional neural network to differentiate between changing aspects of handwritten samples from the HandPD dataset, which included 74 individuals diagnosed with Parkinson's disease and 18 healthy controls. Das et al. [17] proposed a prediction model for the early diagnosis of PD using various classification techniques, and finally, Neural Networks outperform other classifiers, with 92.2% accuracy in classification. Akyol et al. [18] aimed to improve the diagnostic accuracy of automatic PD identification using several classifiers over the hand PD dataset. It is evident from the results that the ANN classifier algorithm outperforms well compared to Random Forest (RF) and Linear Regression (LR) classifiers. Afonso et al. [19] applied the deep Optimum-Path Forest (OPF) clustering for the PD classification using a dynamic handwritten dataset. Later, Kotsavasiloglou et al. [20] presented a PD prediction model using a normalised variable velocity of the drawing dataset; the authors explored the features composed of twenty healthy subjects and twenty-four PD patients. On the other hand, Gil-Martin et al. [21] developed a convolutional neural network to separate the hand drawings' features for PD classification. The prediction model achieved an accuracy of 96.5%. Naseer et al. [22] implemented transfer learning through Alex Net using the PaHaW dataset to classify the PD patients from healthy. The authors achieved a classification accuracy of 98.28% using fine-tuned ImageNet features. In another work, Meghakamble et al. [23] pointed out that digitalized spiral drawings will be a promising biomarker for PD prediction. With the assistance of four machine learning classifiers implemented on the mathematically processed dataset with feature engineering, they also summarized results with an accuracy of 91% and an AUC of 98.1%. Goyal et al. [24] applied an adjusting learning rate as a function of minibatch size in the training phase of the ImageNet dataset to achieve excellent performance by overcoming the optimization challenges. Akter et al. [25] discovered an approach to identifying PD-affected patients early using hand-drawn wave and spiral images. Several machine learning classifier algorithms are proposed with HOG feature descriptors in that KNN outperforms well with an accuracy of 89.33%. Canturk et al. [26] applied transfer learning through popular CNN architectures like Alex Net and Google Net models to analyse the performance of PD classification using dynamic spiral tests and achieved an accuracy of 94%. Loschilov et al. [27] investigated the stochastic gradient descent with warm restarts (SGDR) by scheduling the learning rates during the training phase to achieve better results on ImageNet datasets. Alissa et al. [28] examined the spiral pentagon drawings in the discrimination process of PD patients from healthy subjects. The author has achieved an accuracy of 93.5% by using the convolutional classifier. Riberio et al. [29] developed the LIME approach, which offers a reliable and easy-to-understand way of explaining classifier predictions. LIME leverages local interpretation and explanation by simplification techniques to construct an interpretable model specific to each prediction. Das et al. [30] provided a comprehensive overview of the current state of explainable artificial intelligence (XAI) within the context of deep learning, highlighting different algorithmic approaches and categorizing them in detail. The authors also discussed potential future directions for improving XAI evaluation.

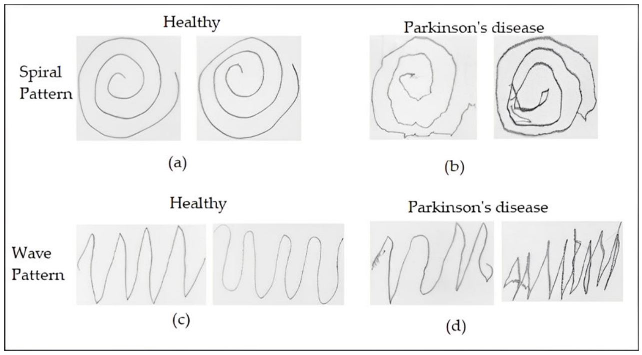

FIGURE 1. (a) Spiral images of healthy subjects (b) Spiral images of PD patients (c) Wave images of healthy subjects (d) Wave images of PD patients. [31].

III. MATERIALS AND METHODS

This section discusses the collection of datasets and data preprocessing techniques. We also see the proposed approach to the early diagnosis of PD using various pre-trained models.

A. DATASET DESCRIPTION

The drawing dataset contains spiral and wave drawing samples of 102 subjects, i.e., 51 PD patients and 51 healthy subjects, downloaded from Kaggle. The dataset provided by the authors [31] comprises two distinct types of images intensely, 102 spiral drawings and 102 wave drawings. Recordings from each subject were performed by drawing a spiral and a wave image. The Dataset 2 comprises spiral drawings contributed by a total of 124 PD patients and 141 healthy subjects, generously provided by the authors [32] The dataset1 and dataset2 is parted into a training set and the validation set as the proportion of 70/30. Therefore, only a few sample images of spiral and wave patterns drawn by the subjects with PD / without PD are displayed in Fig. 1.

B. DATA AUGMENTATION

The key challenge in deep learning is the need for better data quality within datasets or the imbalance of data within the datasets. Specifically, collecting the PD patient datasets is challenging as PD symptoms may vary from person to person. Usually, a data augmentation technique is adopted to overcome this issue. In this study, data augmentation is used to enrich the data samples so that the model can learn very well during training. In this proposed work to enrich the drawing dataset, some image preprocessing techniques were implemented using python script during test-time. As a result, the original image's brightness is enhanced through max lighting, and the original image's size is enlarged using vertical flipping.

1) FLIPPING
Flipping is a widely employed method of data augmentation in computer vision applications, particularly in tasks like image classification. It entails the horizontal mirroring of an image to generate an augmented variant. This technique operates under the assumption that the visual characteristics of an object are typically maintained even when it is horizontally flipped.

2) ROTATION
Rotation involves the process of applying a specific angle of rotation to an image, resulting in the creation of diverse versions of the original image. This application of rotation aids in training the model to identify objects from various orientations, thereby enhancing its capacity to generalize effectively to unfamiliar data.

3) SHEARING
Shearing technique presents an opportunity to increase the variety of training data by introducing geometric transformation.

Additionally, to prevent the images from distortion and retain the original information, we implemented a preprocessing technique that maintains the same proportion and darkens the shorter portions. In that fashion, new augmented samples are generated to increase the size of the original dataset. Fig. 2. displays the sample augmented images of spiral and wave drawings.

C. DEEP TRANSFER LEARNING
Transfer learning transfers knowledge from the pre-trained models by fine-tuning it with the exact domain data [33]. Despite training the prediction model from scratch by assigning random weights, it is better to initialize the pre-trained model weights to enhance the network's performance on large public datasets [34], [35]. Deep transfer learning discovers the suitable base networks, and the weights of the pre-trained models are assigned to the bottom layers of CNN [36]. Fig.3. Shows the transfer learning process of CNN architecture, which includes convolutional, ReLU, Max Pooling layer and fully connected layer. In this proposed work, we modified the neural networks by inserting and deleting the fully connected layers and then training the model with the newly created deep networks using drawing datasets.

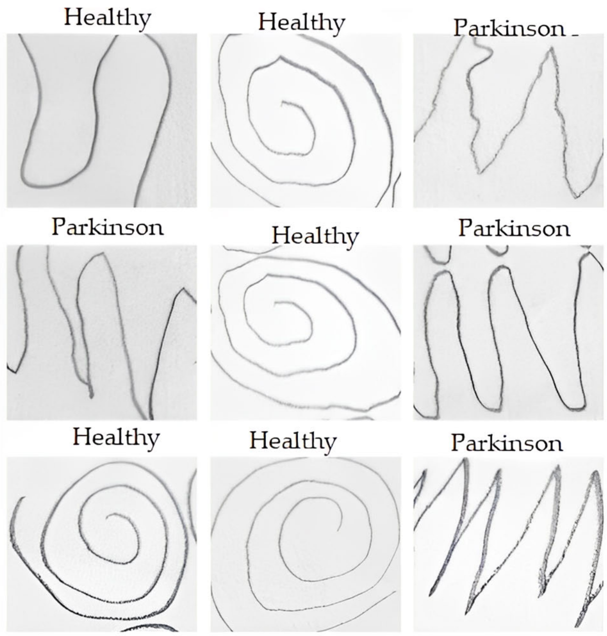

FIGURE 2. Augmented images of spiral and wave pattern drawings.

D. PROPOSED METHODOLOGY
In this study, we examined that the VGG19 Net performed admirably in the 2014 Large-Scale Visual Recognition competition. The proposed architecture of the VGG19 Net-INC new deep transfer fusion model is depicted in Fig.4. In this proposed method, the VGG19 Net and Inception modules are used to develop a new deep transfer fusion learning model for PD classification. VGG19 Net extracts the basic features from spiral and wave drawings, but Inception modules extract the high-dimensional features. Deep transfer learning models are preferred over starting from scratch with a limited dataset to distinguish PD patients from healthy individuals in order to reduce overfitting. One of the biggest challenges with many deep learning models is that they are often "black boxes" it can be difficult to understand how they arrive at their predictions or decisions. This lack of transparency can make it difficult for practitioners to trust the model. To overcome this, we explored Explainable Artificial Intelligence (XAI).

The main goal of XAI is to address the challenge in black box model by developing methods and tools to make AI models are interpretable and transparent. In this study, LIME operates by locally approximating a black-box machine learning model with a straightforward, interpretable model that is simple enough for people to understand. To do this, a set of disturbed samples surrounding a certain data point are generated, and a local, understandable model is trained using these perturbed samples. The predictions of the original black-box model for that data point may then be explained using this local model. The main benefit of LIME is that it is model-agnostic, which means that it may be used with any machine learning model, independent of the underlying technique or architecture [37]. This makes it an effective tool for

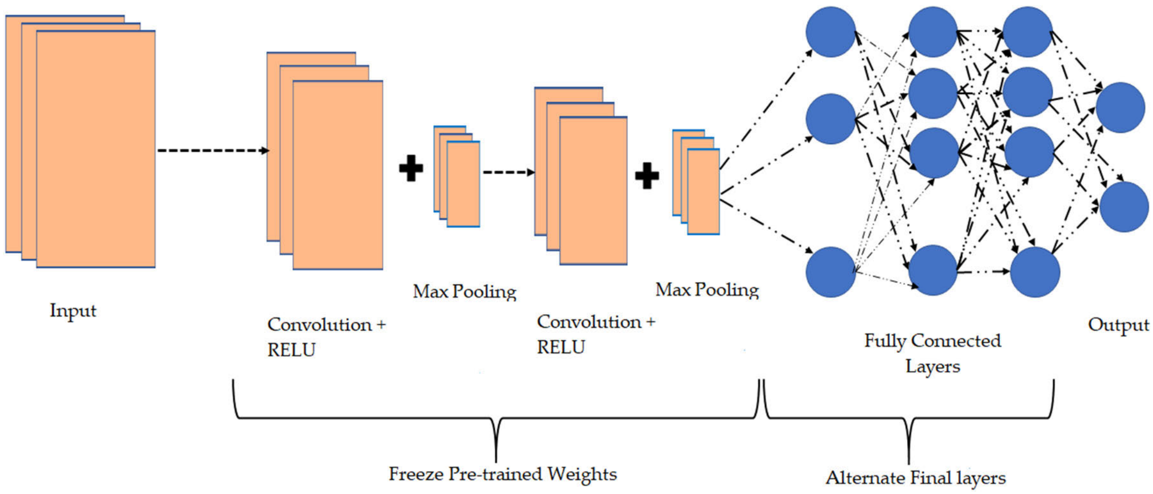

FIGURE 3. Transfer learning process of general CNN architecture.

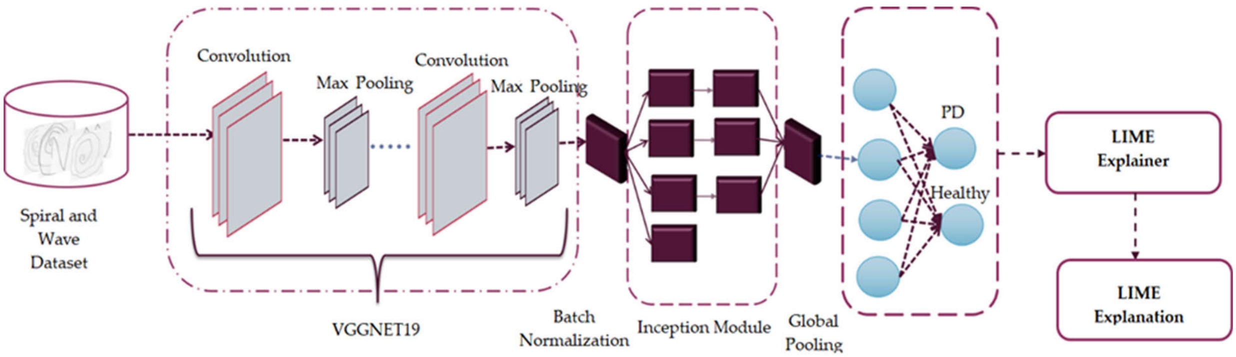

FIGURE 4. Proposed architecture of hybrid deep transfer learning VGG19-INC model.

illuminating complicated models like deep neural networks. we will look at some of the most popular CNN architectures, like Alex Net, ResNet-50, DenseNet-201, VGGNet-19, and Squeeze Net 1.1, used for deep transfer learning by replacing the network's bottom layers. In addition, we presented a comprehensive examination of the early diagnosis of PD by extracting drawing samples from the PD patients. One of the most crucial hyperparameters to adjust is called the Learning Rate (LR), and it controls the rate at which the weights are updated. we explored the deep transfer CNN models with a differential rate as opposed to a single common learning rate in order to increase the diagnostic accuracy of PD detection. The differential learning rate improves the diagnostic accuracy of Parkinson's disease. Fig.5 represents the overall flow of the proposed approach for the early diagnosis of PD based on drawing datasets using deep neural networks. At first, however, we presented a comparative analysis of various pre-trained models for diagnosing PD over the original and augmented dataset. Nevertheless, there are certain disadvantages to augmenting medical datasets under inappropriate situations that may affect the network's performance. To cope with this challenge, in this work, we examined the various pre-trained CNN models through deep transfer learning for PD identification, and we trained the deep neural networks with differential learning rates on the original dataset. The limitations of constant learning rate approaches during the training phase are overfitting problems, considerable execution time and loss of the model [47]. Therefore, it is always critical to discover the optimal learning rate for CNN faster convergence using the trial-and-error method. The idea behind the differential learning rate is to divide the network into cluster layers. Then, during training, apply different learning rates to the various layers by freezing and unfreezing cluster layers as an alternative to the constant learning rate across the pre-trained network to obtain the optimum learning rate.

IV. RESULTS AND ANALYSIS

In this section, we provide a thorough account of our experimental setup, performance metrics, and outcomes for the deep learning models used in classification. Additionally,

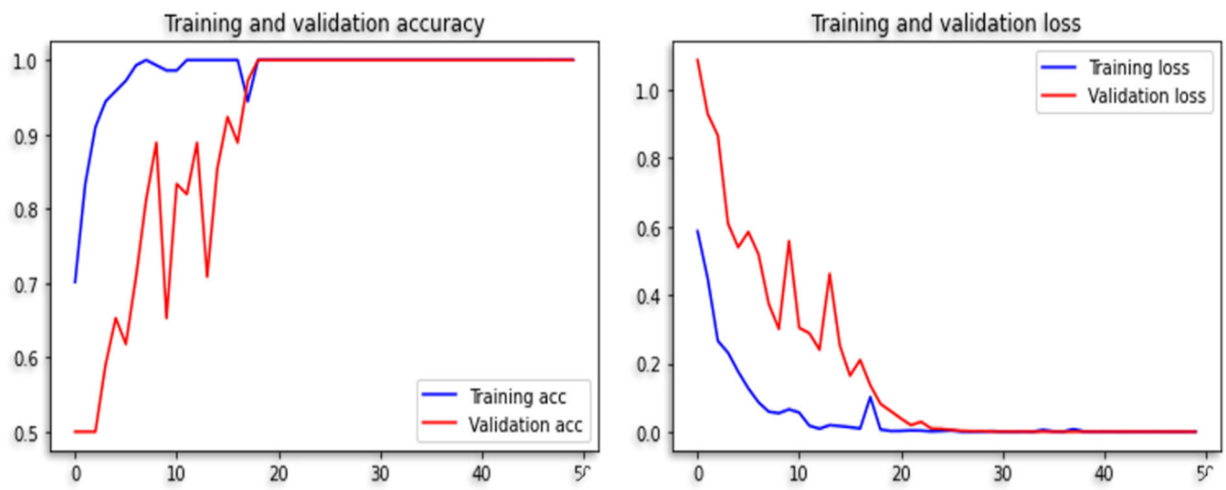

FIGURE 5. VGG19-INC, left is the accuracy and right shows the loss of the model.

TABLE 1. Demographic details of the participants.

Demographics	PD	Healthy Group
Number of Subjects	51	51
Ages, Years	70.1+9.79	72.87+6.5
Gender Male, Female	44,7	47,4
No. of Spiral images	175	192
No. of Wave images	51	51

we deliberate on the findings of the interpretability model we employed and exhibit the marked regions.

This section discusses the PD classification prediction results using several pre-trained models with the differential learning rate method. Table 1 present a comparative assessment of various pre-trained models for PD diagnosis. The diagnostic accuracy of the models with and without different learning rates are tabulated, with bold text indicating parameters, outperforming the other state-of- the-art methods experimented on the drawing dataset. It can be seen from the performance graph Fig.5 that the proposed method experimented on the publicly available drawing dataset outperforms well with the other different pre-trained models. The key intention of the proposed method is to combine the advantages of VGG19 Net and Google Net to improve the classification performance significantly. It has been observed from fig.5. that the training loss and validation loss both decrease and stabilise at a particular point and proving that it is an optimal model for PD classification. According to the experimental results of the pre-trained models with differential learning rates, it is revealed that ResNet-50 outperforms well compared to the other CNN models in the task of PD diagnosis using drawing datasets. In this study, we considered a minimum number of epochs for training the model from end to end.

Fig.11. illustrates the confusion matrix of various pre-trained models for the early diagnosis of PD. It summarises the number of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) used to compute the performance metrics of accuracy, sensitivity, and specificity. The impression of FP and FN rates in models can be observed with the assistance of a confusion matrix. Additionally, based on the TP, TN, FP, and FN, we may calculate the other performance metrices of the model like precision, Recall, F1-score etc., Table 3. Shows the summary of the evaluation of performance metrices. ResNet-50 model provides less FP and FN rates than the other pre-trained models. We computed classification accuracy, error rate, and area under receiver operating characteristics to evaluate the proposed model's performance. As a result, we can conclude that the proposed (VGG19-INC) classification model outperforms well with the other state-of-art techniques.

A. PERFORMANCE EVALUATION METRICS

This proposed work incorporates several performance metrics to evaluate its effectiveness, including accuracy, specificity, sensitivity, precision, recall and F1 score. These metrics play a vital role in assessing the performance and overall quality of the approach.

(1) Accuracy is a metric that quantifies the proportion of accurately classified data instances out of the total number of data instances.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

(2) Specificity is a performance metric that assesses a model capacity to accurately predict the true negatives for each available category.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{2}$$

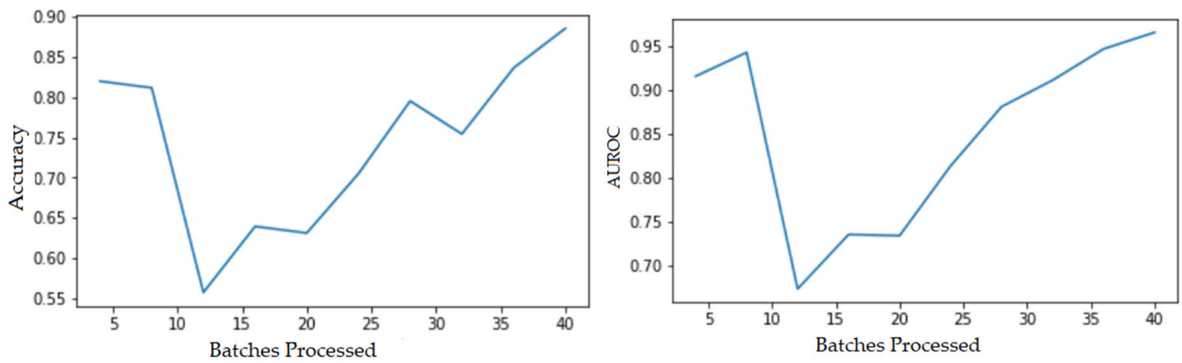

FIGURE 6. DenseNet-201, left is the accuracy and right shows the area under ROC of the model.

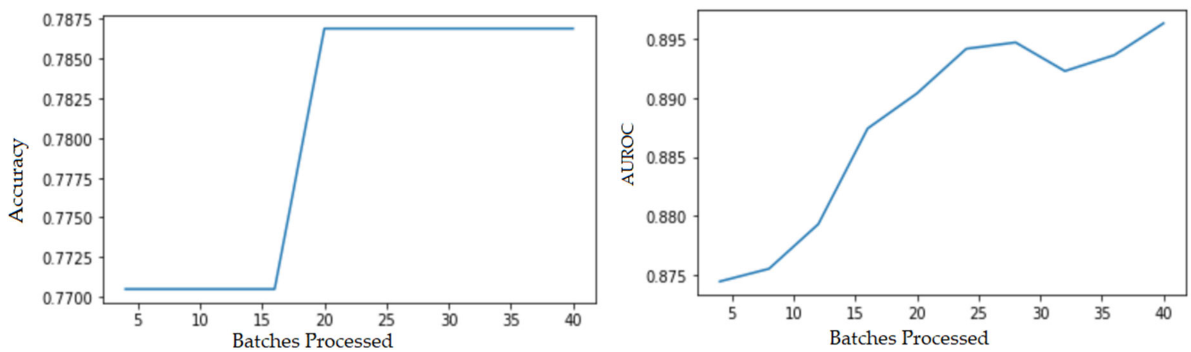

FIGURE 7. AlexNet, left is the accuracy and right shows the area under ROC of the model.

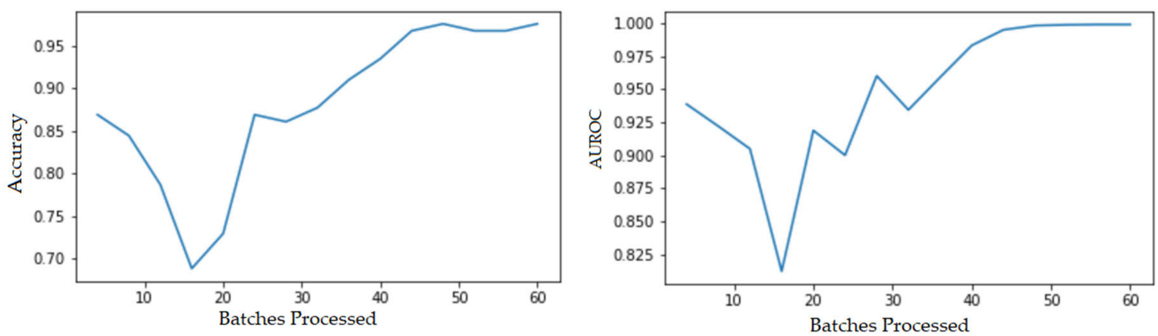

FIGURE 8. VGG-19 Net, left is the accuracy and right shows the area under ROC of the model.

(3) Sensitivity can be defined as the metric employed to evaluate a model's effectiveness in predicting the true positives available category.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{3}$$

(4) Precision can be defined as the ratio between the number of True Positives and the total number of positive predictions. It represents the measure of correctly identifying patients with PD out of all the patients who are diagnosed with it. Mathematically

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

B. BASELINE MODEL COMPARISON

1) ALEX NET

Alex Net is a classical conventional neural network. It consists of eight layers: five convolutional layers and three fully-connected dense layers [38]. It enriches the learning capacity of CNN by building it deeper than LeNet. By increasing the depth of the network, there is a possibility of overfitting. It can be overcome by using dropout layers, and to compute the non-linearity function, ReLU is used instead of the sigmoid function [39].

2) VGG19 NET

VGG19Net consists of 19 layers that are used to simulate the large-scale image classification. VGG19 has some

TABLE 2. Summary of different pre-trained CNN models experimental results.

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**

TABLE 3. Performance evaluation metrics of PD classification.

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

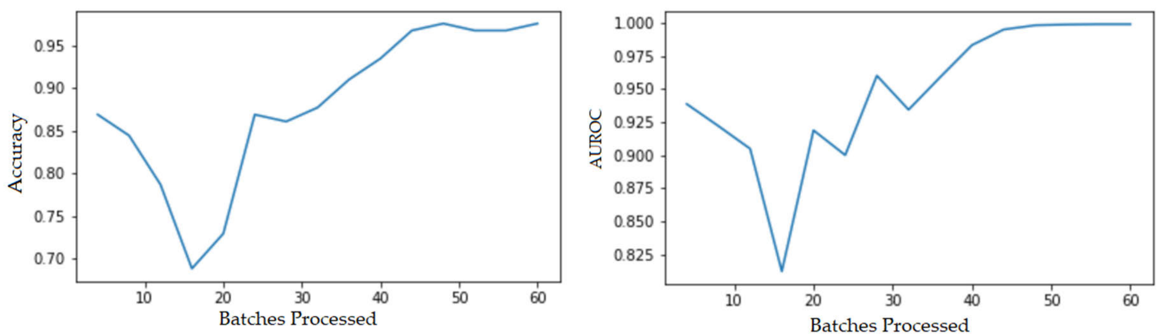

FIGURE 9. ResNet50, left is the accuracy and right shows the area under ROC of the model.

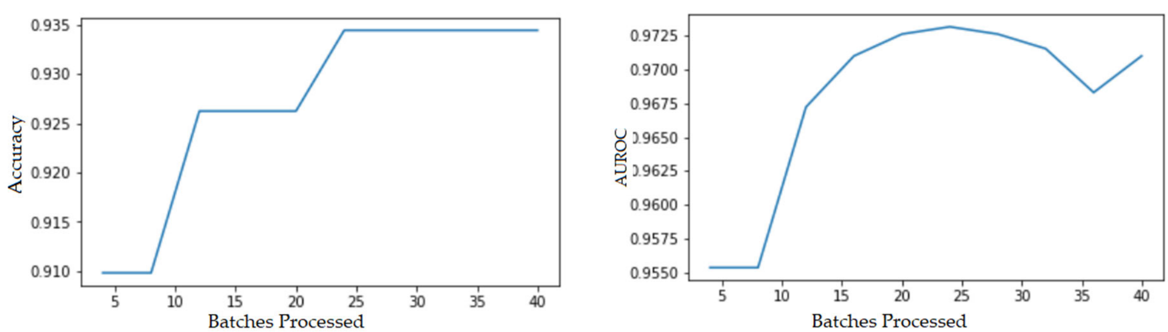

FIGURE 10. SqueezeNet, left is the accuracy and right shows the area under ROC of the model.

extra convolution layers in the middle of the architecture to enhance the model's accuracy [40]. The small size (3 × 3) kernel filters could induce the same effect as the large size filter (5 × 5 and 7 × 7) was experimentally

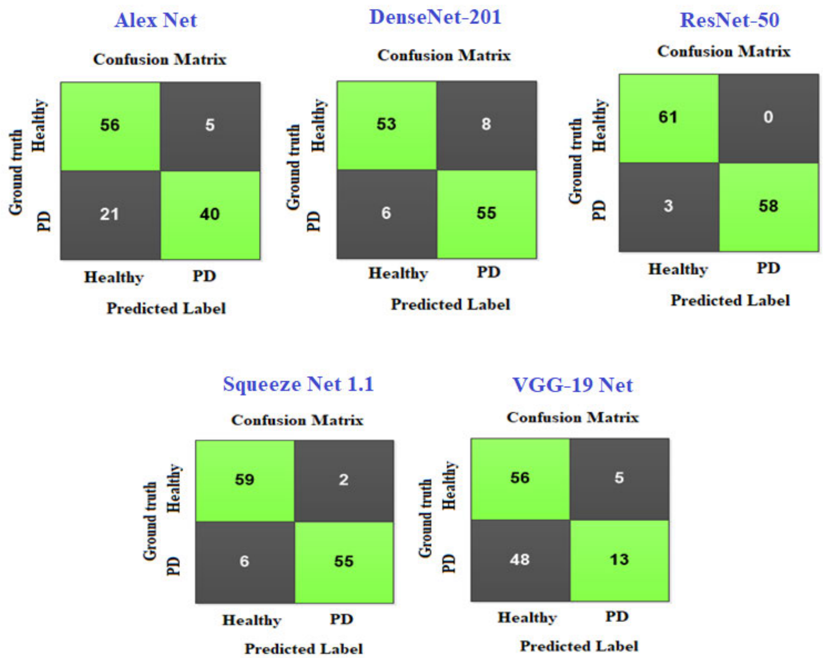

FIGURE 11. **The confusion matrix obtained by the deep neural networks in the classification of PD.**

proved [41]. Also, the small-size kernel filters provide less

3) ResNet50

Typically, increasing the neural networks' depth decreases the model accuracy, whereas ResNet modernised the CNN architecture by familiarizing the concept of residual learning in CNNs and increasing the model accuracy by increasing the networks' depth [42]. It has a significantly less error rate on image classification tasks than 34 layers direct Net.ResNet101can be made by adding more three-layer blocks [43].

4) DenseNet201

Dense Net presents a powerful architecture to resolve the vanishing gradient problem in ResNet by modifying the layers in that architecture [44]. The main drawback with the ResNet was that it could provide very little information from many layers. It can be overcome by efficiently using cross-layer connectivity. However, DenseNet is quite expensive due to an increase in the feature maps.

5) SqueezeNet1_1

Squeeze Net is one of the famous lightweight CNN architectures which comprises fire modules and pooling layers. Each fire module consists of a squeeze layer and an expanded layer. The squeeze layer aims to reduce the feature map size while the expanded layer increases the feature map's size. The performance of the squeeze net is excellent when compared with Alex Net [45].

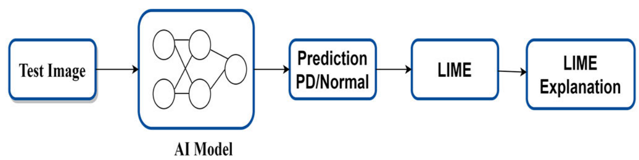

FIGURE 12. **Block diagram of proposed model using LIME.**

C. NEED FOR EXPLAINABLE AI

Healthcare-related applications of artificial intelligence (AI) face a huge issue in explaining things. It is crucial for a model to explain why it made certain predictions or recommendations, even if it shows great accuracy. Although certain models, such as decision trees, provide transparency, most cutting-edge models now being employed in AI applications in healthcare are neural networks, which are fundamentally opaque and lack the ability to provide explanations for their predictions.

Fig.12 Shows the block diagram of the proposed model using LIME. In this work, we apply the input test images to the proposed models, which then predict whether the subject is PD or healthy. The LIME receives the expected output and, using the top five attributes, provides an explanation for the prediction.

D. MODEL INTERPRETABILITY USING LIME

The EXAI model classifies explanations as either "local" or "global," depending on how much information is needed to comprehend the idea in consideration. Whereas the local

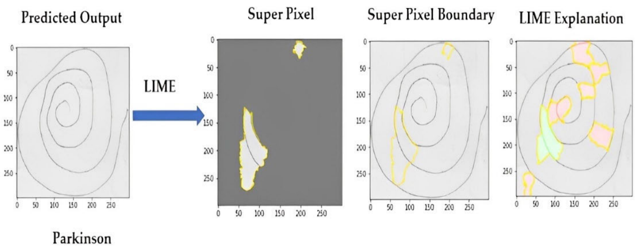

FIGURE 13. LIME explanation for PD prediction model based on spiral drawing.

method simply necessitates an explanation of the specific prediction at present, the global method necessitates an explanation of the entire model. Local Interpretable Model-Agnostic Explanation (LIME) is one of the most widely used Explainable AI techniques due to its effectiveness, and thus, in this research, we examined the explainable capability of the LIME on the decisions of our proposed model in distinguishing Parkinson's diseases from healthy individuals. In this work we evaluate our proposal using spiral and wave images of PD and healthy individuals for PD prediction [46], [47].

Fig.13 showcases the performance of LIME on the proposed model. LIME serves as an ''explainer'' by modifying the features of a particular data point and examining the resulting impact on the output. This approach provides local interpretability and enables a more accurate approximation of the data point [48]. The model is trained using data that has undergone small perturbations, such as adding noise, hiding parts of the image, or removing a few pixels. By doing so, LIME produces an explanation of the prediction that is easily comprehensible to humans.

The main goal of this work is to clarify the super pixels of the spiral and wave drawings that contribute to PD prediction and to identify the pixels that cause misclassification. The study used LIME to methodically process the spiral and wave images of a specific sample instance, as shown in Figure 13, to accomplish this. The super pixels of the spiral drawings that are responsible for the PD prediction are initially shown in this picture, followed by the borders of the super pixels. Finally, the red highlighted region displays the pixels that result in misclassification, whereas the green highlighted area displays the super pixel based on the top five features of the test image used for PD prediction.

V. DISCUSSIONS

In this study, we presented several deep transfer learning models for the early diagnosis of PD. The main objective of this work, to previous works, is to reduce the losses and improve the neural network performance by employing a new hybrid deep transfer learning model (VGG19-INC). Moreover, the pre-trained models with Explainable AI framework increases the trustworthiness and transparent for the PD predictive model. In comparison, it has been realised that our recommended approach helps enhance the PD classification's performance. Among these various pre-trained models,

TABLE 4. Comparison of previous works related to early diagnosis of PD based on handwriting biomarkers.

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**

ResNet-50 has a classification performance of 98.3%, which is extremely high compared with the other state-of-art models. After incorporating the additional database images into the training and testing process, we have not seen any appreciable improvements in accuracy. Following hyper parameter adjustment and taking into account the new dataset, accuracy is improved by 0.08 percent. As shown in Table 3, the proposed methods and the performance metrics obtained from each model are represented. By comparing the other performance evaluation metrices like precision, recall, and F1-score, we can conclude that our proposed system enhances classification performance and gives significantly better accuracy.

However, one of the most important topics has also been discussed. Deep transfer learning-based techniques are used to discriminate PD patients from healthy subjects. The main benefits of deep transfer learning are to utilise the resources effectively and lower the volume of data required. Transfer learning is much needed when data collection is too expensive or rare to collect inaccessible data.

The Lime process involves generating super pixel boundaries in the input image, measuring the difference between the predicted and actual feature maps, and producing a corresponding label. The resulting image displays the distance with color patches highlighting the critical regions that contributed to the classification come. These highlighted regions represent the essential features that influenced the classification results.

Training the new models using deep transfer learning-based techniques helps us to improve accuracy. In this work, the proposed method for early PD recognition differs from the literature in terms of trivial data preprocessing techniques and the combined pre-trained models.

Table 4 compares the performance of early diagnosis of PD based on handwriting biomarkers with previous studies. The limitations of the present study include a smaller amount of hand drawing dataset. The study of the severity level of the disease and fine-tuning of the concatenated pre-trained models for enhancing the model performance will be carried out in our future work.

VI. CONCLUSION

The aim of this study is to develop a modified deep learning models for detecting PD in its earliest stages that combines the advantages of two deep transfer learning models. To improve diagnostic accuracy and speed up convergence, we fused the benefits of a pre-trained model with those of a dynamically varying learning rate. Analyzing the various performance measures allows one to verify the precision and efficiency of the calculation. Our proposed model, VGG19-INC, is shown to perform well in experiment results. When compared to other cutting-edge methods, it provides the greatest accuracy. Furthermore, we have utilized LIME to comprehend and validate the predictions generated by our model, which illustrates the superior performance of our proposed model in detecting Parkinson's disease. It is anticipated that the findings of our study will offer future researchers and practitioners' valuable insights into the implementation of transfer learning models and explainable AI for developing reliable and secure Parkinson's disease diagnosis models.

AUTHOR CONTRIBUTIONS

All the authors equally participated in technical discussion, design, implementation, testing, performance measurement and writing the article.

CONFLICT OF INTEREST

The authors have no relevant conflicts of interest to disclose.

ETHICAL APPROVAL

This article does not contain any studies with human participants or animals performed by any authors.

DATA AVAILABILITY STATEMENTS

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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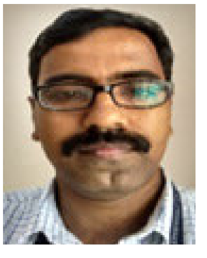

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