DETECTION OF PARKINSON'S DISEASE BASED ON GEOMETRIC DRAWING ANALYSIS

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ORIGINAL LITERARY WORK DECLARATION

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DETECTION OF PARKINSON'S DISEASE BASED ON GEOMETRIC DRAWING ANALYSIS

Field of Study: **Parkinson's Disease Diagnosis**

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DETECTION OF PARKIN'S DISEASE BASED ON GEOMETRIC DRAWING ANALYSIS

ABSTRACT

In biology, human brain cells produce a chemical called dopamine, which sends signals through neurotransmitters to muscles and makes movements, such as running when a dog is being chased, or pulling back when touching something hot. Parkinson's disease (PD) degenerates the nerves in the brain, causing humans to gradually lose their ability to move, and is widely known as a neurological movement disorder. It severely affects the quality of life, and patients will have difficulty walking in a straight line even if walking is the simplest activity. Thus, early diagnosis has great potential to slow disease progression, as there is currently no cure for PD. Two types of geometries, such as spirals and waves, were collected and used to train a predictive model. To analyze and predict the probability of contracting the PD by using the image recognition methods. The image will go through a preprocessing stage to resize, grayscale, and remove noise from the image to minimize memory usage and maximize computation. The classification process uses three machine learning algorithms, RandomForestClassifier, XGBClassifier, and KNeighborsClassifier. The classifier performance was evaluated using a confusion matrix, and the random forest classifier was chosen because of its excellent performance, achieving 83 percent accuracy and 93 percent precision in this PD prediction with spirals drawing and 73 percent accuracy and 73 percent precision in this PD prediction with waves drawing.

Keywords: Classification, Confusion Matrix, Parkinson's Disease, Spiral, Wave

PENGESANAN PENYAKIT PARKINSON BERDASARKAN ANALISIS LUKISAN GEOMETRI

ABSTRAK

Dalam biologi, sel-sel otak manusia menghasilkan bahan kimia yang dipanggil dopamin, yang menghantar isyarat melalui neurotransmitter kepada otot dan membuat pergerakan, seperti berlari apabila anjing sedang dikejar, atau menarik balik apabila menyentuh sesuatu yang panas. Penyakit Parkinson (PD) merosakkan saraf di otak, menyebabkan manusia secara beransur-ansur kehilangan keupayaan mereka untuk bergerak, dan dikenali secara meluas sebagai gangguan pergerakan neurologi. Ia memberi kesan buruk kepada kualiti hidup, dan pesakit akan mengalami kesukaran berjalan dalam garis lurus walaupun berjalan adalah aktiviti yang paling mudah. Oleh itu, diagnosis awal mempunyai potensi besar untuk melambatkan perkembangan penyakit, kerana pada masa ini tiada ubat untuk PD. Dua jenis geometri, seperti lingkaran dan gelombang, dikumpulkan dan digunakan untuk melatih model ramalan. Untuk menganalisis dan meramalkan kebarangkalian kontrak PD dengan menggunakan kaedah pengecaman imej. Imej akan melalui peringkat prapemprosesan untuk mengubah saiz, skala kelabu dan mengeluarkan bunyi daripada imej untuk meminimumkan penggunaan memori dan memaksimumkan pengiraan. Proses klasifikasi menggunakan tiga algoritma pembelajaran mesin, RandomForestClassifier, XGBClassifier, dan KNeighborsClassifier. Prestasi pengelas dinilai menggunakan matriks kekeliruan, dan pengelas hutan rawak dipilih kerana prestasinya yang sangat baik, mencapai ketepatan 83 peratus dan ketepatan 93 peratus dalam ramalan PD ini dengan lukisan lingkaran dan ketepatan 73 peratus dan ketepatan 73 peratus dalam ramalan PD ini dengan lukisan gelombang.

Kata Kunci: Klasifikasi, Matriks Kekeliruan, Penyakit Parkinson, Lingkaran, Gelombang

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LIST OF SYMBOLS AND ABBREVIATIONS

ACC	:	Accuracy
ASR	:	Automatic Speech Recognition
CNN	:	Convolutional Neural Network
CRISP-DM	:	Cross-Industry Data Mining Standard Process
DT	:	Decision Trees
FN	:	False Negative
FOG	:	Freezing of Gait
FP	:	False Positive
HOG	:	Histogram of Oriented Gradients
IMU	:	Inertial Measurement Unit
KNN	:	K-Nearest Neighbor
LBD	:	Lewy Body Dementia
LC	:	Locus Coeruleus
LSTM	:	Long-Term Short-Term Memory
MDS-UPDRS	:	Movement Disorders Society-Unified Parkinson's Disease Rating Scale
MRI	:	Magnetic Resonance Image
NM	:	Neuromelanin
PD	:	Parkinson's Disease
PPV	:	Precision
SN	:	Substantia Nigra
SPECT	:	Single-Photon Emission Computed Tomography
TN	:	True Negative
TNR	:	Specificity

TP	:	True Positive
TPR	:	Sensitivity
VGRF	:	Vertical Ground Reaction Force

CHAPTER 1: INTRODUCTION

1.1 Research Background

Parkinson's disease (PD) is a neurological movement disorder in the early experiments showed that PD causes pathological changes in a region of the brain called Caudate_R, which is part of the basal ganglia (Zhang, L. et al., 2016). Humans control muscle movement by signaling through a neurotransmitter called dopamine, a chemical produced by brain cells in the caudate brain region (Shamli, N. et al., 2016) (Niethammer, M et al., 2013). Due to the degeneration of this hormone, Parkinson's patients gradually have difficulty walking and talking (U.S. Department of Health and Human Services, 2017). Common symptoms include tremor, movement slowness, muscles stiffness, unsteady walk, and coordination disorders. The symptoms develop slowly over years. Although PD cannot be cured by any medical method, early detection can minimize significant symptoms and preserve the quality of life. PD is the second most common neurological disorder, affecting 6.3 million people worldwide. People diagnosed with PD can live many years, but while many people diagnosed with PD can continue to live, their quality of life is reduced (Sonu, S. R. et al., 2017). Therefore, it is critical to have a fast and convenient method to detect PD as early as possible to prevent the disease from deteriorating.

1.2 Problem Statement

This project focuses on classifying the geometric drawings into bi-classes of positive and negative detection for Parkinson's disease. At present, the diagnosis of Parkinson's disease is needed relies on a specialist by using observation method and visible

symptoms. However, Parkinson's disease is always misdiagnosed due to the significant overlap of PD symptoms with those of other neurodegenerative diseases and atypical Parkinsonian disorders.

1.3 Research Questions

The research questions for this study are

a) How to use the machine learning methods to detect Parkinson’s disease on geometric drawing analysis?
b) What are the suitable machine learning methods to classify the geometric drawings into bi-classes of positive and negative detection?
c) How to evaluate and compare the selected machine learning method with previous works in detecting Parkinson's disease using geometric drawings?

1.4 Research Objectives

The objectives of this research are

a) To investigate the existing machine learning methods used for Parkinson's disease detection based on geometric drawing analysis.
b) To identify a suitable machine learning method to classify the geometric drawings into bi-classes of positive and negative detection
c) To evaluate and compare the selected machine learning method with previous works in detecting Parkinson's disease using geometric drawings.

1.5 Research Deliverables

The deliverables of this study provide a detection model for diagnosing Parkinson's disease by using geometric drawing analysis. These results could improve human understanding that early diagnosis is crucial. In this research, humans are able to use very low cost and perform diagnoses by themselves anytime anywhere.

1.6 Research Significant

The significance of this research is to easy and early diagnose Parkinson's disease. Although Parkinson's disease cannot be cured by any medical method, early detection is still able to slow down the symptoms of Parkinson's disease and preserve the quality of life.

1.7 Scope of Study

In this research, geometric drawing will be used for analysis purposes. The data are split into two parts which are Parkinson’s patient drawing and non-Parkinson’s patient drawing. Since the data used in this research is not statistical data, no time range limits are applied for data collection. Moreover, this research will prove that geometric drawing analysis able to early detect Parkinson’s disease.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The aging world population is responsible for the increase in neurodegenerative diseases. Parkinson's disease (PD) is one of the common neurodegenerative diseases and there is no effective treatment for this disease (Billingsley et al., 2018). Normally, PD will result in a decreased quality of life because the patient will have some symptoms including fatigue, memory loss, sleep problems, and depression. In severe cases, there will be difficulty walking and talking (U.S. Department of Health and Human Services, 2017). These symptoms are the result of the gradual loss of midbrain dopaminergic neurons (Rios-Urrego et al., 2019). Although there is no cure for PD, it has the potential to slow disease progression. Early diagnosis can help prevent the progression of the disease in this situation. The goal of this literature review is to compare the diagnosis methods and the techniques used for PD.

2.2 Structural Magnetic Resonance Image (MRI) Data Diagnosis

Magnetic Resonance Imaging (MRI) is a technique for visualizing the function and structure of the human brain (Geddes, J. R., & Andreasen, N. C., 2020). Early experiments with structural MRI showed that Parkinson's disease causes pathological changes in a region of the brain called the Caudate_R (part of the basal ganglia) (Zhang, L et al., 2016). Recent studies have shown that neuromelanin (NM), substantia nigra (SN) dopaminergic characteristic pigments, and locus coeruleus (LC) noradrenergic neurons can be detected with magnetic resonance imaging (MRI). NM is an autophagy product synthesized by oxidation and subsequent reactions of catecholamines, and in SN and LC, it increases

linearly during normal aging. However, pigment is lost when SN and LC neurons die (Sulzer, D. al et., 2018). This phenomenon occurs in a patient with Parkinson's disease. MRI scans are able to measure living brains safely and noninvasively. Recent technological improvements now provide MRI with a way to distinguish between patients with Parkinson's disease and age-matched healthy controls and should be able to identify changes in SN NM with an individual's age. This experiment proved that Parkinson's disease and brain regions are closely related. Automatic classification of structural MRI data through statistical analysis and machine learning methods can effectively diagnose Parkinson's disease.

2.3 Single-Photon Emission Computed Tomography (SPECT) Data Diagnosis

SPECT scans is same as the MRI scan which are showing the brain by using 3D images. However, SPECT is showing the brain activities and MRI is showing the structure of the brain. The SPECT is able to early diagnose Parkinson's disease. Therefore, it is famous among clinicians. Unlike other studies that have only considered low-level features such as gray matter, white matter, or cerebrospinal fluid, this study explores nonlinear relationships between different biomarkers (SPECT+ biology) that use deep learning and multiple logistic regression. The striatum binding ratio was obtained using 123i-ioflupane SPECT scans from four brain regions, which were further integrated with five biological biomarkers to improve diagnostic accuracy. Experimental results show that this method of study can distinguish subjects with 100 percent accuracy. The results obtained were superior to those reported in the literature. In addition, logistic regression models have been developed to estimate the probability of Parkinson's disease. Such a model could help clinicians diagnose the disease.

2.4 Gait Data Diagnosis

Freezing of gait (FOG) is a walking disturbance in advanced Parkinson's disease (PD), which is associated with an increased risk of falls and a decrease in quality of life. It can alleviate or prevent frozen seizures through external interventions such as visual or auditory cues and activate through a FOG prediction and detection system. While most studies on FOG detection and prediction are based on inertial measurement unit (IMU) and accelerometer data, bottom pressure data can capture the subtle weight transfer of FOGs. Different machine learning algorithms have been used for FOG detection and prediction. However, long-term short-term memory (LSTM) deep learning methods have advantages when working with time-series data, such as sensor data (Shalin, G. al et, 2021). As patients with Parkinson's disease gradually lose the ability to walk (Balaji, E. et al. 2021), gait data can be used for early diagnosis. Because the gait of patients with Parkinson's disease often differs from that of healthy age-matched adults, the evaluation of gait abnormalities by machine learning methods can lead to a diagnosis of Parkinson's disease. These gait data are provided by foot sensors via Vertical Ground Reaction Force (VGRF) (Zhao, Aite et al., 2018). In the research paper, intelligent robots have also been used to diagnose Parkinson's disease by observing patients' walking trajectories and changes (Sivaparthipan, C. B. et al., 2020).

2.5 Voice Recording Diagnosis

Humans control muscle movement by signaling through a neurotransmitter called dopamine, a chemical produced by brain cells (Shamli, N. et al., 2016). Parkinson's disease causes this hormone to decrease and degenerate. This will leave the patient unable to control these muscles for certain activities. Shaking hands, speaking slowly, and slurring are all symptoms of Parkinson's disease. In the research paper, the system will

use data mining methods to analyze the recording data because Parkinson's disease patients often speak with the spread of vowels, repetition of syllables, and gaps between sentences (Sonu, S. R. et al., 2017). Through these characteristics, medical personnel can quickly analyze Parkinson's disease in advance.

Voice recordings are considered a potential (non-invasive and low-cost) biomarker for the diagnosis of certain voice-related diseases. An indicator of sound impairment is one of the methods to diagnose Parkinson's disease. Through some studies, listeners may not be able to detect subtle abnormalities in some sounds through speech if the patient is suffering from an early stage of Parkinson's disease. However, we can objectively assess and differentiate between healthy and Parkinson's disease patients by acoustic analysis of recorded speech signals (Naranjo, L. al et, 2016).

Taking into account the features extracted from the voice recordings, developing an accurate remote system is very useful to help with the early diagnosis of Parkinson's disease. This idea may also be helpful for patients who have been undiagnosed and misdiagnosed for a long time. Besides that, we can also transfer the voice recording and perform the features extracted from the voice recordings anywhere. In addition, the scientific literature considers tracking Parkinson's disease progress remotely by considering recordings. The success of these systems will mean improving the quality of life for patients because they can be remotely diagnosed.

Building a predictive model with minimal bias aims to distinguish between healthy and people with Parkinson's disease. A model that maximizes the generalization of predictions to perform well on new samples. To achieve this, an appropriate classification model must be considered. In this context, it has become common to conduct experiments with replicated recordings. The most commonly used Parkinson's disease dataset contains 22 features extracted from 195 recordings of sustained "a" vocalization. The different

overall accuracy rates depend on many factors, such as the features used, the reduction of features, the classification method, and the cross-validation scheme.

2.6 Handwriting Diagnosis

Handwriting is a complex activity involving cognitive, kinesthetic, and perceptual-motor components and these changes may be promising biomarkers for assessing Parkinson's disease (De Stefano, C. al et., 2019; Impedovo, D., & Pirlo, G., 2018). In fact, there is evidence that automatic distinctions between unhealthy and healthy individuals can be achieved based on several traits acquired through simple handwriting tasks (Pereira, C.R. al et., 2018). Developing handwriting-based decision support systems is desirable because it can provide a free, non-invasive, and very low-cost approach to standard assessment by clinical specialists.

The most common symptoms in the handwriting of patients with Parkinson's disease include micro writing related to reduced handwriting size and dysgraphia related to difficulty controlling the fine motor movements required for writing. In the research paper, kinematic features were extracted from the handwriting of Parkinson's disease patients who wrote down their addresses and full names. The average time on the tablet surface, the average airtime of the pen, the velocity of the trajectory, and the average pressure of the pen will be included in the analysis part.

Various handwritten features are proposed in the literature to predict Parkinson's disease and other neurological disorders. These features can be roughly divided into two categories, static and dynamic according to their acquisition and measurement methods. Static features are typically obtained from offline handwritten samples and include spatial properties such as shape or character size (e.g. slant and skew, etc.) and scale (e.g.

height/width, aspect ratio, etc.), distance, position on the x-y plane, loop, closure package, and stroke curvature. These features have been used in the literature to indicate microscopic and tremor signs (Zhi et al., 2015).

In contrast, dynamic features describe events and therefore require additional time information, which can only be obtained from online handwritten examples. These mainly include handwritten motion or kinematic measurements such as vertical/horizontal stroke velocity and acceleration and trajectory. Popular ways to access these features include devices such as digital tablets and smart pens. These devices can also capture air/ground time intervals to reflect the time it takes for subjects to plan subsequent writing operations; More time indicates cognitive decline (Johnson et al., 2015; Rosenblum, 2015; Dirlikov et al., 2017). Pressure or grip on writing instruments is another useful indicator. As Parkinson's disease progresses, pen pressure decreases. While changes in pen pressure can be calculated by measuring changes in pixel density in offline images, the use of specialized equipment when acquiring online samples is often used to quantify pen pressure more precisely.

Handwriting analysis provides the possibility of evaluating and monitoring the exercise skills of patients with Parkinson's disease. Patients with Parkinson's disease have observed different handwriting abnormalities. For example, 5 % of patients suffer from micrographia before other exercise symptoms, and about 30 % of handwriting deterioration cases after medical diagnosis. Handwriting tasks have great advantages: they are simple, invasive, natural, do not require special infrastructure, and can be managed remotely. Several studies in the literature are concentrated on the automatic assessment of the handwriting of PD patients with different tasks and machine learning algorithms. These studies take into account different tasks, including spirals, sentences, and characters.

2.7 Discussion

In the current literature review, a major limitation found was the context in which diagnostic data were collected. Some equipment may only be available in designated locations, such as MRI machines in hospitals. Noise can also affect voice recording diagnostic results. Besides that, gait data collection from high-severity patients is difficult because they can barely walk. Those limitations will make it challenging to extract features that are robust within participants.

2.8 Conclusion

PD is a subject that must be paid attention to. Humans over the age of 60 have a greater chance of having the disease. Numerous experimental results suggest that early detection of disease will facilitate clinical monitoring of older adults, increasing their lifespan and improving their lifestyle (Shamli, N. et al., 2016). The purpose of this literature review was to compare diagnostic methods and techniques for PD. The diagnostic methods were (a) MRI data diagnosis, (b) SPECT data diagnosis, (c) gait data diagnosis, (d) voice recording diagnosis, and (e) handwriting diagnosis. The reviewed literature suggests that early diagnosis is critical for slowing the condition of PD. Combining diagnostic methods helps provide diagnostic accuracy.

CHAPTER 3: METHODOLOGY

3.1 Research Design

This research entitled detection of Parkinson's disease based on geometric drawing analysis is quantitative research that is to classify which drawings are drawn by Parkinson's patients. This research discusses the suitable machine learning method to classify geometric drawing. The quantitative approach will be used to validate the observations in this research. In this research, secondary data will be used for the analysis process. For example, the geometric drawing data are provided from the paper (Zham P et al., 2017). In this project, we will use the Jupyter notebook to develop a Parkinson Detection Model by using python.

3.2 CRISP-DM

The Cross-Industry Data Mining Standard Process (CRISP-DM) is an approach that has 6 stages in the data science life cycle which are business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

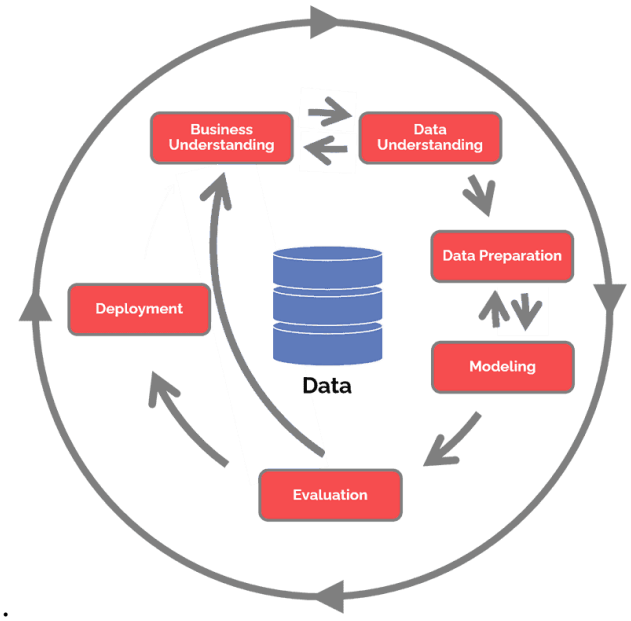

Figure 3.1 CRISP-DM Methodology (Quantum, 2019)

3.2.1 Business Understanding

At this stage, understanding the business reasons for analytics efforts helps ensure everyone is on the same page before spending valuable resources. The first task is to try to understand as much as possible about the business goals of data analysis and to construct specific primary goals.

In this thesis, we will perform image processing to classify spiral and wave images into healthy or Parkinson classes, and the spiral and wave images will be used to train and test multiple classifiers. Finally, the model with the highest accuracy and precision will be deployed.

The code will be written in python using Jupyter notebooks. We can import all the necessary packages and libraries into it, and we can call and use the function directly without coding the function from the beginning, which can save a lot of development time.

First, we must understand which packages and libraries are suitable and required in this Parkinson's disease model detection. We need to import os to provide the functionality to interact with the operating system and import Path to get the dataset directory into the notebook. Next, import pandas to manipulate and analyze the data. On the other hand, we can also define functions ourselves in other notebooks and import them when needed, such as preprocessing_img. The preprocessing_img function includes resizing, grayscale conversion, thresholding, noiseless, and Histogram of Oriented Gradients (HOG) preprocessing methods to convert the image into a sharper and better image, helping us minimize memory usage and maximize computation. After the images are preprocessed, they will be classified into healthy or Parkinson's classes and modeled using three different classifiers: RandomForestClassifier, KNeighborsClassifier, and XGBClassifier. The model will evaluate accuracy and precision using a confusion matrix. Ultimately, high performance will be deployed. All necessary packages and libraries are shown in Figure 3.2.

```
In [21]: # Import Necessary Packages / Libraries
         # Do manipulation and analysis of the data
         import pandas as pd
         # Provide functions for interacting with the opearting system
         import os
         # To save and load the machine learning models with scikit-learn
         import joblib
         # Resize/Gratscale conversion/Threshold/Noiceless/HOG
         from ipynb.fs.full.preprocessing_image import preprocessing_img
         # Get the dataset directory
         from pathlib import Path
         # Normalize labels (y), transform non-numerical labels to numerical labels
         # Encode tagert labels with the value between 0 to n_classes-1.
         from sklearn.preprocessing import LabelEncoder
         # a set of decision trees (DT) from a randomly selected subset of
         # the training set and then It collects the votes from different decision trees
         # to decide the final prediction.
         from sklearn.ensemble import RandomForestClassifier
         # Classifier implementing the k-nearest neighbors vote
         from sklearn.neighbors import KNeighborsClassifier
         # To evaluate the accuracy of a classification
         from sklearn.metrics import confusion_matrix
         # Xgboost stands for eXtreme Gradient Boosting
         # It developed on the framework of gradient boosting
         from xgboost import XGBClassifier
```

Figure 3.2: Import Necessary Packages and Libraries

3.2.2 Data Understanding

Data understanding involves accessing and exploring data using tables and graphs. This determines the quality of the data and describes the results of these steps in the project documentation.

Load the dataset into the notebook and append all png images to the data frame. As shown in Figure 3.4, there are 5 columns, namely file_path, image_code, disease, validation, and geometry_type. file_path is the location of the image, image_code is the name of the image, and disease shows whether the image was drawn by someone with Parkinson's symptoms. The validation column shows the image used for training or testing, and the geometry type is used to distinguish whether the image is spiral or wave.

```
In [3]: dataset_dir = Path(r'C:\Users\ZHENGYU\Desktop\detect-parkinsons\detect-parkinsons\dataset')
        dicts_temp = {}
        df_dataset = pd.DataFrame(columns=['file_path'])

        for path, subdirs, files in os.walk(dataset_dir):
            for filename in files:
                if filename.endswith('.png'):
                    dicts_temp['file_path'] = Path(os.path.join(path, filename))
                    df_temp = pd.DataFrame([dicts_temp])
                    df_dataset = pd.concat([df_dataset, df_temp], ignore_index=True)

        df_dataset['image_code']    = df_dataset['file_path'].map(lambda x: x.stem)
        df_dataset['disease']       = df_dataset['file_path'].map(lambda x: x.parent.stem)
        df_dataset['validation']    = df_dataset['file_path'].map(lambda x: x.parent.parent.stem)
        df_dataset['geometry_type'] = df_dataset['file_path'].map(lambda x: x.parent.parent.parent.stem)

        df_dataset.sample(3)
```

Figure 3.3: Import Image Dataset into Jupyter Notebook

Out[3]:

	file_path	image_code	disease	validation	geometry_type
46	C:\Users\ZHENGYU\Desktop\detect-parkinsons\det...	V09HE02	healthy	training	spiral
82	C:\Users\ZHENGYU\Desktop\detect-parkinsons\det...	V07PE02	parkinson	training	spiral
175	C:\Users\ZHENGYU\Desktop\detect-parkinsons\det...	V03PO06	parkinson	training	wave

Figure 3.4: Characteristics of the Dataset

3.2.3 Data Preparation

Data preparation is one of the most important stages in data mining and takes a lot of time to complete. Putting enough effort into the early business understanding and data understanding stages can minimize this overhead, but it still needs to spend a lot of effort preparing and packaging the data for mining. Data cleansing and data transformation also fall under this stage and that is the reason why it needs to spend a lot of time to complete this process.

To navigate the dataset and read the images using OS and OpenCV modules, once we successfully read the images, we need to do image preprocessing. We understand that image data can be in different formats such as natural and grayscale, so images can have complexity, inaccuracy, and inadequacy. Based on machine learning architecture, images can only be computed in the same dimension. To reduce computational requirements and complexity, several techniques can be used to preprocess image data, namely image resizing, grayscale conversion, and image augmentation.

The OpenCV module is used to resize the image to 200 X 200 pixels and convert the image to grayscale, which helps to minimize memory usage and maximize computation. The threshold function will turn the drawing like spirals and waves to white, and the background of the image to black. In addition, the Skimage module is used to remove small components in noise-free images that are less than 1 percent of active pixels defined by a cutoff, and the Histogram of Oriented Gradients (HOG) is a structural descriptor that will capture and quantify directional changes in spirals and waves.

```
In [3]: def preprocessing_img(df_dataset, show_sample_img = True):
            list_data = []
            list_labels = []
            list_temp = []
            show_img = False

            for index, row in tqdm(df_dataset.iterrows(), total = df_dataset.shape[0], desc = df_dataset.iloc[0]['validation'] + ' data
                key_list = row['geometry_type'] + '_' + row['disease']
                if key_list not in list_temp:
                    list_temp.append(key_list)
                    show_img = True

                ori_img = cv2.imread(str(row['file_path']))
                label = row['disease']

                resize_img = cv2.resize(ori_img, (200, 200))
                gray_img = cv2.cvtColor(resize_img, cv2.COLOR_BGR2GRAY)
                threshold_img = cv2.threshold(gray_img, 0, 255, cv2.THRESH_BINARY_INV | cv2.THRESH_OTSU)[1]
                noiseless_img = closing(label_sort(threshold_img)>0, disk(1))

                hog_img = feature.hog(noiseless_img, orientations = 9, pixels_per_cell = (10, 10),
                                      cells_per_block = (2, 2), transform_sqrt = True, block_norm = "L1")

                list_data.append(hog_img)
                list_labels.append(label)
```

Figure 3.5: Image Preprocessing Python Code

Once the images go through the preprocessing, then the image will be split into 4 sets randomly. The image will be split into training X and Y when the validation is training; whereas the image will be split into testing X and Y set when the validation is testing.

```
In [22]: # loading the training and testing data
         print("[INFO] loading data...")
         (train_X, train_Y) = preprocessing_img(df_dataset.loc[(df_dataset['validation'] == 'training')
                                                               & (df_dataset['geometry_type'] == 'spiral')], False)
         (test_X, test_Y) = preprocessing_img(df_dataset.loc[(df_dataset['validation'] == 'testing')
                                                             & (df_dataset['geometry_type'] == 'spiral')], True)

         [INFO] loading data...

         training data load: 100% 72/72 [00:01<00:00, 74.43it/s]

         testing data load: 100% 30/30 [00:00<00:00, 37.59it/s]
```

Figure 3.6: Split the Image into Training and Testing Set

3.2.4 Modeling

Modeling is usually done in multiple iterations. Normally, multiple models are selected with default parameters and fine-tune the parameters or go back to the data preparation stage to prepare the data are needed for the selected model.

Three classifier machine learning algorithms, RandomForestClassifier, XGBClassifier, and KNeighborsClassifier, are used for Spiral and Wave classification. Labels (y) need to be normalized by converting non-numeric labels to numeric labels

before modeling. For label normalization, the LabelEncoder function is imported from the Scikit-learn module, which encodes target labels as values between 0 and n_classes - 1. The label-encoded Python code is shown in Figure 3.7.

```
In [30]: # encode the labels as integers
         le = LabelEncoder()
         trainY = le.fit_transform(train_Y)
         testY = le.transform(test_Y)
```

Figure 3.7: Label-encoded Python code

Random Forest is a supervised learning method, which means there are labels and mappings between our inputs and outputs. It can be used for classification tasks such as determining the type of flower based on measurements such as petal length and color, or regression tasks such as predicting tomorrow's weather based on historical weather data. As the name suggests, random forests consist of multiple decision trees, every decision tree will output a prediction value. When the classification task is performed, each decision tree in a random forest vote for one of the classes the input belongs to. For example, if we have a dataset of flowers, and we want to determine the species of a flower, a decision tree in a random forest will vote everyone on which species it thinks a flower belongs to. Once all the trees are over, the random forest will calculate which class (species) has the largest voting population, and that class will be the prediction of the random forest's output. In the case of regression, the random forest will average the results of each decision tree instead of determining the most populous vote. Random forest is an ensemble machine learning algorithm since it utilizes the results of multiple learners (decision trees). The ensemble learning method reduces variability and improves the performance of the learning models that make it up.

RandomForestClassifier is imported from the Scikit-learn module, it is a set of decision trees (DT) from a randomly selected subset of the training set, then it collects

votes from the different decision trees to decide the final prediction. It improves prediction accuracy and overfitting control. This classifier has several parameters, for example, n_estimators is the number of trees in the forest, defaults to 100, if bootstrap is True (default), the subsample size is controlled by the max_samples parameter, otherwise the entire dataset is used to build each tree. The advantage of random forest is that it is flexible and performs well on both classification and regression problems. It reduces overfitting in decision trees and helps improve accuracy. Whereas the disadvantage of random forest is that it requires a lot of computational cost and training time because it combines many decision trees to determine classes.

XGBoost is an integrated machine learning algorithm based on decision trees that uses a gradient boosting framework. In prediction problems involving unstructured data such as images, and text, artificial neural networks tend to outperform all other algorithms or frameworks. However, when it comes to small and medium-sized structured or tabular data, algorithms based on decision trees are now considered best-in-class.

XGBClassifier is imported from the XGBoost module representing eXtreme Gradient Boosting. It implements machine learning algorithms under the gradient boosting framework. XGBoost provides a parallel tree boost that provides higher performance and accuracy compared to other algorithms. The advantage of the XGBoost algorithm is that it is efficient because it exploits the power of parallel processing and is very flexible for both classification and regression problems.

The k Nearest Neighbor (KNN) algorithm is a data classification method that estimates the likelihood that a data point will be a member of one or another group based on the group to which it belongs. The k-nearest neighbor algorithm is a supervised machine learning algorithm for solving classification and regression problems. However, it is mainly used for classification problems. KNN is an inert learning and nonparametric

algorithm. It is called a lazy learning algorithm or lazy learner because it does not perform any training when providing training data. Instead, it simply stores data during training and doesn't perform any calculations. It does not generate a model until a query is executed on the dataset. This makes KNN ideal for data mining.

KNeighborsClassifier is imported from the Scikit-learn module, it is a classifier that implements k-nearest neighbor voting using the K-Nearest Neighbor (KNN) algorithm for machine learning. KNN is one of the simplest machine learning algorithms based on supervised learning techniques. First, it needs to choose the number K of neighbors, denoted as n_neighbors, which is defined as 7 in this study. Next, it will calculate the Euclidean distance between the data points. Once Euclidean distance is calculated, all nearest neighbors are grouped into a class and the number of data points in each class is counted, then new data points are assigned to the class with the largest number of neighbors. The advantage of the KNN algorithm is that it is simple to implement, robust to training noisy data, and can effectively train large data, while the disadvantage of the KNN algorithm is that it is difficult to determine the number K of neighbors in complex situations, and the computational cost is high because it requires to calculate the Euclidean distance between all training data points. Figure 3.8 is showing the modeling machine learning algorithms for the random forest, XGB, and KNeighbors classifiers.

```
models = {
    "Rf": {
        "classifier": RandomForestClassifier(n_estimators=100),
        "accuracy": 0,
        "sensitivity": 0,
        "specificity": 0,
    },
    "Xgb": {
        "classifier": XGBClassifier(),
        "accuracy": 0,
        "sensitivity": 0,
        "specificity": 0,
    },
    "KNN": {
        "classifier": KNeighborsClassifier(n_neighbors=7),
        "accuracy": 0,
        "sensitivity": 0,
        "specificity": 0,
    }
}

for model in models:
    print(model)
    models[model]["classifier"].fit(train_X, trainY)
    prediction_result(models[model]["classifier"], test_X, testY)
    print('\r\n')
```

Figure 3.8: Modeling Machine Learning Algorithms for Classification

3.2.5 Evaluation

Evaluate the results generated from the selected model. The final model with the highest accuracy is selected based on the model comparison results. Any conclusions or inferences are drawn from the model itself and from the data mining process. These are called findings.

A confusion matrix is a matrix used to determine the performance of a classification model given a test dataset. There are only two predicted categories in this Parkinson's disease detection, such as healthy or Parkinson, so the matrix is in a 2 X 2 table. The matrix is divided into two dimensions, the predicted and actual values along with the total number of predictions. The predicted value represents the value predicted by the model, and the actual value represents the true value of the known test data. A sample of the confusion matrix table is shown in Figure 3.9.

	Predicted Negative	Predicted Positive
Actual Negative	14	1
Actual Positive	4	11

Figure 3.9: Confusion Matrix Table Sample

Figure 3.10 shows the prediction_result function defined in the notebook, which includes the computation of the confusion matrix. The confusion matrix is used to evaluate the performance of classification models by calculating accuracy, misclassification, sensitivity, precision, and f1-score. P is the condition positive which represents the number of real positive cases in the data and N is the condition negative which represents the number of real negative cases in the data. A true positive (TP) is a test result that correctly indicates the presence of the condition. A false positive (TP) is a test result that correctly indicates that the condition does not exist. A true negative (TN) is a test result that falsely indicates a specific condition. A false negative (FN) is a test result that falsely indicates a specific condition.

All the evaluation formulas are shown as below,

$$Accuracy\ (ACC) = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Misclassification = 1 - ACC$$

$$Sensitivity\ (\text{TPR}) = \frac{TP}{TP + FN}$$

$$Specificity\ (\text{TNR}) = \frac{TN}{\text{TN} + FP}$$

$$Precision\ (\text{PPV}) = \frac{\text{TP}}{\text{TP} + FP}$$

$$F1\ Score\ (\mathrm{F}_1) = 2\left(\frac{(\mathrm{PPV})(\mathrm{TPR})}{\mathrm{PPV} + \mathrm{TPR}}\right)$$

```
In [2]: def prediction_result(model, test_X, test_Y):
            # make predictions on the testing data and initialize a dictionary
            # to store our computed metrics
            pred_Y = model.predict(test_X)

            # compute the confusion matrix and and use it to derive the raw
            # accuracy, sensitivity, and specificity
            cm = confusion_matrix(test_Y, pred_Y)
            (tn, fp, fn, tp) = cm.flatten()

            # calculate accuracy
            conf_matrix_accuracy = (float (tp + tn) / float(tp + tn + fp + fn))

            # calculate misclassification
            conf_matrix_misclassification = 1- conf_matrix_accuracy

            # calculate the sensitivity
            conf_matrix_sensitivity = (tp / float(tp + fn))

            # calculate the specificity
            conf_matrix_specificity = (tn / float(tn + fp))

            # calculate precision
            conf_matrix_precision = (tp / float(tp + fp))

            # calculate f_1 score
            conf_matrix_f1 = 2 * ((conf_matrix_precision * conf_matrix_sensitivity) /
                                  (conf_matrix_precision + conf_matrix_sensitivity))

            print('-'*55)
            print(f'Accuracy         : {round(conf_matrix_accuracy, 2)}')
            print(f'Misclassification: {round(conf_matrix_misclassification, 2)}')
            print(f'Sensitivity      : {round(conf_matrix_sensitivity, 2)}')
            print(f'Specificity      : {round(conf_matrix_specificity, 2)}')
            print(f'Precision        : {round(conf_matrix_precision, 2)}')
            print(f'f1-Score         : {round(conf_matrix_f1, 2)}')
            print('-'*55)

            # Assigning columns names
            cm_df = pd.DataFrame(cm,
                                 columns = ['Predicted Negative', 'Predicted Positive'],
                                 index = ['Actual Negative', 'Actual Positive'])

            print(cm_df)
```

Figure 3.10: Define the prediction_result function in the notebook

3.2.6 Deployment

Deployment is the process of deploy the final selected model. The deployed model can directly use to analyze data without pass through the model training and model compilation stage.

Each model was evaluated, and we weighed the model best suited for Parkinson's disease detection based on the evaluation. The model with low misclassification and high accuracy, sensitivity, specificity, precision, and F1-score were considered the best model. After selecting the model, we need to deploy it using the joblib module and save the machine learning model with Scikit-learn. The python code is shown in Figure 3.11. Note that the training, evaluation, and deployment process is the same in Spiral and Wave. Therefore, at the end of this study, we will deploy two models, one dedicated to predicting spirals and the other dedicated to waves.

```
In [31]: # encode the labels as integers
         le = LabelEncoder()
         train_Y = le.fit_transform(train_Y)
         test_Y = le.transform(test_Y)

         model = RandomForestClassifier(n_estimators=100)
         model.fit(train_X, train_Y)

         # Save the model as a pickle in a file
         joblib.dump(model, './model/finalized_spiral_model.joblib', compress=True)

         print("Spiral Prediction Result:")
         prediction_result(model, test_X, test_Y)
```

Figure 3.11: Save the Model using the joblib Module

CHAPTER 4: RESULTS

4.1 Quantify Image

Histogram of Oriented Gradients (HOG) is a feature descriptor that is often used to extract features from image data. It is widely used in computer vision tasks for object detection. HOG is able to extract the gradient and direction of the edges.

In Figure 4.1, we will show the steps how to quantify the spiral sketches. The first image “healthy (Original)” is showing the sample original image data we used. The second image “healthy (Gray)” is the image after converting to grayscale image output. The purpose of a grayscale image is because the color image is hard to visualize and complex. The color information in a picture doesn’t help in the identification of edges or extracting features. After that, the thresholding image process is performed, and we can refer to the third image as “healthy (Threshold)” for the expected output. During the thresholding image process, the image will become a binary image and the pixel of the image will be changed to make sure the image is easier to perform analysis steps. For the fourth image “healthy (Noiseless)”, we will remove the noise in the loaded image and the respective function is created to remove small components in noise-free images that are less than 1 percent of active pixels. After completing all the previous steps we mentioned, we will use the HOG to quantify the image.

The Figure 4.1 will show the steps to quantify the spiral sketches in data preparation.

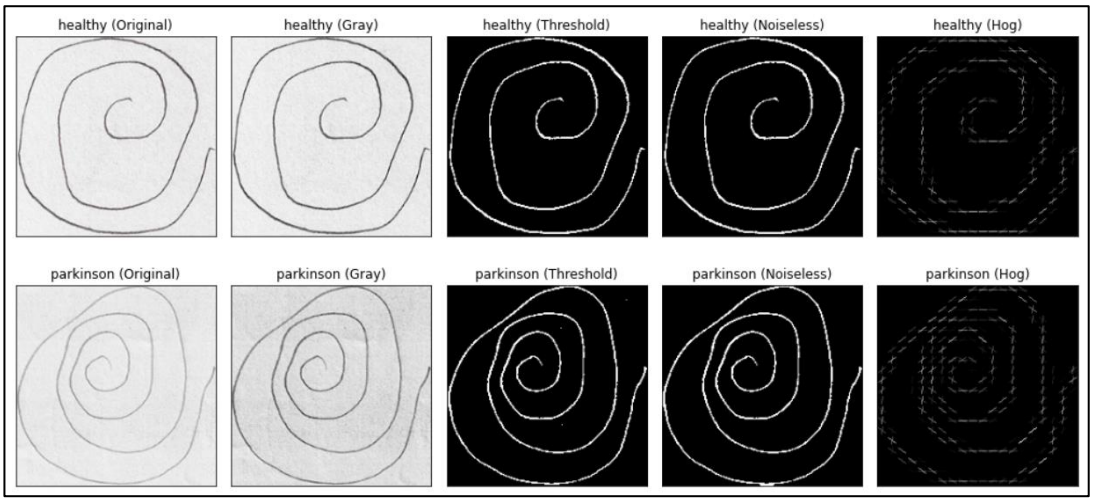

Figure 4.1: Steps to Quantify Spiral Sketches

Figure 4.2 will show the steps to quantify the wave sketches in data preparation. Only one sample output is shown in the figure with healthy and Parkinson's sketches.

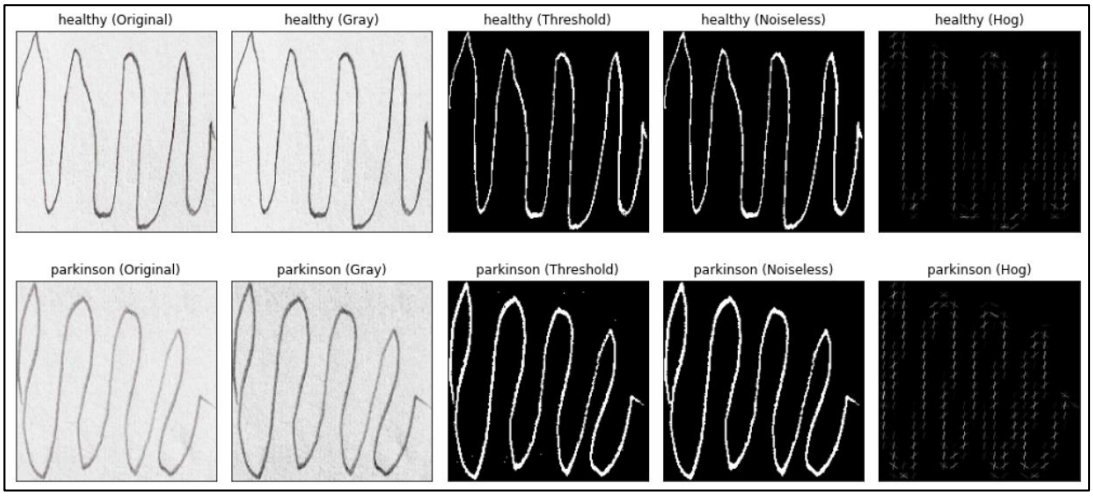

Figure 4.2: Steps to Quantify Wave Sketches

4.2 Train and Test Result

In this study, 3 classification methods are selected to classify geometry drawing which is random forest classification, XGBoost classification, and K-nearest neighbors

classification. Before we are selected the final classification model for our prediction, we need to train each of the classification model and test it by using the sample dataset.

Table 4.1 shows the confusion matrices with spiral drawing obtained as a result of classification. The success parameters calculated according to the equation (3.2.5 Evaluation) are given in Table 4.2.

Table 4.1: Confusion Matrices with Spiral Sketches

		Predicted Value	
		N	**P**
Actual Value (Random Forest)	**N**	14	1
	P	3	12
Actual Value (XGBoost)	**N**	13	2
	P	4	11
Actual Value (K-nearest neighbors)	**N**	10	5
	P	4	11

Based on the classification result in Table 4.2, we can conclude that the random forest classification is most suitable for classify the spiral sketches. The model developed in the work prompted an accuracy of 87 percent, sensitivity of 80 percent, specificity of 93 percent, precision of 92 percent, and f1 score of 86 percent respectively.

Table 4.2: Classification Results with Spiral Sketches

	Random Forest	**XGBoost**	**K-nearest neighbors**
Accuracy	0.87	0.8	0.7
Misclassification	0.13	0.2	0.3
Sensitivity	0.8	0.73	0.73
Specificity	0.93	0.87	0.67
Precision	0.92	0.85	0.68
f1-Score	0.86	0.79	0.76

Table 4.3 shows the confusion matrices with spiral drawing obtained as a result of classification. The success parameters calculated according to the equation (3.2.5 Evaluation) are given in Table 4.4.

Table 4.3: Confusion Matrices with Wave Sketches

		Predicted Value	
		N	**P**
Actual Value (Random Forest)	**N**	11	4
	P	3	12
Actual Value (XGBoost)	**N**	8	7
	P	5	10
Actual Value (K-nearest neighbors)	**N**	9	6
	P	2	13

Based on the classification result in Table 4.4, we can conclude that the random forest classification is most suitable for classify the wave sketches. The model developed in the

work prompted an accuracy of 77 percent, sensitivity of 80 percent, specificity of 73 percent, precision of 75 percent, and f1 score of 77 percent respectively.

Table 4.4: Classification Results with Wave Sketches

	Random Forest	**XGBoost**	**K-nearest neighbors**
Accuracy	0.77	0.6	0.73
Misclassification	0.23	0.4	0.27
Sensitivity	0.8	0.67	0.87
Specificity	0.73	0.53	0.6
Precision	0.75	0.59	0.68
f1-Score	0.77	0.62	0.76

Based on the classification result in spiral and wave sketches, the random forest classification model has been selected as final classification model in this study. Random forest classification model has high accuracy and sensitivity in each category. Therefore, we will use this model to predict the patient's sketches.

4.3 Prediction Result

Figure 4.3 is shown the result in spiral sketches by using a random forest classification model. 25 pieces of the image are selected for this prediction and 9 pieces of the image are shown in the Parkinson's sketches.

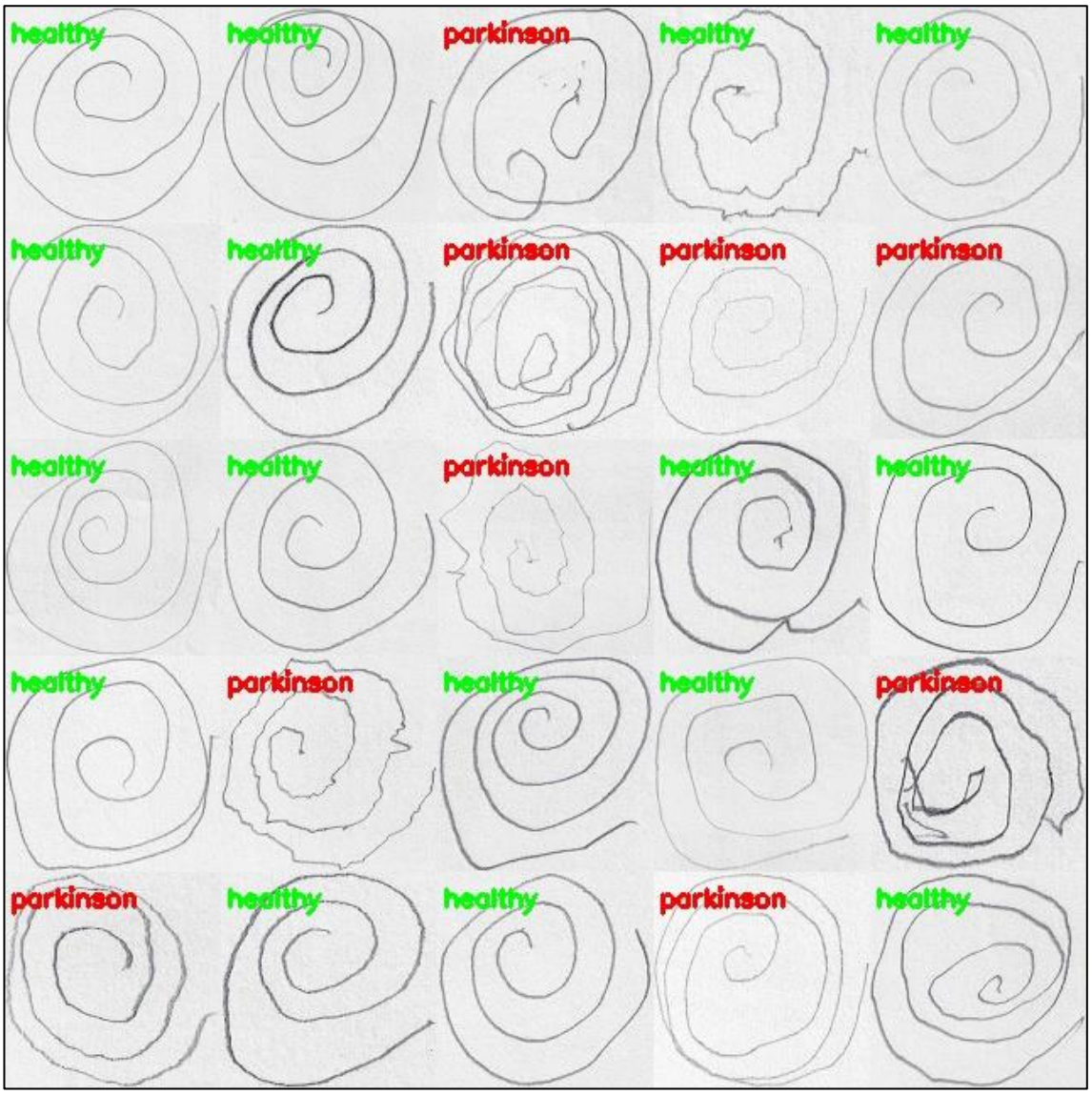

Figure 4.3: Prediction Result in Spiral Sketches

Figure 4.4 is shown the result in wave sketches by using a random forest classification model. 25 pieces of the image are selected for this prediction and 12 pieces of the image are shown in the Parkinson's sketches.

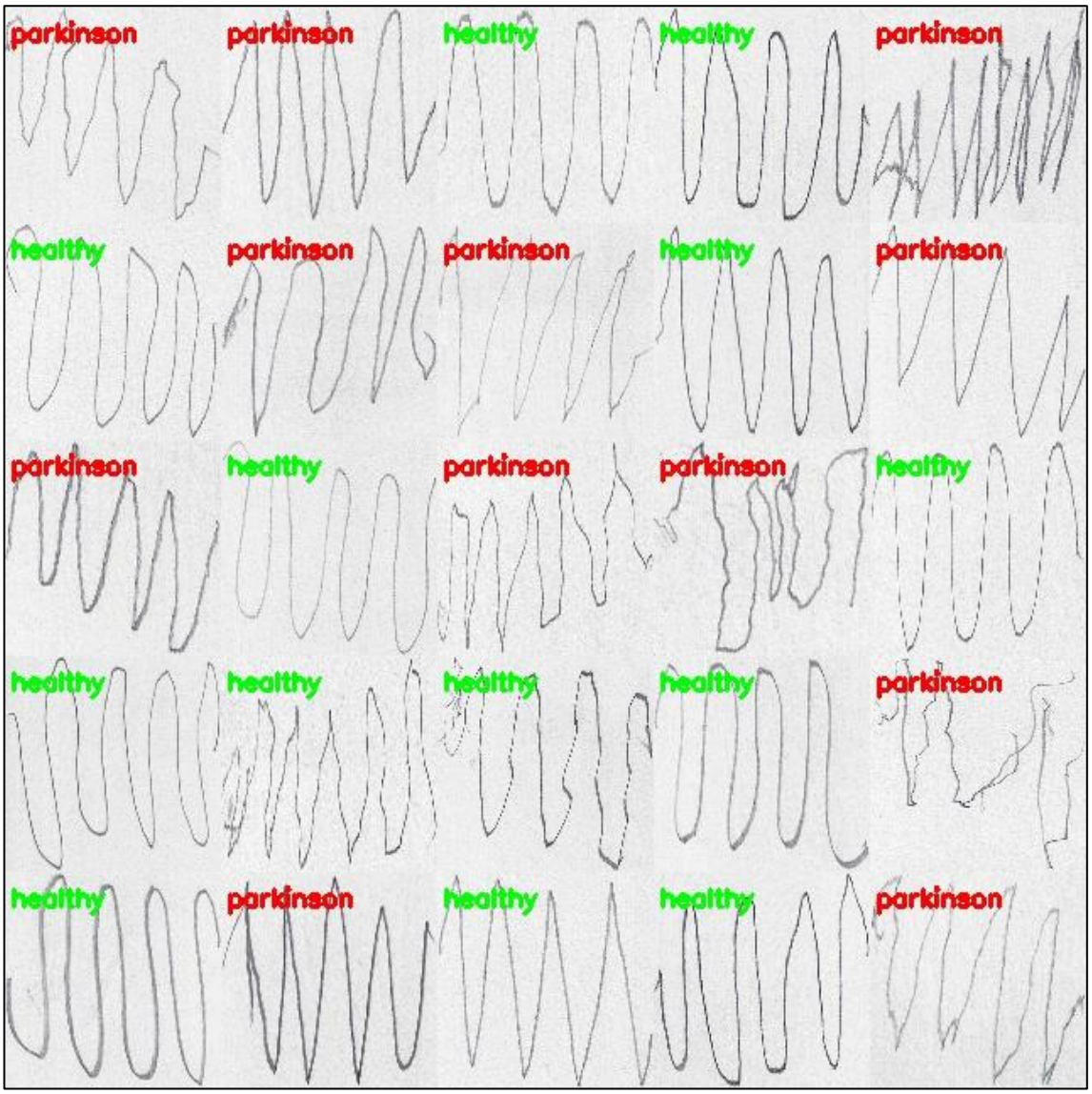

Figure 4.4: Prediction Result in Wave Sketches

CHAPTER 5: DISCUSSION

5.1 Future Diagnostic Recommendations

5.1.1 Drawing Shape Recommendations

The choice of drawing shape is one of the most important aspects of the brushed test design. We infer that these unique mathematical relationships are very suitable for quantitative analysis of digital drawing. The deviation of these mathematical relationships inherent in the figure can be used to distinguish between patients and control groups, and even evaluate the stage of disease progression. The Archimedean spiral used in this study is an example of this mathematical interesting shape. It has a unique curvature characteristic and a unique relationship between the radius and theta relative to the origin. Other mathematical and interesting shapes include the shape of non-constant curvatures, such as lemniscates and spirographs. The change of curvature may have diagnostic significance.

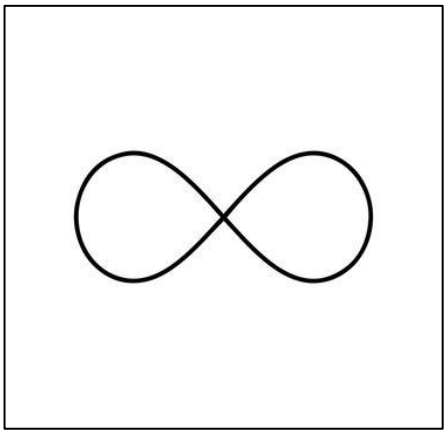

Figure 5.1: Lemniscates

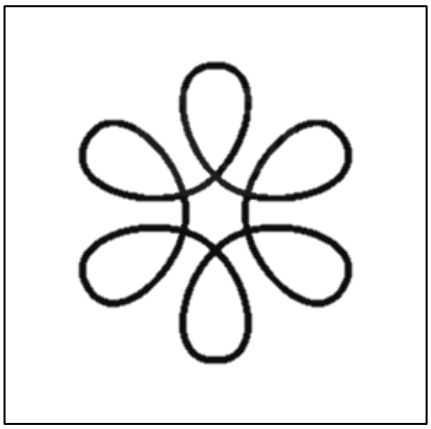

Figure 5.2: Spirographs

Unorthodox shapes are also suitable for use because they "normalize" the level of education and painting experience of the test subject. Examples include numbers of type Poppelreuter or other figures that the subject has not encountered before. These shapes are particularly beneficial for more cognitive and memory-based diseases, such as Alzheimer's disease, but they are also conducive to revealing Parkinson's disease-related motor functions.

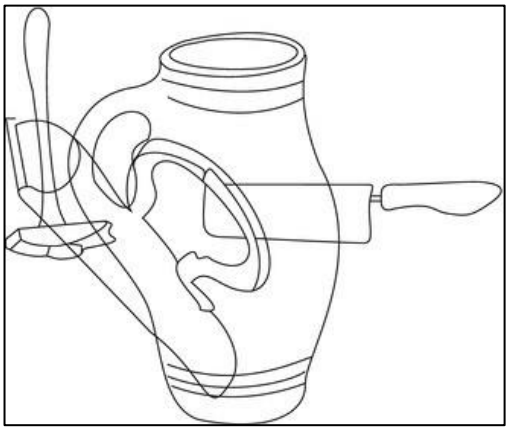

Figure 5.3: Poppelreuter

5.1.2 Task Variation

In addition to more granular assessments using adaptive testing frameworks that take into account patient capabilities, drawing tasks can also use repetitive assessments of the same shape, such as measures for multiple trials, to collect informational data about plotting variability and patient learning rates. Drawing tasks can also include variations in the form of test conditions, such as asking patients to draw shapes in multiple trials with different goals or obstacles. Conditions can range from emphasizing accuracy or speed to displaying intermittent flickering template lines for tracking. These deviations from previously completed drawing tasks by patients may make it easier to distinguish Parkinson's disease patients from control data (Stegemöller, E. L. et al., 2019).

5.1.3 Template for Drawing

The structure and guidance provided to the patient during the drawing task are tricky balancing issues. The options include tracking shapes, providing general guidelines, such as flashing lines or moving points, and empty drawings that only provide hand drawn drawings. Although the use of hand-drawn clock maps in the mini-COG test and automatic test of MIT scientists can indicate Parkinson's disease (Seitz, D. P., et al., 2018) (Souillard-Mandar, W. et al., 2016). It has shown that the huge changes in hand-drawn spirals are significantly confusing and analyzed complicated (Drotár, P. et al., 2016). We are based on the preliminary feature extraction of the PAHAW dataset collected by Drotár, P. et al. Due to the high variability of these spiral charts, it is also confirmed the difficulty in the analysis of the hand drawn spirals. This variability makes identifying disease related features more challenging.

On the other hand, simple tracers have been shown to be useful for detecting Parkinson's disease (Kotsavasiloglou, C. et al., 2017). By drawing templates of shapes

such as spirals, the standardization of the tracer greatly improves the uniformity of the drawings, and the difference between patients and control groups is more pronounced. Finding the middle ground, some guidance without pure tracking may produce sufficient inter-patient variability and allow some uniformity at the same time, which will allow current analytical methods to detect the characteristics of Parkinson's disease.

5.1.4 Adaptive Testing Framework

The rigidity of drawing tasks with only a single normalized shape can be improved on the basis of (Chakraborty, S. et al., 2020). It is largely unable to explain the different stages of Parkinson's disease (Lonini, L. et al., 2018), different natural drawing abilities (Lin, P. C. et al., 2018), and different situations, from cognitive proficiency levels and work experience to technical literacy, especially in older adults who are more likely to be tested for Parkinson's disease. Because the clinical needs of patients with early-stage Parkinson's disease and patients with advanced Parkinson's disease vary widely, placing patients with both diseases in the same category is of no benefit to patients or physicians who wish to better understand their disease outcomes (DeMaagd, G., & Philip, A., 2015). These concerns guarantee the development of drawing tests of varying difficulty. For future studies, the good structure of this drawing test is an adaptive testing framework in which patients are assigned drawing tasks of varying difficulty based on their performance in previous drawing tasks. For example, ask patients to draw a shape, and if they draw well, ask them to draw a more complex shape. If they don't draw well, let them draw a simpler shape. This fitness test can more clearly distinguish between different stages of Parkinson's disease.

5.1.5 Data Sharing

There are many studies that have collected digitized drawings or handwriting of patients with Parkinson's disease. However, the datasets used in most studies were not publicly available and had very small sample sizes, such as fewer than 50 subjects. Models trained on such small datasets may be biased by limited generalization (Panch, T. et al., 2019). In addition, non-publicly available datasets hinder the possibility of external validation for similar handwriting or drawing tasks (Steyerberg, E. W., & Harrell, F. E., 2016). To address these issues, merging datasets from heterogeneous populations could help reduce imbalances in the race, gender, age, etc., which will affect model classification accuracy for the general population. In addition, it is important to generate public data sets with certified access and de-identified data information so that more researchers can come together to validate automated drawing analysis as an effective and accurate method for Parkinson's disease screening. These datasets can even be found in the context of Michael S. Thompson's Found on J. Fox Foundation Dataset page (Datasets. The Michael J. Fox Foundation for Parkinson's Research | Parkinson's Disease, 2022).

5.1.6 Combining Various Data

Future developments in this study may explore new classification strategies to further improve predictive performance. For example, combining handwritten dynamic features with static features, such as features based on the obtained image, can provide additional insight and better data performance. New insights can also be gained by treating other motor features of human motion control as features. For example, the data is analyzed by calculating the proportional relationship between the calculated speed and the ratio of motion, which is called the two-thirds law. The law applies to a variety of trajectories and

has recently been successfully applied to the remote-control operation of mobile robots (Impedovo, D. al et., 2018). Besides that, combining multiple Parkinson's disease handwritten datasets and applying different data enhancement techniques are able to enhance diagnostic performance. According to the experimental results, it can provide the best performance by using data-enhanced images when combined with CNN fine-tuning architectures (Kamran, I. al et., 2021). On the other hand, voice record analysis can also be combined with handwriting analysis to increase the features. As a result, the diagnosis of Parkinson's disease can significantly improve.

5.1.7 CNN Image Classification Model

A convolutional neural network (CNN) is a type of fed neural network that usually specializes in image data (Multiaraire Data). The design of the CNN structure can effectively preserve the structure of the original data and generate hierarchical representations. A typical CNN structure consists of multi-stage processing layers ordered from left to right. CNN typically has four types of layers: convolutional, pooling, fully connected, and classification layers. Convolutional and pooling layers are the core layers of the design, and they are usually used in the first few stages.

CNN is able to continuously extract and compress image features to obtain higher-level features. It repeatedly compresses the original image features and obtains more reliable features. Various tasks such as classification and regression can be performed using the features of the last layer. CNN has unique advantages in automatic speech recognition (ASR) and image processing due to its special structure that shares local weights and a layout similar to that of real biological neural networks. Weight sharing reduces network complexity; Since images with multidimensional input vectors can be fed directly into the network, the complexity of data reconstruction in feature extraction

and classification is avoided (Sharma, N. al et., 2018). Through the study of the current image classification recognition algorithm, it is found that various algorithms fail to effectively integrate the multi-layer deep learning features of CNN, and the accuracy rate is poor.

In the IoT environment, convolutional neural networks (CNNs) are an important tool and method for image classification. In order to further improve the classification accuracy of CNN models, we need to effectively integrates deep features through cascading strategies, increases the diversity and expressiveness of extracted features, and improves the classification performance of network patterns.

Convolutional neural networks (CNNs) are ubiquitous. Arguably the most popular deep learning architecture. The recent surge in interest in deep learning is due to the huge popularity and effectiveness of convnet. The main advantage of CNN over its predecessor is that it can automatically detect important features without any human supervision.

5.2 Limitation

Although our approach to extracting image features and model construction on a Parkinson's geometric drawing dataset has reached extreme precision, it is important to validate the generalization of our method, especially given the class imbalances in the Parkinson's geometry drawing datasets, such as controlling the small number of drawings and the relatively low overall sample size. In addition, it is possible to detect Parkinson's disease early using this automated approach, but there are currently no datasets or studies that strongly demonstrate the ability to detect it early. Lack of Movement Disorders Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) scores or similar disease progression scores is one of the limitations of this study. Future studies should

aim to collect MDS-UPDRS from many patients so that we can adequately test for automated detection of disease severity

Furthermore, given that the symptoms of Parkinson's disease overlap significantly with those of other neurodegenerative diseases and atypical Parkinson's diseases, the distinction needs to be assessed using subtle quantitative features that build a powerful tool for clinicians (Ali, K., & Morris, H. R., 2015). This necessity remains the subject of ongoing research, with many solutions proposed, and the digitization of screening assessments will only further complicate the discussion. In the previous literature, to distinguish Parkinson's disease motor symptoms from those of diseases such as primary tremor, multisystem atrophy, and Lewy body dementia (LBD), numerous solutions are used including modified shape mapping, assistive imaging, and alternative examinations (Thanawattano, C. al et., 2015). To distinguish Parkinson's disease from progressive supranuclear palsy, a common cause of atypical Parkinson's syndrome, recommendations have been made to range from identifying motor declines without reducing handwriting tasks to extracting features by gait analysis (Amboni, M. al et., 2021). In the treatment of dementias such as Alzheimer's disease and LBD, the visuospatial symptoms affecting a patient's handwriting have been the subject of ongoing research due to their striking resemblance to those symptoms of Parkinson's disease (Foguem, C., & Manckoundia, P., 2018). Differentiating between Parkinson's disease and similar diseases remains a major barrier to the development of diagnostic tools and requires further research. Some of the features we extracted will be more relevant to general anomalous states (e.g., radius vs theta regression R2) as it captures the overall drawing capability. Other subtle features, such as pressure reversal rate and curvature regression, may be better at distinguishing Parkinson's disease from similar diseases.

Apart from this, the source of the dataset is also one of the obstacles to this study. Ordinary researchers do not have access to the official Parkinson's dataset. The dataset is too small for the dimensions we found on the internet. For example, this study uses only 73 images as the training set and 30 images as the test set. Therefore, we cannot train the model properly. If the dataset is large enough, the accuracy of the model should be higher than the current results. So datasets are one of the limitations, regardless of the source of the datasets or the dimensionality of the datasets we use.

CHAPTER 6: CONCLUSION

Nowadays, the early diagnosis of Parkinson's disease is important and cannot be ignored. Once overlooked, we will miss the best treatment period. Parkinson's disease is a neurodegenerative disorder that can cause symptoms such as tremors, stiffness, and difficulties in balance and coordination. Since Parkinson's disease is difficult to diagnose, we need some effective diagnostic methods for early prevention of the exacerbation of Parkinson's disease. In the study, the diagnosis of Parkinson's disease was made through analysis of the Parkinson's spiral and wave tests. We will use some machine learning methods to analyze the geometry drawing such as spirals and waves to classify which drawings are drawn by the Parkinson's disease patients. In addition, unlike studies in the literature, the Parkinson's spiral and wave test are considered a recognition problem. The proposed method was tested using a dataset created by the NIATS of Federal University of Uberlandia. When considering the results, it can be seen that the results are successful.

Machine learning models, especially in the medical field, require great caution when balancing the real positives with the real negatives. In fact, when they are positive for Parkinson's disease, we don't want to classify them as "Parkinson's disease." Similarly, we don't want to classify someone as "Parkinson's positive" but, they don't have the disease in reality.

In the study, OpenCV and computer vision was used to detect Parkinson's disease via analysis of the geometry drawings such as spirals and waves. The Histogram of Oriented Gradients (HOG) image descriptor was utilized to quantify all the geometry drawing images. It is able to show how the direction changes in the geometry drawings. A few machine learning methods are used such as random forest classification, XGboost

classification, and K-nearest neighbors classification. When examining the success rate of classification, it can be seen that the random forest classification process using genetic algorithms gives the best results in terms of accuracy, sensitivity, specificity, and precision parameters.

In the absence of a feature selection process, the classification method using random forest has achieved good results in terms of accuracy and sensitivity parameters. There are showed an accuracy of 87 percent and a sensitivity of 93 percent for the Parkinson's disease detection with spirals drawing. Other than that, there is shown an accuracy of 77 percent and a sensitivity of 73 percent for the Parkinson's disease detection with waves drawing. Notably, random forests trained on the spiral dataset and wave dataset gained 73 percent sensitivity, meaning the model can predict true positives which the patients have Parkinson's disease with a nearly 73 percent probability.

Early detection and appropriate drug therapy can significantly improve symptoms and quality of life, although Parkinson's disease cannot be cured. This is an important topic to explore for computer vision and machine learning practitioners.

When examining the success parameters of the classification, it can be said that the feature selection method contributes to the success rate. In addition, the use of pattern recognition methods can be successful in Parkinson's spiral testing and wave testing. Diagnosis of Parkinson's disease is difficult to diagnose early, and this approach can be more effectively determined.

In future studies, the availability of spiral and wave tests for research could be studied when monitoring patients with Parkinson's disease. In addition, drug interactions in patients with Parkinson's disease can be measured in this way.

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