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Parkinson's Disease Detection Through Spiral Drawing Recognition Using Machine Learning Approach

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Abstract. Parkinson's Disease (PD) is a neurodegenerative disorder characterized by motor impairments, and early detection is crucial for effective intervention. PD patient diagnose the disease only after having serious symptoms and the diagnosis requires huge amount of time. The self-serves diagnostic can be applied with the help of computer aided technology. This paper aims to identify the features of Parkinson's disease symptoms by assessing on the spiral drawing images and develop a Parkinson's disease prediction system using machine learning model. By leveraging the power of machine learning algorithms, ResNet50 and Random Forest with Histogram Oriented Gradient (HOG) models are trained on spiral and waves imaging datasets comprising spiral drawings of healthy individuals and with PD symptoms. Data are pre-processed. After the data is cleaned, the models were trained with different experiments for ResNet50 model, also random state for Random Forest with HOG and to be compared to find the best model with highest accuracy and lowest loss. As the results, the best model is ResNet50 model with 50 epoch and 32 batch size as it has the highest validation accuracy (0.8967) and lowest validation loss (0.245). The ResNet50 Model 2 is chosen to be embedded in the PD detection system, which is being developed using Python. The model can be enhanced further in the future by increasing the number of features on detecting spiral drawings such as speed and pressure of pen when drawing.

Keywords: Parkinson's Disease, Machine Learning, ResNet50, Random Forest, Spiral Drawing

1 Introduction

Parkinson's Disease (PD) is a neurodegenerative disease that generally affects the brain neurons which are responsible for overall body reflexes, movements and responses. According to research, the symptoms are mild at first and gradually worsen as time passes. The loss of certain brain cell clusters that produce the neurotransmitters including dopamine [1] results in various movement disorder symptoms such as rigidity, bradykinesia, and postural instability [2].

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Many patients diagnosed with Parkinson's disease are unaware on the symptoms of the disease before the condition becomes worst and affecting the patients' quality of life, social functions and family relationships, and daily activities [3]. People with PD are affected by tremors and much worse, rapid shivering. The patients need to consults with the neurologists and require a huge amount of time as diagnosis demands the neurologists to observe the patient's neurological record. Hence, neurologists came up with the opportunity of using spiral drawing and waves to diagnose for early detection of the disease [4].

Sketching of spiral and waves has been established for early detection of PD [5]. However, the expert needs to interpret multiple patients' sketches, causing much longer times for the patients to get the diagnosis results. Therefore, it is essential to use the potential of machine learning techniques on the imaging dataset to provide early detection and more accurate diagnosis of PD by analyzing the motor features and hand-drawn images of patients [6]. Hence, there is a need to develop Parkinson's disease prediction system by implementing the machine learning algorithms on the imaging datasets to reduce time and increase efficiency and productivity of diagnosing the disease during the early stage.

The paper consists of five sections. It starts with Section 1 Introduction; continues with Section 2 Related Works. It follows Section 3 Methodology to explain the methods used in this study. Then, Section 4 includes the results and discussion, and the last section concludes the study.

2 Related Works

2.1 Parkinson's Disease

According to National Institute of Neurological Disorders and Stroke (NINDS), Parkinson's disease (PD) is a chronic neurodegenerative disorder that affects the nervous system specifically the nerve cells in the brain. The name of Parkinson's disease comes from James Parkinson, the first person who discovered this disease. Estimated 6.3 million people worldwide are affected by this disease, primarily those in the age range of 60 and above [7]. It is caused by the death of dopamine-producing neurons that the disease does not have a cure, but only a treatment. The malfunctions of neurons in the cerebrum reduces the measure of dopamine that send messages to the brain, thus results in inability for individuals to control voluntary actions [8].

2.2 Machine Learning

Machine Learning (ML) is a subdomain of artificial intelligence that makes data collection from multiple sources and formats. ML can be used for statistics, knowledge analytics and processing data as it can solve complex domain problems [9]. Machine learning applications consist of algorithms that can learn from data without a user. There are many categories of machine learning algorithms that can be used in the field of healthcare systems such as unsupervised, supervised and semi-supervised learning. Unsupervised learning divides huge unlabeled datasets into smaller groups based on traits and similarities shared by each piece of data [10].

2.3 Spiral Drawing Classification Using Machine Learning

Spiral drawing is a sensitive motor assessment as it is a complex and coordinated motor activity. The most frequently used and acknowledged rating scale for Parkinson's disease (PD) is the Unified Parkinson's Disease Rating Scale (UPDRS-III) [11]. Motor functions that are affected by PD includes speaking, handwriting, walking, and coordination. As PD is considered a motor condition owing to the neurodegenerative process, all quantitative measures of motor decline and non-motor biomarkers have been proposed to evaluate the severity [12].

2.4 Convolutional Neural Network

Convolutional Neural Network (CNN) is a deep neural network technique that are widely used in computer vision and use input such as images with the automated ability to learn and recognize crucial features of the images. The input of the model may exist from handwriting images such as spiral and circle images. Convolution layer, max-pooling layer, and classification layer are the three layers that make up the CNN layers. Convolutional layers in CNN perform input convolution based on kernels and weights. The output from the layer where the picture features are extracted and identified is sent into the first layer of the feature extractor section [13].

2.5 Past Studies on Parkinson Disease

Early diagnosis of PD is important for early intervention and better patient outcomes. Hence, spiral drawing tests have been used as a non-invasive way to measure tremors and other motor symptoms in PD patients, providing quantitative measures of its severity simultaneously with the development of machine learning algorithms to analyze these drawings and aid in early diagnosis [14]. Several studies have investigated the use of machine learning algorithms for spiral drawing recognition. A study has developed a two-dimensional CNN model and voting ensemble classifier to detect PD based on wave and spiral datasets. The voting ensemble was performed using a meta classifier that includes techniques such as Logistic Regression and Random Forest Classifier. The model was developed based on learning rate, weight decay and penalty parameter to achieve the accuracy of 83.3% [15].

Another study applies Histogram Oriented Gradient (HOG) feature on the weighted Random Forest (WRF) classifier for effective PD classification of small amount of image dataset. This method has been tested using NIATS dataset consists of handwritten spiral and waves patterns for both PD and healthy cases. The classifier gave an accuracy of good percentage of wave and spiral datasets by 93% and 92% respectively. The analysis of comparing the classifier with other ML approaches such as KNN and SVM using the same dataset shows that the classifier performs better and effective than others [16].

A study has developed a logistic regression (LR) model that predicts the risk of people suffering a low nerve impulse one year after surgery based on imaging and neurophysiology. The classifier was trained on 89 patients and tested using five-fold cross-validation, and the model assesses preoperative factors. With an estimated AUC of 79%, this model predicts poor responders [17]. A study suggests using surface-based morphometry (SBM) based model to identify mild cognitive impairment. 93 patients with PD images were examined, with 20 healthy control subjects were used as training. The Support Vector Machine (SVM) with SBM features obtain an accuracy of 80% [18].

In addition, a study used 2D convolutional networks (CNN) as the classification algorithm by applying hyperspectral imaging (HSI) technology for food packaging defect recognition. The 2D approach is used in the work as the spatial and spectral content are present that the shape of the anomaly and spectral can be combined to obtain the highest rate of classification accuracy. CNN networks were trained using 40 × 40 (ROI) for image surface dimensions, getting the accuracy higher than 94% of founded defects in the reduced area of images [19].

From past studies, machine learning models have been used to do the image detection and classification for various sectors as it developed rapidly. Therefore, this study applied Convolutional Neural Network (CNN) and Random Forest for image detection and classification.

3 Methodology

The phases of the methodology structure involve knowledge acquisition, data collection, data preparation, model design, model evaluation and system development (see Figure 1).

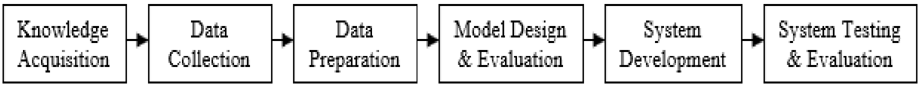


Fig. 1. Methodology

3.1 Knowledge Acquisition

Relevant information and data about Parkinson's disease, its symptoms, and the analysis of spiral drawing images are gathered from various sources such as research papers, journal articles, conference proceedings, and books related to Parkinson's disease diagnosis, motor symptoms, and image analysis techniques from IEEE Xplore and Scopus.

3.2 Data Collection

One approach to acquire a spiral drawing dataset of normal individuals and Parkinson's disease (PD) patients is by utilizing the dataset available on Kaggle, specifically the "Parkinson's Drawings" dataset provided by Kyle Mader. The dataset contains a total of 102 images of spiral drawing which can be used for Parkinson's disease recognition. These images are divided into training and testing groups consists of 15 healthy spiral images and 15 Parkinson's spiral images for testing and 36 healthy spiral images and 36 Parkinson's spiral images for training.

3.3 Data Preparation

Data preparation consists of data augmentation and data pre-processing that involves resizing the images and changing the images into greyscale. During data augmentation, the amount of imaging data increases as they are modified through flipping, shifting and rotating as the image of spiral will not affect the accuracy results throughout the process. Before augmentation, the total number of spiral images for both healthy and Parkinson is 51 images. Since the dataset is already in the form of testing and training for both the class, the augmentation process immediately increases the number of images without having to split the dataset.

Table 1. Total spiral images

Image	Total (Before Augmentation)	Total (After Augmentation)	Total Images for Training and Testing
 Healthy	51	2871	Training: 2556 Testing: 315
 Parkinson's	51	2871	Training: 2556 Testing: 315

3.4 Model Design and Evaluation

In this phase, the model is designed to several experiments for ResNet50 and Random Forest. For ResNet50 model, it was trained with various batch size and epochs to identify the best model. The models are ResNet50 Model 1 (batch Size: 32 and epoch: 35) and ResNet50 Model 2 (batch Size: 32 and epoch 50). For Random Forest model, the two models are Random Forest Model 1 (Random State: 1) and Random Forest Model 2 (Random State: 42). Model evaluation involves assessing the model's accuracy, precision, recall, F1 score and loss.

3.5 System Development

In this phase, the system is developed by combining the Python programming language with the Google Colab platform and HyperText Markup Language (HTML). This combination is utilized to design and present the system within a web browser. HTML is employed to create the structure of the web pages, including text, tables, headings, and images. On the other hand, the StreamLit framework is utilized to construct and deploy the web application for the spiral drawing image recognition system.

3.6 System Testing and Evaluation

System testing and evaluation involve assessing the system's performance, accuracy and reliability. Functional testing is conducted to ensure that the system operates as expected and meets the specified requirements by verifying the functionalities of the system, such as uploading spiral drawing images, pre-processing the data, running the machine learning model for detection, and displaying the results accurately. Performance testing is conducted using appropriate evaluation metrics to measure model performance. The testing images from the dataset is uploaded into the system.

4 Results and Discussion

4.1 Model Training Results

For the PD detection system, it is crucial to train both the ResNet50 and Random Forest models. This is because the model needs to absorb a large amount of data to distinguish the differences in each image accurately. Once the data pre-processing phase is complete, the images are imported into the ResNet50 network and HOG feature for algorithm training. The models' results are then compared, and the one with the highest accuracy and lowest loss is chosen as the classification model.

The model was trained with various batch sizes and epochs to identify the best model with best results for detection system as the amount of data for training and testing are the same.

Table 2. Comparison result of ResNet50 experiments

Model	Experiment	Accuracy	Precision	Recall	F1 Score	Loss
ResNet50 Model 1	Batch Size: 32 Epoch: 35	0.9427	0.9000	0.7700	0.8300	0.1659
ResNet50 Model 2	Batch Size: 32 Epoch: 50	0.8967	0.9000	0.9000	0.8900	0.2450

Table 2 shows the models for two experiments using ResNet50 in CNN. Based on the result, ResNet50 Model 2 is the better model for detecting Parkinson's disease, despite having a slightly lower accuracy of 89.67% than 94.27% of ResNet50 Model 1. ResNet50 Model 2 has a higher recall and F1-Score, which means it correctly identifies a higher percentage of actual Parkinson's cases. However, ResNet Model 2 has a higher loss value, which means the model may have higher probability to have error on detecting the PD. So ResNet50 Model 2 has been chosen as the best model.

In Table 3, the RF Model 1 has an accuracy of 0.80, while the RF Model 2 had an accuracy of 0.77, indicating a slight decrease in overall accuracy. Precision for health improved slightly from 0.74 to 0.75, while for Parkinson, it decreased from 0.91 to 0.79. Recall for health decreased from 0.93 to 0.80 but improved for Parkinson from 0.67 to 0.73. The F1-score for health decreased from 0.82 to 0.77, and for Parkinson, it decreased slightly from 0.77 to 0.76. Hence, the best model for detection is RF Model 2, which has a recall of 0.73 for Parkinson, better than RF Model 1, which has a recall of 0.67 for Parkinson.

Table 3. Comparison results of Random Forest with HOG experiments

Model	Random State	Accuracy	Precision	Recall	F1 Score
RF Model 1	1	0.80	0.74	0.93	0.82
RF Model 2	42	0.77	0.75	0.80	0.77

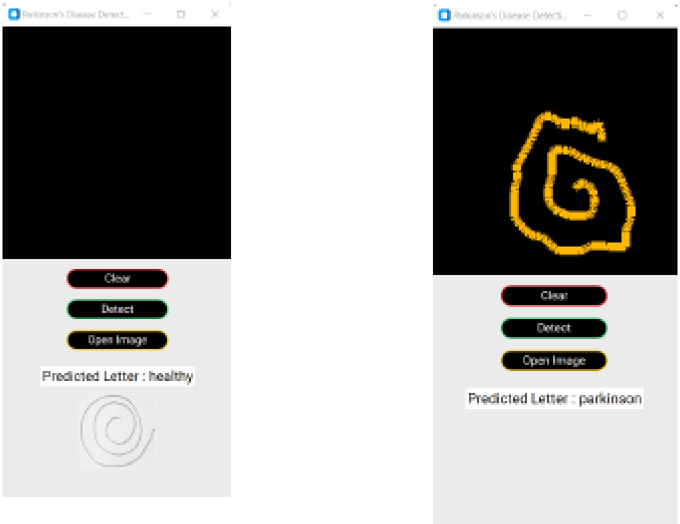
From Table 4, ResNet50 Model 2 has an accuracy of 0.8967, precision of 0.9000, recall of 0.9000, F1 score of 0.8900, and a loss of 0.2450 while RF Model 2 has an accuracy of 0.77, precision of 0.75, recall of 0.80, F1 score of 0.77. The loss is not provided for this model. Based on the values, ResNet50 Model 2 outperforms RF Model 2 in all the provided metrics (accuracy, precision, recall, and F1 score), and it also has a lower loss value. Therefore, based on the provided metrics, ResNet50 Model 2 (Batch size: 32, Epoch: 50) would be considered the best model among the two.

Table 4. Comparison between best model of ResNet50 and RF with HOG

Model	**Experiment**	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**Loss**
ResNet50 Model 2	Batch Size: 32 Epoch: 50	0.8967	0.9000	0.9000	0.8900	0.2450
RF Model 2	Random State: 42	0.7700	0.7500	0.8000	0.7700	-

4.2 User Interface

From Figure 2, there are two options for the user to use the system. The user can upload the images from the folder into the system. Then the system will show the uploaded image as preview and give results in the form of label either healthy or Parkinson after clicking "Detect" button. Besides that, the user can draw the spiral on the black canvas. Then ask the system to diagnose it whether healthy or Parkinson. The "Clear" button is clicked to clear all the input for new detection.



a) Prediction: Healthy b) Prediction: Parkinson

Fig. 2. User interface of Parkinson's Disease Detection System

4.3 Discussion

For the Parkinson's disease detection system, it is crucial to train both the ResNet50 and Random Forest models. This is because the model needs to absorb a large amount of data to distinguish the differences in each image accurately. The datasets are imported into the ResNet50 network and HOG feature for algorithm training. The models' results are then compared, and the one with the highest accuracy and lowest loss is chosen as the classification model. The best model, which is ResNet50 Model 2 (Batch size: 32, Epoch: 50) able to give precise result on the classification between two classes which are PD and normal.

5 Conclusion

The importance of this study is to detect the PD detection. The purpose of this project is to develop a system capable of detecting and classifying Parkinson's disease between normal and PD. Through the implementation of a deep-learning model, people would be able to identify and classify Parkinson's disease symptoms in the spiral drawings. The system's functionality extends to aiding in the early detection and interpretation of Parkinson's disease symptoms by the people through the analysis of spiral drawing images into actionable response to get appointment with neurologists.

For future study, the number of spiral drawing images dataset should be increase to improve accuracy. Besides the number of features on detecting spiral drawings such as the speed and pressure of pen should be added when drawing the spiral in the mobile app.

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References

1. Maitín AM, García-Tejedor AJ, Muñoz JPR (2020) Machine Learning Approaches for Detecting Parkinson's Disease from EEG Analysis: A Systematic Review. Applied Sciences 10:8662. https://doi.org/10.3390/app10238662
2. Kamoji S, Koshti D, Dmello VV, et al (2021) Prediction of Parkinson's Disease using Machine Learning and Deep Transfer Learning from different Feature Sets. In: 2021 6th International Conference on Communication and Electronics Systems (ICCES). IEEE, pp 1715–1720
3. Swami S, SJ KP, S MK (2021) Detection and Prediction of Neurological Disorder Using Tremor Signals and Machine Learning Algorithms. In: 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT). IEEE, pp 43–50
4. Elazazy SA, Eldesoky MA, El-Wakad MT, Soliman AM (2021) An Efficient Algorithm for Analysis of Handwriting Task for the Detection of Parkinson's disease. In: 2021 9th International Japan-Africa Conference on Electronics, Communications, and Computations (JAC-ECC). IEEE, pp 79–84
5. San Luciano M, Wang C, Ortega RA, et al (2016) Digitized Spiral Drawing: A Possible Biomarker for Early Parkinson's Disease. PLoS One 11:e0162799. https://doi.org/10.1371/journal.pone.0162799
6. Kaur S, Aggarwal H, Rani R (2020) Hyper-parameter optimization of deep learning model for prediction of Parkinson's disease. Mach Vis Appl 31:32. https://doi.org/10.1007/s00138-020-01078-1
7. S S, S Ashok, Rao GVV, et al (2022) Parkinson's Disease Prediction Using Machine Learning Algorithm. In: 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS). IEEE, pp 1–5
8. Kumar M, Shukla M, Agarwal S (2014) A hybrid approach of requirement engineering in agile software development. In: Proceedings - 2013 International Conference on Machine Intelligence Research and Advancement, ICMIRA 2013
9. Kushwaha PK, Kumaresan M (2021) Machine learning algorithm in healthcare system: A Review. In: 2021 International Conference on Technological Advancements and Innovations (ICTAI). IEEE, pp 478–481
10. Tumpa ES, Dey K (2022) A Review on Applications of Machine Learning in Healthcare. In: 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI). IEEE, pp 1388–1392
11. Kamble M, Shrivastava P, Jain M (2021) Digitized spiral drawing classification for Parkinson's disease diagnosis. Measurement: Sensors 16:100047. https://doi.org/10.1016/j.measen.2021.100047

12. Moetesum M, Siddiqi I, Javed F, Masroor U (2020) Dynamic Handwriting Analysis for Parkinson's Disease Identification using C-BiGRU Model. In: 2020 17th International Conference on Frontiers in Handwriting Recognition (ICFHR). IEEE, pp 115–120
13. Roy SK, Krishna G, Dubey SR, Chaudhuri BB (2020) HybridSN: Exploring 3-D–2-D CNN Feature Hierarchy for Hyperspectral Image Classification. IEEE Geoscience and Remote Sensing Letters 17:277–281. https://doi.org/10.1109/LGRS.2019.2918719
14. Drotár P, Dobeš M (2020) Dysgraphia detection through machine learning. Sci Rep 10:21541. https://doi.org/10.1038/s41598-020-78611-9
15. Chakraborty S, Aich S, Jong-Seong-Sim, et al (2020) Parkinson's Disease Detection from Spiral and Wave Drawings using Convolutional Neural Networks: A Multistage Classifier Approach. In: 2020 22nd International Conference on Advanced Communication Technology (ICACT). IEEE, pp 298–303
16. Medhi VN, Basumatary KM, Murugan R, Goel T (2022) An Early Detection of Parkinson's Disease from Geometric Drawings. In: 2022 2nd International Conference on Artificial Intelligence and Signal Processing (AISP). IEEE, pp 1–5
17. Habets JGV, Janssen MLF, Duits AA, et al (2020) Machine learning prediction of motor response after deep brain stimulation in Parkinson's disease—proof of principle in a retrospective cohort. PeerJ 8:e10317. https://doi.org/10.7717/peerj.10317
18. Zhang J, Li Y, Gao Y, et al (2020) An SBM-based machine learning model for identifying mild cognitive impairment in patients with Parkinson's disease. J Neurol Sci 418:117077. https://doi.org/10.1016/j.jns.2020.117077
19. Medus LD, Saban M, Francés-Víllora J V., et al (2021) Hyperspectral image classification using CNN: Application to industrial food packaging. Food Control 125:107962. https://doi.org/10.1016/j.foodcont.2021.107962