Parkinson's disease detection using a novel weighted ensemble of CNN models

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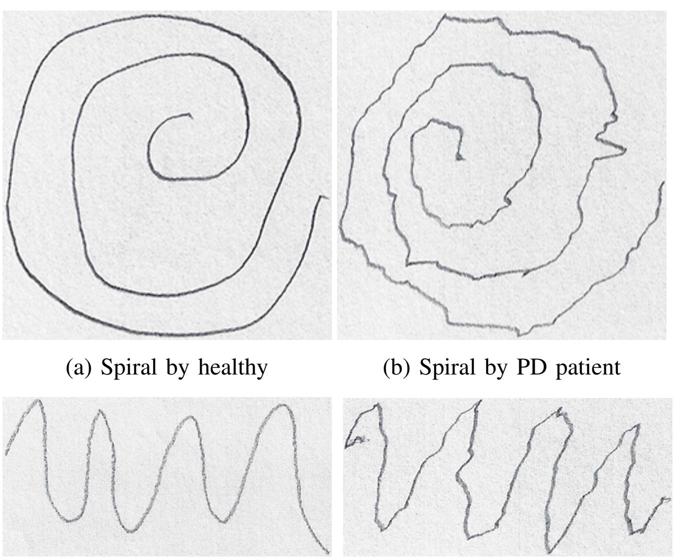
***Abstract*—Parkinson's disease is a common and chronic neurodegenerative disorder that results mainly from the death of dopaminergic neurons in the substantia nigra part of the brain. Early and correct diagnosis of Parkinson's disease is crucial for clinical research, prognostication, and therapeutic purposes. Different clinical methods and tests like INSIT, ISHA articulation assessment, olfactory testing, MRI, etc, can be used to diagnose and verify Parkinson's disease in any patient. But these tests are costly, tedious, and complex. In recent years, deep learning techniques have shown promising results in various medical applications, including disease diagnosis. In this study, we propose an efficient ensemble learning-based model to assist doctors in detecting Parkinson's disease effectively and correctly through figure-drawing task images which is a literacy-independent, cost-friendly, simple, and less time-consuming process. Preprocessing techniques are applied to standardize the images and enhance relevant features. We have employed deep transfer learning and have designed a weighted ensemble of three convolutional neural network models, wherein the weights given to three base learners are determined by a novel method. The proposed model has achieved an accuracy rate of about 95% and 90% for spiral and wave figure drawing tasks respectively. The results given by our proposed model are better than individual models and state-of-the-art deep learning methods.**

***Index Terms*—Parkinson's Disease, spiral and wave drawing, CNN, Ensemble learning, MobileNetV2, DenseNet121, NASNet-Mobile**

I. INTRODUCTION

Parkinson's disease(PD) is a common and chronic central nervous system neurodegenerative disorder that results mainly from the death of dopaminergic neurons in the substantia nigra part of the brain. PD is affecting patients in large numbers throughout the world. One or two people out of 1000 people of the population over the age of 60 worldwide have been found to have PD [1]. Older age is a risk factor for this disease. PD is a fatal disease, as in the initial state, the patient does not realize or consider that he is in the starting state of a disease. But, with time, the different symptoms of PD can be seen in patients. The main predominant symptoms of PD which can be used for PD detection are Tremors, Change in speech (speech impairment), Bradykinesia (slow movement), Change in handwriting mainly due to tremors, Rigid muscles causing impaired posture and balance (gait disturbance), Loss of automatic movements, etc [2]. One of the most common and initial symptoms is tremors. Often, a tremor in one hand signals the beginning of Parkinson's. PD is also an incurable disease. Hence, a lot of research is going on in the whole world for its cure. The main obstacle in developing a permanent cure for PD is the limited understanding of the critical events that provoke neurodegeneration. Even though PD does not yet have a permanent cure, a proper diagnosis is crucial for clinical research, prognostication, and therapeutic purposes. In the case of PD, early detection is very crucial for better monitoring and medical help. Diagnosis of PD can be made by using different clinical methods and tests like INSIT, ISHA articulation assessment, etc, which can be used to conclude and verify PD in any patient. Clinical diagnostic determinations are aided by genetic testing and other auxiliary tests like olfactory testing, MRIs, and dopamine-transporter single-photon-emission computed tomography imaging [3]. But, these tests are costly, tedious, and complex. All the above-mentioned tests and diagnosis methods require a well-trained and experienced doctor or clinician to perform them. Also, these tests and methods are limited to equipped clinics and hospitals only. In recent years, deep learning techniques have shown promising results in various medical applications, including disease diagnosis [18]–[20]. In this paper, we have developed an effective ensemble learning-based model to assist doctors in detecting PD effectively and correctly. This paper is mainly based on detecting PD in patients as there must be a change in handwriting mainly due to tremors. As the tremor is an early and predominant symptom, it will help in early detection of PD in the patients which will lead to better monitoring and medical help to the patients. We have selected handwriting disturbance due to tremors but, in a modified way of drawing tasks called handwritten dynamics like the spiral and wave dynamics or simple drawing task images as these simple drawing tasks are literacy-independent in the context of the low literacy rate in India, less time-consuming, uncomplicated, and also cost-friendly [4]. The proposed method is evaluated on the dataset collected from

51 patients and 51 healthy persons in two figure drawing tasks of spirals and waves drawing. There are a total of 102 images in the collected dataset. The remaining images, 20 images, are used for testing, leaving a total of 82 images used for training and validation. We have included four images from each class, displayed in a cascade as shown in Figure 1, the images from each class exhibit distinct features and can be reliably differentiated using our proposed approach. Preprocessing techniques are applied to standardize the images and enhance relevant features. We have employed deep transfer learning and have designed a weighted ensemble of three convolutional neural network(CNN) models, i.e., DenseNet121, MobileNetV2, and NASNetMobile, wherein the weights given to base learners are determined using a novel method explained in the methodology section. By leveraging the complementary information captured by different models, the ensemble approach aims to improve the overall accuracy and robustness of PD detection. The proposed model has achieved an accuracy rate of about 95% for spiral drawing and 90% for wave drawing. Our proposed weighted ensemble CNN model is giving better and more valid predictions with the ensemble of the three mentioned CNN models. The findings of this study indicate the potential of our deep learning-based weighted ensemble model in the accurate and reliable detection of Parkinson's disease using figure-drawing task images. The ensemble model achieved a high accuracy rate, outperforming individual models and state-of-the-art methods as discussed in the results and discussion section of the paper.



(a) Spiral by healthy (b) Spiral by PD patient

(c) Wave by healthy (d) Wave by PD patient

Fig. 1: Images of the figure drawing tasks from the dataset by the healthy and PD patients

II. LITERATURE REVIEW

The second most typical degenerative illness is Parkinson's disease(PD). PD doubled between 1990 and 2016 [5]. There is currently no complete cure. As a result, extensive worldwide research is being done to find a treatment. But for the deep learning aspect, the most competent effort is to determine the most effective method for PD detection and support the physicians. Early identification is essential for improved monitoring and medical care in the case of PD. Adopting deep learning techniques to identify PD is the subject of numerous articles. Researchers typically concentrate on tremors for detection since tremor is the most common symptom. Haozheng Zhang et al in their paper [6] stated that more than 70% of patients have one type of tremor and tremor has strong generalizability. Some researchers worked on other predominant symptoms like speech/voice impairment, postural abnormalities/gait disturbance. Vinod J Kadam et al [7] in their research work discussed voice data-based PD detection using feature ensemble learning based on sparse autoencoders. An accuracy of approx 90% is achieved on the UCI dataset. Similarly, Onur Karaman et al [8] also worked on PD detection using voice signals but, with transfer learning using a convolutional neural network. They have achieved 91.17% accuracy. Also, Rohit Lamba et al [9] discussed a novel genetic algorithm and random forest classifier-based PD detection using speech signals. An accuracy of about 95.58% is achieved using this hybrid system. Although voice or speech impairment is one of the predominant symptoms, there are some limitations to PD detection using this symptom. In India, due to the large number of languages people speak and their different pronunciation habits vary significantly which imposes problems in the effective detection of PD. Also, the effective detection of PD is hampered by a variety of vocal abnormalities, including hypophonia (lowered sound), dysphonia (defective voice), dysarthria (difficulty with articulation), and monotone (lowered pitch). X Yang et al [10] in their research paper discussed PD detection based on gait disturbance in patients using residual network architecture named PD-ResNet. An accuracy of 95.51% is achieved using this model. It also helps to classify the different severity levels with an accuracy of 92% approx. Similarly, in their paper [11], J Hwan Shin et al talked about postural abnormalities measurement using a deep learning-based pose estimation algorithm. They measured anterior flexion angle (AFA) and dropped head angle (DHA), which were verified using traditional manual labeling techniques. Also, H Zhang et al in their work [12] discussed pose-based tremor classification for PD diagnosis from video using a novel SPAPNet (pyramidal channel-squeezing and channel-fusion architecture with graph neural network). The public dataset TIM-TREMOR is used. An accuracy of about 90.9% is achieved. But, postural impairments and abnormalities are not early-stage symptoms. It can be only used for PD confirmation methods in later stages. Also, Video datasets are hard to analyze for crucial feature extraction. For handwriting or drawing tasks-based PD detection, there are many previous research works in which researchers tried to find a machine or deep learning-based PD detection system. Clayton et al in their paper of 2015 [13] discussed PD detection based on handwriting exams of patients, mainly on spiral drawing with templates. Then, they analyzed the spiral drawing using image processing techniques and supervised machine learning techniques like OPF, SVM, and NB classifier for feature extraction and effectiveness. The NB classifier, which reached roughly 78.9% of recognition rates, had the best outcome, closely followed by OPF. Clayton et al in their paper of 2016 [14] worked on PD automatic detection using a convolutional neural network(CNN) where the dataset is made up of features that were gathered when the person was being examined using a smart pen that contained a number of sensors that extracted data while the person was drawing handwritten dynamics like spiral and meander by the patients and control group. The average overall accuracy achieved considering the spiral dataset is 83.77% and the meander dataset is 87.14%. Also, Clayton et al in their paper of 2018 [15] worked on a new dataset of handwritten dynamics like drawing the circle, spiral, and meander for PD detection using a CNN and achieved a high accuracy of approx 95%. Similarly, in their work [16], Saman Khawar et al, in order to improve the overall prediction, suggested a decision fusion-based alternative that makes use of both online and offline parameters. They verified the efficacy of the method using the benchmark database PaHaW. Also, Zhu Li et al [17] proposed a novel model named CC-Net (Continuous convolutional network) based on AlexNet for PD detection using spiral hand-drawing without the template. Good accuracy of about 89.3% was achieved by them. Similarly, Mohamad Alissa et al [18] discussed drawing tasks like a spiral pentagon, wire cube, etc, to detect PD using CNN. They achieved an accuracy of 93.5%. Nihar Ranjan et al [1] took handwriting or drawings into account as a factor for diagnosing Parkinson's disease utilizing machine learning algorithms like Random Forest Classifier and Histogram of Oriented Gradients (HOG) for an in-depth examination of the drawings. These papers are hand drawing-based PD detection as tremor is an initial symptom and PD needs to be detected in the initial stage. So, in our proposed work, we have also tried to detect PD in the initial stage using hand drawings of spirals and waves without a template. In table I, we can compare that the accuracy given by our proposed model is better than approximately all of the previous works for spiral drawing and the accuracy for wave drawing is also par with many previous works. The methodology and results of the work are in the next sections respectively.

TABLE I: Comparative study of some important previous papers with spiral or wave drawing

Previous papers	Method	Drawing Task	Achieved Accuracy (Highest)
Clayton et al, 2015 [13]	OPF, SVM, and NB Classifier	Spiral and meander	78.9%
Clayton et al, 2016 [14]	CNN	Spiral and meander	87.14%
Clayton et al, 2018 [15]	CNN	Spiral and meander	95%
Zhu Li et al, 2022 [17]	CC-Net (CNN)	Spiral	89.3%
M. Alissa et al, 2022 [18]	CNN	Spiral pentagon and wire cube	93.5%

III. METHODOLOGY

The conceptual framework for the study is shown in Figure 2. Images of figure-drawing tasks serve as the main inputs. Drawing assignments like spirals and waves are photographed. The two key procedures are image processing to improve hand-drawn traces and the proposed model training, which makes use of preprocessed drawing task images as training and validation datasets. The successful detection of the PD by the proposed weighted ensemble model using the test set of drawing task images is the final output. Additionally, we evaluate the accuracy of each CNN model separately and in comparison to other similar studies.

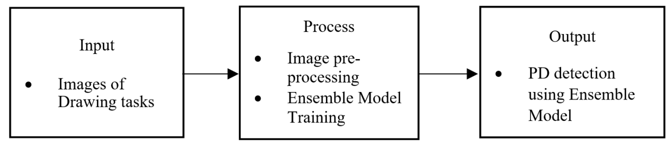


Fig. 2: Conceptual Framework

A. Dataset and classes

The image dataset is collected from the research papers [1], [19]. This dataset is available publicly on Kaggle. The dataset is collected from 51 patients and 51 healthy persons in two figure-drawing tasks of spirals and waves without the template. The dataset is split into 80% for training, and 20% for testing the model. A total of 82 images are used for training the network and for validation, and the remaining images are used for testing, which is 20 images.

B. Image Pre-processing

Image pre-processing is a technique for enhancing the quality of the photos and emphasizing the key details that are already present. As the dataset used in this paper is composed of real-time drawing task images that were real-time captured with a smartphone to facilitate effective model training, some of the photographs are overexposed and occasionally have dark areas that are apparent due to varying lighting conditions and the timing of image acquisition. Using image pre-processing during dataset construction helped to eliminate these kinds of issues. Image segmentation is a technique for dividing a digital image into more manageable, connected chunks, or "image segments", which in turn makes each segment easier to handle or analyze. This study compiles all of the real-time photos or images taken with a smartphone in natural lighting. The thresholding segmentation approach, which enables the separation of important image pixels, is utilized first. The thresholding method uses the OpenCV inRange function.

C. CNN base learners and novel method to assign weights

In this study, we have selected pre-trained CNN models which have comparatively less trainable parameters. We have tried different pre-trained models present in the keras library. But, after analyzing the performance and comparing the change in performance with the number of parameters, we have selected DenseNet121, MobileNetV2, and NASNet-Mobile as base learners for our proposed ensemble model. For assigning weights to these selected models, we have used a novel method of comparing the accuracies given by these selected models separately in four trains and tests. Based on the accuracies of these tests, we have calculated the normalized values as weights to them. For the ensemble model used for the spiral figure drawing task, we have given 0.4, 0.35, and 0.25 weights to DenseNet121, MobileNetV2, and NASNetMobile respectively. And, for the ensemble model used for the wave figure drawing task, we have given 0.35, 0.4, and 0.25 weights to DenseNet121, MobileNetV2, and NASNetMobile respectively.

D. Proposed weighted ensemble CNN model

As mentioned earlier, the objective of this work is to detect PD using a weighted ensemble of convolutional neural network models. The architecture of the weighted ensemble model is shown in figure 3. We have created a novel weighted ensemble model using libraries like TensorFlow, Keras, sklearn, etc. The base learners for the proposed ensemble models are DenseNet121, MobileNetV2, and NASNetMobile which are available in the Keras library. We have directly used these pre-trained models [20]–[22]. The novel method for assigning weights to these CNN models is explained in the above subsection.

The proposed model is used in training using the dataset

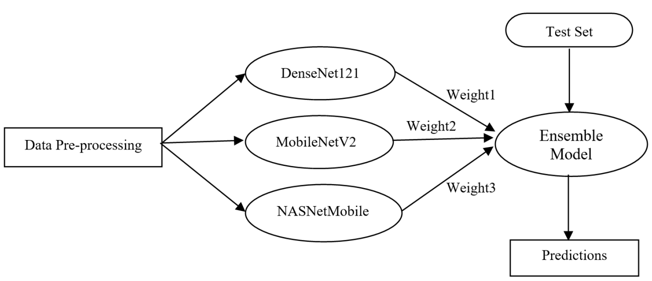


Fig. 3: Architecture of the proposed weighted ensemble CNN model

that we have gathered. The two labels of the categories are healthy and Parkinson which contain the respective figure drawing task images. The dataset is divided into two sections: 20% is used to test the model, and 80% is used for training. Out of 102 images, 20 images are used for testing, leaving a total of 82 images that are used for training and validating the network. Data augmentation is used using the ImageDataGenerator function to further increase the number of images. The mentioned model is composed of three base learners, i.e., DenseNet121, MobileNetV2, and NASNetMobile. These base learners are trained using the training set, and the validation set is used to validate. Then, we have to save each base learner after training and validation. Then, we have to load the saved models and create the proposed weighted ensemble model. This ensemble model created after loading and combing the base learner is again trained using the training set and validated on the validation set. Then, the final trained model is used for testing on the test set.

During the training and validation process of the base learners and the proposed model, we have used the "Binary Crossentropy" as the loss function since there are two classes and this loss function is practically the most appropriate for this task. The model's adaptive learning rate method uses the 'Adam' optimizer and the learning rate is 0.001. The proposed weighted ensemble model was also trained using different optimizers such as RMSprop, and Adagrad before choosing this one, however, this optimizer gives the best results. The 'sigmoid' activation function is utilized in the last dense layer of the base learners because there are two classes for the detection task, and it is best suited in the last dense layer if there are two classes.

IV. RESULTS AND DISCUSSIONS

In this study, all model development, training, and testing procedures are carried out on an 80 GB NVIDIA Tesla A100 server using a machine with 8 GB of RAM and a 4 GB NVIDIA GEFORCE GTX 1650Ti graphics card. As explained in the methodology section, we have created and used our proposed weighted ensemble model on the collected dataset. The architecture of the proposed weighted ensemble CNN model is as follows in figure3. The mentioned model is composed of three base learners, i.e., DenseNet121, MobileNetV2, and NASNetMobile. With the help of Python libraries like TensorFlow, Keras, and other libraries, we have directly imported these pre-trained models. These base learners are trained using the training set, and the validation set is used to validate. After training, the best training accuracy on the spiral drawing given by the proposed model is 100%, and the validation accuracy is 83.33% as shown in figure4. After that, the proposed model is tested on the testing set and received overall accuracy of 95% for the spiral drawing. The F1-score value attained by the proposed model for both the healthy and Parkinson classes is 0.95 and the recall value of 1.00 for the healthy class and 0.90 for the Parkinson class. The confusion matrix created using the seaborn library for the test set of the spiral drawing is shown in figure 5.

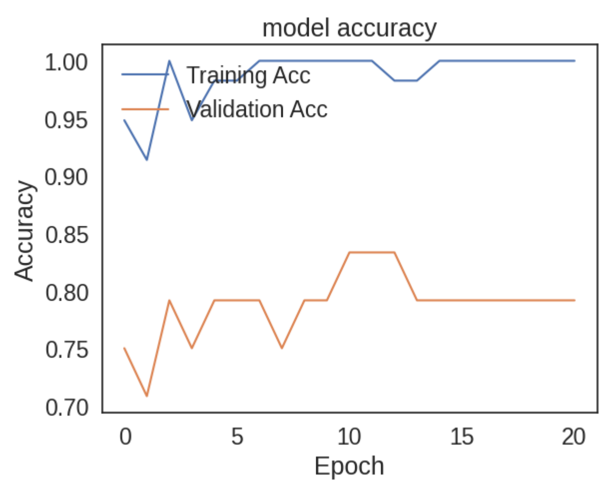


Fig. 4: Training and Validation accuracy graph of the proposed model on the spiral drawing

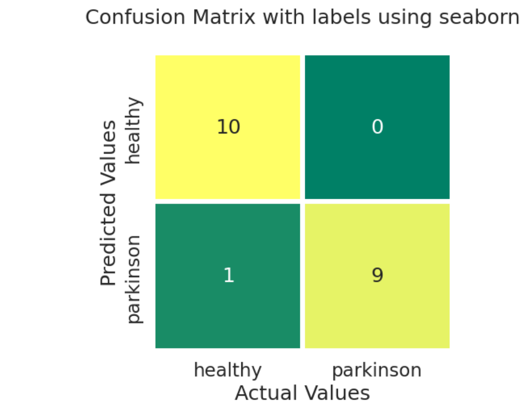


Fig. 5: Confusion Matrix for the test set of the spiral drawing

For the wave drawing, we have used the same steps as the spiral drawing. After training the base learners, the best training accuracy on the wave drawing given by the proposed model is 100%, and the validation accuracy is 91.67% as shown in figure 6. After that, the proposed model is tested on the testing set and received overall accuracy of 95% for the spiral drawing. The F1-score value attained by the proposed model for both the healthy and Parkinson classes is 0.90 and the recall value of 0.90 for both the healthy class and Parkinson class. The confusion matrix created using the seaborn library for the test set of the wave drawing is shown in figure 7.

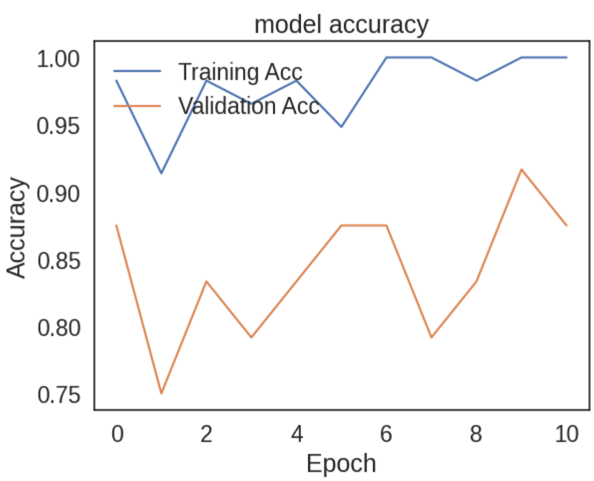


Fig. 6: Training and Validation accuracy graph of the proposed model on the wave drawing

Our proposed weighted ensemble model has outperformed many state-of-the-art models. Our proposed model is composed of the pre-trained model with a very less number of trainable parameters and so, it requires less amount of time and resources for training. Also, according to our study, we can conclude that spiral drawing is giving better results than wave drawing. So, doctors, experts, and clinicians should use spiral drawing over wave drawing for PD detection using this model. For ease of comprehension, a comparison table that compares

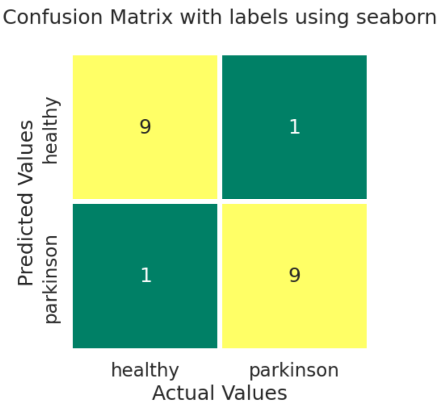


Fig. 7: Confusion Matrix for the test set of the wave drawing

TABLE II: Comparison table of accuracies of some tried and used CNN models

Model	Training Accuracy (Best)		Validation Accuracy (Best)		Testing Accuracy (Best)	
	Spiral	Wave	Spiral	Wave	Spiral	Wave
VGG16	100	98.55	87.28	90.67	80	85
ResNet50	68.17	73.67	55.23	57.10	65	75
DenseNet121	98.28	98.28	83.33	83.33	95	90
MobileNetV2	100	96.55	83.33	87.50	90	85
NASNetMobile	96.55	94.83	83.33	87.50	90	90
Proposed Ensemble Model	100	100	83.33	91.67	95	90

the best accuracy of various distinct pre-trained models, each base learner individually, and the proposed weighted ensemble model is added. The outcomes or results are clearly seen in the table II. With the ensemble of the three previously mentioned CNN models, our proposed weighted ensemble CNN model will perform better than other models from earlier studies and provide more accurate and trustworthy predictions.

V. CONCLUSION AND FUTURE WORK

Based on the findings, our proposed weighted ensemble model has demonstrated remarkable accuracy while utilizing fewer parameters compared to various deep learning models. This advantageous system does not rely on electronic or smart pens, making it cost-effective and easy to understand. By employing an ensemble of CNN models, our approach effectively extracts image characteristics and provides reliable predictions through the combined strength of three CNN models. Parkinson's disease (PD) currently lacks a cure, and its early-stage diagnosis remains challenging due to subtle symptoms. Detecting PD early is crucial for simplifying patients' lives, and the proposed method holds immense potential in this regard. Integrating our approach into a computer-aided diagnosis system would assist healthcare professionals in early PD detection, leading to improved patient care and overall quality of life. Alternatively, transforming our proposed model into a mobile application would enable access from any location, at any time, further enhancing its practicality. Furthermore, our study reveals that spiral drawing yields superior outcomes compared to wave drawing. Therefore, when employing our ensemble model method for PD detection, medical experts should prioritize spiral drawing over wave drawing. Although our model demonstrates impressive accuracy, there is room for improvement to eliminate false positives in predictions. To enhance the performance of the ensemble model, future research directions involve expanding the dataset and exploring additional deep-learning architectures. These efforts aim to refine the accuracy of our model and advance its capabilities in PD detection.

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