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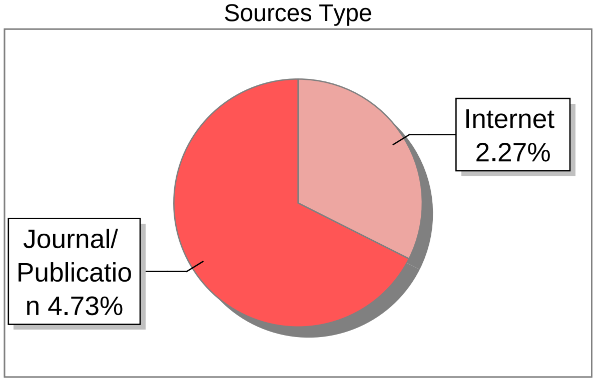

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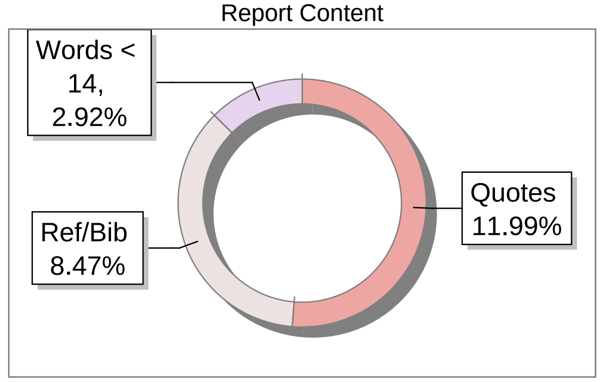

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28	www.dx.doi.org	<1	Publication
30	www.symptoma.co.uk	<1	Internet Data

ABSTRACT

Due to the delayed onset of symptoms and the dependence on subjective clinical evaluations, Parkinson's disease (PD) is commonly diagnosed after the fact. In order to overcome this difficulty, we suggest a brand-new AI-driven diagnostic tool that makes use of spiral handwriting analysis, a task that has been shown to highlight the subtle fine motor impairments linked to early-stage Parkinson's disease. In order to capture both dynamic and static handwriting characteristics, our suggested framework uses a dual-stream deep learning architecture. In order to separate online handwriting data into Beta strokes and extract sophisticated dynamic features (like pressure, velocity, and fluidity), the system first uses a Beta-elliptical model in conjunction with a fuzzy perceptual detector. To model long-term dependencies in the writing movement, a Bidirectional Long Short-Term Memory (BLSTM) network processes these temporal sequences. Convolutional Neural Networks (CNNs) are used in tandem to capture geometric irregularities that dynamic analysis alone frequently overlooks by directly extracting high-level spatial features from the spiral drawings' visual representations. To categorize subjects as either PD-positive or healthy, the outputs from the CNN and BLSTM models are combined. This technology greatly surpasses traditional techniques by successfully fusing the spatial feature extraction of a CNN with the dynamic precision of the Beta-elliptical approach. The end product is an early Parkinson's disease detection tool that is accurate, non-invasive, and computationally efficient.

CHAPTER 1

1.1 OVERVIEW

INTRODUCTION

With an emphasis on spiral drawing tasks, this study offers a novel, non-invasive framework for online handwriting analysis-based Parkinson's disease (PD) detection. We suggest a dual-stream hybrid deep learning architecture that captures both the dynamic and static aspects of handwriting in order to overcome the shortcomings of conventional diagnostic techniques. In the first stream, the system divides online handwriting data into beta strokes using a fuzzy perceptual detector in conjunction with a beta-elliptical model. In order to model temporal motor irregularities, a Bidirectional Long Short-Term Memory (BLSTM) network processes the complex dynamic features that are extracted by these advanced preprocessing and data augmentation steps.

Key Features:

- **Online Handwriting-Based Detection Detects Parkinson’s Disease using real-time digital handwriting input captured via a graphics tablet.**
- **Advanced Feature Extraction Utilizes the Beta-Elliptical approach to capture both kinematic (velocity) and geometric (stroke shape) details.**
- **Fuzzy Perceptual Detector is integrated to extract uncertainty-tolerant visual perception features.**
- **Smart Stroke Segmentation - Divides handwriting into Beta strokes based on the change in the person's velocity, thus enabling a detailed analysis of the motor skills.**
- **Data Augmentation & Preprocessing - Geometric transformations are used to increase the variety of the dataset.**
- **The handwriting is filtered and normalized to make it noise-free and standardize the input.**

1.2 Purpose of the Project

It is still a big problem to figure out the early-stage Parkinson's Disease. This is because subtle motor impairments are easy to miss and people often wrongly attribute them to other causes. The traditional ways of diagnosis take a lot of time, need special clinical settings, and may not be available to everyone, particularly in low-resource areas. As a result, treatment is delayed, and the condition of patients as well as the healthcare systems gets worsened.
10
Most of the existing diagnostic methods have not yet fully realized the potential of handwriting as an easily accessible, real-time, and non-invasive biomarker. The patients and doctors cannot rely on the subjective evaluation that data-driven methods are lacking; thus, they are at variance with one another. This research is aimed at removing these obstacles by creating an AI-powered Parkinson's detection system that incorporates online handwriting analysis, machine learning, and deep temporal modelling. The innovative system will be using the Beta-Elliptical model and Fuzzy Perceptual Detectors to identify and extract fine-grained neuromotor features and SPD networks to classify them, in a highly intelligent manner, from the raw handwritten input. This is a diagnosed support accessible, language-aware, and user-friendly tool, which is clinically and naturally usable. It is the essence of early detection, personalized monitoring, and timely intervention changing radically the concept of the digital era-based neurological diseases like Parkinson's.
A detection system that employs deep temporal modeling, machine learning, and online handwriting analysis. The proposed system will use the Beta-Elliptical model and fuzzy perceptual detectors to smartly extract fine-grained neuromotor features that will be classified through bidirectional LSTM networks. It provides a simple, linguistically informed, and clinically as well as practically-designed diagnostic support tool. The goal is to change the comprehension and therapy of neurological disorders such as Parkinson's in the Digital Era by facilitating early detection, personalized monitoring, and timely intervention.

1.3 Scope of the Project

The goal of this project is to develop a sophisticated, artificial intelligence (AI)-driven 24 system that can identify early indicators of Parkinson's disease by analyzing online handwriting. By utilizing sophisticated methods like the Bidirectional LSTM for classification and the Beta-Elliptical approach for feature extraction, the system is able to precisely detect neuromotor abnormalities associated with Parkinson's disease. The procedure is non-invasive, economical, and real-time

Here's what the platform will cover:

- **Real-Time Detection: Instantly recognizes early Parkinson's disease symptoms from online handwriting input.**
- **AI-Based Analysis: This method looks for neuromotor irregularities in handwriting using trained machine learning models.**
- **Fuzzy Perceptual Detection: The process involves detecting uncertain or very subtle characteristics of the handwriting that are hidden using feature extraction based on fuzzy logic.**
- **Stroke Segmentation: Breaks handwriting into Beta strokes for precise motion tracking and evaluation.**
- **Non-Invasive & Fast: The method of diagnosing Parkinson's disease early is simple, without any direct contact, and quick.**
- **Personalized Assessment: Adjusts to different writing styles to guarantee precise, user-specific outcomes**

1.4 Definitions

1.4.1 Parkinson’s Disease (PD)

A progressive neurological disorder that primarily affects motor functions such as movement, coordination, and balance. Common symptoms include tremors, muscle stiffness, slowness of movement (bradykinesia), and handwriting difficulties (micrographia). Early detection is vital for effective management.

1.4.2 Online Handwriting Analysis

A digital technique for handwriting analysis that uses real-time data from a stylus or tablet to record coordinates (X, Y), time, pressure, and pen angle. It offers dynamic and kinematic characteristics that demonstrate neuromotor control.

1.4.3 Micrographia

Handwriting that is unusually small, cramped, or inconsistent is a clinical symptom of Parkinson's disease. It is caused by diminished fine motor control and motor impairment.

14.3 Beta-Elliptical Model

Handwriting strokes are represented by a mathematical model. In order to assess motor control during writing a crucial component in identifying abnormalities brought on by Parkinson's disease it records both kinematic and geometric features.

1.4.4 Kinematic Features

Motion-based metrics taken from handwriting, such as distance, jerk, acceleration, and velocity. They aid in evaluating a writer's consistency and fluidity, which is crucial for identifying Parkinsonian patterns.

1.4.5 Geometric Features

c\Characteristics of handwriting that are related to shape, including curvature, angle, and stroke trajectory. Alterations in these characteristics frequently signify Parkinson's disease related loss of motor control .

CHAPTER 2
LITERATURE SURVEY
2.1. Contribution of Different Handwriting Modalities to Differential Diagnosis of Parkinson's Disease.

Peter Drotár, Jiri Mekyska, Zdenek Smekal, Irena Rektorova, Lucia Masarova

The use of several handwriting modalities, including pen pressure, in-air movement, and on-surface movement, for the differential diagnosis of Parkinson's disease (PD) is investigated in this study. The authors extracted a rich set of more than 5,000 features from the PaHaW dataset, which contains handwriting samples from 37 PD patients and 38 healthy controls across seven tasks. These included pressure-based features, conventional kinematic and spatiotemporal metrics, and new non-standard features like energy, entropy, and intrinsic mode functions that were obtained through empirical mode decomposition.

Handwriting was recorded using a Wacom tablet capable of capturing both surface and in-air trajectories, as well as pressure and timing. A Support Vector Machine (SVM) classifier with a radial basis function (RBF) kernel was used to distinguish PD patients from controls. After feature selection using the Mann-Whitney U test, the classification achieved its highest performance (AUC = 89.09%) using on-surface movement features. Pressure-based features, although previously underexplored, also demonstrated strong predictive power (AUC 83.8%), while in-air movement was moderately effective (AUC 74.2%).

A full-sentence writing exercise was the handwriting task that provided the most valuable diagnostic information and probably showed the symptoms of PD most clearly due to the higher cognitive and motor demands. The paper finds that handwriting can be used as a very accurate, gentle, and cheap identification source when analysis is enhanced by the inclusion of advanced pressure and in-air movement features. As such, it is a potential instrument for initial diagnosis and regular check-ups, thereby, opening the possibility for its application in remote areas without the availability of advanced neuroimaging tech.   .

2.2. Biometric handwriting analysis to support Parkinson’s Disease assessment and grading.

Antonio Lattarulo, Antonio BrunettiClaudio, Loconsole, Giacomo Donato Cascarano.

One of the main symptoms of Parkinson's disease (PD) is handwriting impairment, which results from a loss of coordination between the various components of the motor sequence. According to clinical studies, PD patients frequently exhibit segmented sequential movements that are marked by abnormalities like bradykinesia (reduced speed and acceleration) and micrographia (decreasing character size). As a result, computer-aided analysis of handwriting tasks—especially those that call for fine motor control, like spiral drawing—has become a vital tool for spotting promising patterns that can be used to rate and detect Parkinson's disease early on.

Cascarano et al. (2019) proved the effectiveness of biometric signals in a ground breaking study. Their study used a Myo Armband to record surface electromyography (sEMG) signals from forearm muscles and a Wacom graphics tablet to record pen-tip trajectories, pressure, and inclination. They were able to distinguish between healthy subjects and PD patients with a classification accuracy of over 90% by extracting dynamic features, such as velocity, acceleration, and jerk, and processing them through an Artificial Neural Network (ANN) optimized by a Multi-Objective Genetic Algorithm (MOGA).

Our suggested system improves on Cascarano et al.'s validation of dynamic feature analysis by removing the requirement for wearable sEMG sensors and concentrating on a non-invasive deep learning architecture. Our project uses a hybrid model, with a Convolutional Neural Network (CNN) to automatically extract spatial features from the visual spiral images and a Bidirectional Long Short-Term Memory (BLSTM) network to capture the temporal dependencies of the drawing path. Cascarano et al. relied on explicit feature extraction and standard ANNs. This development makes it possible to create a powerful diagnostic tool that uses sophisticated representation learning and capitalizes on the dynamic handwriting characteristics that are known to be important.

2.3. Graphical representation & variability quantification of handwriting signals: New tools for Parkinson's disease detection.
R.B. Pachori, S. Mandal, N. Stergiou , K.W. Lange

The difficulties in diagnosing Parkinson's disease (PD), a disorder marked by movement impairments brought on by the degeneration of brain neurons, are discussed in the document. The need for more dependable and affordable alternatives is highlighted by the invasiveness and high cost of traditional diagnostic techniques like DaTscan, magnetic resonance imaging (MRI), and positron emission tomography. Taking advantage of the fact that handwriting is greatly impacted by motor dysfunctions linked to Parkinson's disease, the study suggests handwriting analysis as a non-invasive diagnostic method. By making diagnosis more accessible, this strategy seeks to enhance health outcomes.

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The goal of the study is to use a method known as Empirical Mode Decomposition (EMD) to extract novel nonlinear features from handwriting signals. The area of the second-order difference plot (SODP) and the area of the analytic signal representation (ASR) are two new features. These characteristics are intended to measure handwriting variability, which may be a sign of motor impairments in people with Parkinson's disease. Crucially, the suggested features are appropriate for real-time patient monitoring because they are independent of data length and do not require stroke segmentation. By identifying the hidden variability in handwriting signals, this methodology seeks to improve the detection of Parkinson's disease.

In addition to offering a dependable and effective means of identifying Parkinson's disease (PD), the suggested approach provides neuropsychologists and clinicians with information about motor patterns. 19 For patients who might not have easy access to clinical settings, the system's ability to enable remote health monitoring is especially advantageous. A description of the handwriting database is presented first, then the variability feature extraction techniques based on EMD, and finally 21 the classification results using support vector machines (SVM). Discussions contrasting the suggested algorithm with alternative approaches and providing an overview of the results round out the paper.

2.4. A systematic approach to diagnose Parkinson's disease through kinematic features extracted from handwritten drawings

Rohit Lamba & Tarun Gulati, Kawther A. Al-Dhlan

Parkinson's disease is a neurodegenerative condition that progresses slowly and is difficult to identify in its early stages due to delayed symptoms. The most common methods for diagnosing this illness are either having a neurologist look at the patient's medical history and computerized tomography scans and magnetic resonance imaging or having a body movement analyst examine the patient's movements. Recent studies, however, suggest that handwriting changes can be used to accurately diagnose Parkinson's disease early on. By examining the kinematic characteristics taken from the handwritten spirals that patients draw, the authors of this work have suggested a method for diagnosing Parkinson's disease. This study makes use of the University of California, Irvine Parkinson's disease spiral drawings using digitized graphics tablet dataset, which is publicly available. The dataset is used to extract 29 kinematics features in total. Due to the extreme imbalance of the dataset, the synthetic minority oversampling technique addresses the issue of class imbalance. The mutual information gain feature selection technique and the genetic algorithm are used to choose pertinent features. Four classifiers support vector machine, random forest, AdaBoost, and XGBoost are evaluated based on their accuracy, sensitivity, specificity, precision, F-measure, and area under the ROC curve. The results are verified using the tenfold cross-validation method. With 96.02% accuracy, the mutual information gain feature selection method combined with AdaBoost classifiers performs better.

CHAPTER 3

PROBLEM IDENTIFICATION

3.1 Problem statement

Parkinson's Disease (PD) is a progressive neurodegenerative condition that impairs the brain's ability to regulate motor functions. The major symptoms include tremors, bradykinesia, muscle stiffness, balance problems, and micrographia. As the disease progresses, it becomes increasingly difficult for the affected person to carry out daily routines.

Almost indiscernible early signs are one of the biggest hurdles associated with Parkinson's disease. At first, the symptoms might be so faint that they could be mistaken for the effects of aging or some other health condition. Subsequently, due to this factor, diagnosis is often made at an advanced stage when the disease has caused considerable damage.

About 80% of Parkinson's cases are confirmed through the evaluation of symptoms in a physical examination by the doctor. Unfortunately, this method lacks precision since it is totally dependent on the expertise of the physician and can differ from one doctor to another. Besides, such investigations require some time and might not be accessible in every hospital or clinic, particularly in far-off or less-privileged localities.

3.2 Project scope

The present endeavour is to create a smart device that facilitates the detection of Parkinson's Disease at its very early stage through the medium of handwriting analysis. As micrographia, i.e., very small and irregular handwriting, is one of the earliest symptoms of Parkinson's, the described system leverages machine learning to scrutinize handwriting patterns and uncover features associated with the disease. The users deliver in the system their writing samples that are then processed to find out if there are any motor symptoms in a consistent and objective manner. The instrument is intended to be user-friendly and thus can provide a great deal of assistance to medical professionals by serving as a rapid, non-invasive, preliminary diagnostic tool. Even though currently only handwriting is considered, the layout can later be changed to include the continuation of monitoring or the connection with digital writing instruments. To sum up, the project is committed to the goal of facilitating the diagnosis of Parkinson's at an early stage.

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CHAPTER 4
GOALS AND OBJECTIVES
4.1 Project Goals
This project's primary objective is to use handwriting analysis to detect early indicators of Parkinson's disease. Symptoms of the disease may manifest as changes in writing style. To identify these changes, the system will analyse handwriting using computer programs known as machine learning. This will eliminate the need for complex testing and make the process of checking for Parkinson's disease quicker and easier.
4.2 Project Objectives
- **Detect early signs of Parkinson’s Disease using handwriting analysis.**

- **Track disease progression and provide actionable insights through an AI-powered chatbot.**

- **Transform Parkinson’s care by integrating advanced technology into diagnosis and support.**

- **Help users seek early consultation and maintain regular checkups with engaging chatbot reminders.**

CHAPTER 5

SYSTEM REQUIREMENT SPECFICATION

Software Requirements

- **Programming Languages: Python, JavaScript.**

- **Web Development: Flask, React.js, Express.js, HTML, CSS, TailwindCSS.**

- **Custom Scripts: Developed for Beta-Elliptical modeling and Fuzzy Perceptual Detection.**

- **OpenCV or PIL: handwriting data preprocessing and augmentation.**

- **Machine Learning: Scikit-learn, TensorFlow, Keras.**

Hardware Requirements

- **Laptop : Touchscreen notebook with stylus support**
- **GPU : RTX Dedicated graphics card**
- **Internet : min-60 Mbps, Stable high-speed connection**
- **Storage : 512 SSD**
- **RAM : 16 GB High speed memory**
- **Mongodb Atlas : Database (DBaaS)**
- **Cloud : Scalable cloud platform**
- **Stylus : Precision Pen Digital Input device**

CHAPTER 6
METHODOLOGY

1. Data Collection and Augmentation:

To train and validate the system, we created a unique Arabic dataset in addition to the PaHaW benchmark. Data augmentation methods such as scaling and rotation were used to replicate the variability of natural handwriting in order to maximize the Convolutional Neural Network (CNN). This increases the variety of training, guaranteeing that the model effectively generalizes across subjects and captures important spatial features.

2. Preprocessing and Noise Filtering:

To guarantee consistency and quality, collected handwriting data is first put through preprocessing procedures. Outliers and noise are eliminated by filtering the handwriting signals, which are recorded as a series of pen positions over time. The data is then standardized by applying normalization, which aligns variances caused by writing speed, size, and device settings. In order to guarantee that the feature extraction and classification procedures that follow operate on clear, comparable data, these preprocessing steps are essential.

3. Beta Stroke Segmentation:

The system uses a stroke segmentation method called beta stroke segmentation, which is based on variations in pen velocity. A more detailed examination of motor control is made possible by breaking down each handwriting sample into smaller, meaningful motion components (also known as "beta strokes"). This is especially helpful for capturing the slowness, hesitation, and tremors that are characteristic of Parkinsonian handwriting. Segmentation enhances the quality of features.

4. Feature Extraction via Beta-Elliptical and Fuzzy Perceptual Models
Two sophisticated feature extraction techniques are used to analyze handwriting segments: Each stroke's kinematic (velocity, acceleration) and geometric (shape, curvature) characteristics are extracted by the beta-elliptical model. This offers comprehensive information about the motor function that underlies handwriting.
Fuzzy Perceptual Detector: Models how humans see handwriting using fuzzy logic. It records subtle characteristics and irregularities that may be difficult to measure with conventional models, such as variations in stroke smoothness or hesitation.

5. Classification with Bidirectional LSTM
A Bidirectional Long Short-Term Memory (BLSTM) neural network receives the extracted features as input for classification. Because of its ability to accurately model temporal dependencies and context from both historical and upcoming input sequences, BLSTM was selected. This makes it particularly useful for identifying patterns and changes in neuromotor impairment over time in handwriting strokes. A prediction about whether the handwriting sample exhibits symptoms of Parkinson's disease is produced by the model.

6.1 Work Flow

Fig 6.1 User Authentication and ML Analysis Flow

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6.2 High Level Design

Fig 6.2 User Authentication, Data Processing, Report Generation Flow

CHAPTER 7
IMPLEMENTATION

7.1 Files Used

Python Files:

- **RandomModel.py**
- **TrainedModel.py**
- **App.py**

React files:

- **PatientDashboard.jsx**
- **AdminDashboard.jsx**
- **Layouts.jsx**
- **SetupProfile.jsx**
- **AuthPage.jsx**
- **Learning.jsx**
- **Medication.jsx**
- **Assignment.jsx**

Files:

- **ProctedRoute.jsx**
- **PrivateRoute.jsx**
- **Footer.jsx**

7.2 Code Snippets

App.py

```
  #Packages Required for training model
import os
import pandas as pd
import numpy as np
import joblib
import matplotlib.pyplot as plt
from flask import Flask, render_template, request, jsonify
import base64
import io


#load pkl
model_path = 'parkinsons_model.pkl'
if not os.path.exists(model_path):
raise FileNotFoundError(f"Model file not found at {model_path}. Please run
train_and_save_model.py first.")

model_pipeline = joblib.load(model_path)


#data preprocessing function
def calculate_features(file_path):


#Y coordinate, X coordinate, time stamp, button state, azimuth, altitude, pressure
data = pd.read_csv(file_path, header=None, skiprows=1, sep=' ')
data['time_diff'] = data[2].diff().fillna(0)
data['y_diff'] = data[0].diff().fillna(0)
data['x_diff'] = data[1].diff().fillna(0)
data['distance'] = np.sqrt(data['x_diff']*2 + data['y_diff']*2)
data['velocity'] = data['distance'] / data['time_diff']
data['velocity'].replace([np.inf, -np.inf], 0, inplace=True)
#time_diff, y_diff, x_diff, distance, velocity
```

```
#convertion
data['velocity_diff'] = data['velocity'].diff().fillna(0)
data['acceleration'] = data['velocity_diff'] / data['time_diff']
data['acceleration'].replace([np.inf, -np.inf], 0, inplace=True)
data['acceleration_diff'] = data['acceleration'].diff().fillna(0)
data['jerk'] = data['acceleration_diff'] / data['time_diff']
data['jerk'].replace([np.inf, -np.inf], 0, inplace=True)
total_duration = data[2].iloc[-1] - data[2].iloc[0]
num_pen_lifts = (data[3] == 0).sum()
on_surface_time = data[data[3] == 1]['time_diff'].sum()
in_air_time = data[data[3] == 0]['time_diff'].sum()

if on_surface_time > 0:
ratio_air_surface = in_air_time / on_surface_time
else:
ratio_air_surface = 0.0


pressure_mean = data[6].mean()
pressure_std = data[6].std()
pressure_max = data[6].max()

features = {
'velocity_mean': data['velocity'].mean(),
'velocity_std': data['velocity'].std(),
'velocity_max': data['velocity'].max(),
'acceleration_mean': data['acceleration'].mean(),
'acceleration_std': data['acceleration'].std(),
'jerk_mean': data['jerk'].mean(),
'total_duration': total_duration,
'num_pen_lifts': num_pen_lifts,
'ratio_air_surface': ratio_air_surface,
'pressure_mean': pressure_mean,
'pressure_std': pressure_std,
'pressure_max': pressure_max,
```

```
}
return features


def generate_plot_data(file_path):
try:
# Read the .svc file, skipping the first row and using whitespace as a separator.
df = pd.read_csv(file_path, sep=r'\s+', skiprows=1, header=None)

# Assign column names based on the user's provided schema
df.columns = ["Y_coordinate", "X_coordinate", "Timestamp", "Button_state",
"Azimuth", "Altitude", "Pressure"]

# Rename columns for plotting
df = df.rename(columns={"X_coordinate": "X", "Y_coordinate": "Y", "Button_state":
"ButtonStatus"})

# Normalize pressure for line thickness
min_p, max_p = df["Pressure"].min(), df["Pressure"].max()
df["Thickness"] = 1 + 5 * (df["Pressure"] - min_p) / (max_p - min_p + 1e-6)
# Create the plot
plt.figure(figsize=(7, 6))


# Draw strokes only when ButtonStatus == 1 (pen touching surface)
# Handle cases where the first point is on the surface
for i in range(1, len(df)):
if df.iloc[i]["ButtonStatus"] == 1 and df.iloc[i-1]["ButtonStatus"] == 1:
x1, y1 = df.iloc[i-1][["X", "Y"]]
x2, y2 = df.iloc[i][["X", "Y"]]
t = df.iloc[i]["Thickness"]

plt.plot([x1, x2], [y1, y2], color="black", linewidth=t)
plt.gca()
plt.axis("equal")
plt.axis("off")
```

```
# Save the plot to a buffer and encode it
buf = io.BytesIO()
plt.savefig(buf, format='png')
buf.seek(0)
image_data = base64.b64encode(buf.read()).decode('utf-8')
plt.close() # Close the figure to free up memory

return image_data
except Exception as e:
print(f"An error occurred during plotting: {e}")
return None

model_accuracy = 0.7417


app = Flask(_name_)
app.config['UPLOAD_FOLDER'] = 'uploads'
os.makedirs(app.config['UPLOAD_FOLDER'], exist_ok=True)


@app.route('/', methods=['GET', 'POST'])
def index():
prediction = None
prediction_accuracy = None
message_prefix = "The model predicts that the patient is likely"
plot_data = None

if request.method == 'POST':
# Get uploaded file and task type
if 'svc_file' not in request.files:
return "No file part", 400
svc_file = request.files['svc_file']
task_type = request.form['task_type'
if svc_file.filename == '':
return "No selected file", 400
```

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```
# Save the file to the uploads folder
file_path = os.path.join(app.config['UPLOAD_FOLDER'], svc_file.filename)
svc_file.save(file_path)
plot_data = generate_plot_data(file_path)


# Calculate features from the uploaded file
features = calculate_features(file_path)
features['task_type'] = task_type

# Create a DataFrame for prediction
input_df = pd.DataFrame([features])

# Make a prediction using the loaded model pipeline
predicted_proba = model_pipeline.predict_proba(input_df)[0]
predicted_label = model_pipeline.predict(input_df)[0]

# The probability of the predicted class is the accuracy for this specific prediction
prediction_accuracy = predicted_proba[predicted_label]

if predicted_label == 1:
prediction = "Positive for Parkinson's Disease"
message_prefix = "The model is"
else:
prediction = "Negative for Parkinson's Disease"
message_prefix = "The model predicts that the patient is likely"
os.remove(file_path)
return render_template('index.html', prediction=prediction, accuracy=model_accuracy,
prediction_accuracy=prediction_accuracy, message_prefix=message_prefix,plot_data=plot_data)
if _name_ == '_main_':
app.run(debug=True)
```

This page is extracted due to viral text or high resolution image or graph.

CHAPTER 8
SNAPSHOTS

Fig 8.1 Sign Up

Fig 8.2 Sign In

This page is extracted due to viral text or high resolution image or graph.

Fig 8.3 Home Page

Fig 8.4 Home Page

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Fig 8.5 User Data Form

Fig 8.6 Patient Dashboard

CHAPTER 9

APPLICATIONS

1. NeuroSense ClinicPad

A tablet or desktop application called NeuroSense ClinicPad was created especially to help neurologists and clinical staff conduct objective, real-time screening for Parkinson's disease (PD). Quick assessments during patient visits are made possible by the system's deployment in neurology centers and outpatient clinics.

2. NeuroSense Home

NeuroSense Home is a user-friendly mobile application for individuals to monitor their motor health from the comfort of their homes. This tool is especially valuable for patients at risk of PD or in its early stages, enabling them to track neuromotor performance over time. and potentially seek earlier consultation.

3. NeuroSense Research Suite

A desktop or web-based program designed for research labs and academic institutions is called NeuroSense Research Suite. In order to generate fresh perspectives in Parkinson's research, it facilitates extensive data collection, feature extraction, and comparative analysis.

4. NeuroSense Dashboard

A web dashboard for hospitals and long-term care facilities to remotely track motor performance of PD patients enrolled in home care programs. Its primary use is to remotely track motor performance of PD patients enrolled in home care programs.

5. NeuroSense Insight
An extended version of the NeuroSense engine that uses handwriting not just for PD detection. It uses handwriting analysis for more than just PD detection.

6. Personalized Disease Progression Tracking
An AI tracker that tracks handwriting evolution on a daily or weekly basis can be introduced by the system. This tracking is used to evaluate the effectiveness of therapy over time or identify motor decline. Physicians can assess the stage of the disease and the effectiveness of treatment with the use of graphical visualization, such as a smoothness score over time.

7. Multi-Modal Biomarker Fusion
By merging handwriting data with other modalities, future research attempts to advance NeuroSense. In particular, it will combine facial expression and speech analysis to provide a thorough diagnosis of Parkinson's disease. By using a wider range of neuro-motor and cognitive characteristics impacted by Parkinson's, this combination would improve diagnostic accuracy.

CHAPTER 10
CONCLUSION AND FUTURE ENHANCEMENT

10.1 CONCLUSION

AI-driven handwriting analysis provides a dependable, non-invasive, and economical approach for the early detection of Parkinson's disease (PD), as the NeuroSense project shows. The system successfully separates handwriting irregularities associated with Parkinson's disease (PD) symptoms like tremors, bradykinesia, and micrographia by incorporating machine learning techniques like the Beta-Elliptical model.

It is clear from the cited case study that handwriting parameters like pressure, speed, in-air movement, and entropy-based features have significant diagnostic value and can classify PD with almost greater accuracy. By combining these discoveries with NeuroSense's neural network methodology, diagnostic accuracy is further improved, and real-time handwriting assessment via digital tablets is made possible.

Overall, this project demonstrates that handwriting can serve as a biomarker for Parkinson's disease detection, providing medical professionals with an effective and scalable automated decision-support tool. It provides quicker, data-driven, and easily accessible Parkinson's screening by bridging the gap between medical science and artificial intelligence.

10.2 FUTURE ENHANCEMENT

1. Mobile & Web Integration

Create a cross-platform application that enables patients to remotely submit handwriting samples for analysis by artificial intelligence. Patients will be able to use the diagnostic tool from any location thanks to the improved accessibility.

2. Continuous Monitoring

For continuous motor pattern analysis, incorporate real-time tracking using smart pens or tablets with styluses. The system would be able to identify subtle, long-term changes in a patient's handwriting thanks to this ongoing monitoring.

3. Multi-Modal Biomarker Fusion

For a thorough diagnosis of Parkinson's disease, combine speech and facial expression analysis with handwriting data. Since other methods also use voice or breath detection to identify Parkinson's disease, this would integrate multiple biomarkers to create a robust system.

4. Dataset Expansion

Future research attempts to overcome the Czech-specific constraints of the existing PaHaW benchmark by creating an extensive dataset covering a variety of languages and demographics. The Convolutional Neural Network (CNN) needs this expansion because it keeps the model from overfitting to particular linguistic templates by exposing it to a variety of scripts. We make sure the CNN learns universal spatial features of motor impairment rather than just language-specific shapes by training it on a variety of writing styles. This ensures a more reliable, broadly applicable, and genuinely language-neutral diagnostic instrument.

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5. Cloud-Based Healthcare Dashboard

Give medical professionals the ability to see longitudinal handwriting changes, risk levels, and patient progress. 20 For patients who might not have easy access to clinical and facilities, this feature facilitates remote health monitoring, which is especially helpful for tracking the motor performance of PD patients in home care programs.

6. Adaptive Learning Model

Utilize incremental learning strategies to allow the model to get better on its own with every new handwriting sample. As the diagnostic 26 tool comes into contact with increasingly varied patient data over time, this adaptive approach guarantees that it stays current and accurate.

7. Personalized Disease Progression Tracking

Introduce an AI tracker that tracks the evolution of handwriting on a daily or weekly basis to identify therapy response or motor decline. Physicians can assess the stage of a disease and the effectiveness of treatment with the use of graphical visualizations, such as smoothness scores over time. Timely intervention and individualized monitoring are supported by this tracking.

CHAPTER 11

CONTRIBUTIONS TO SOCIETY AND ENVIRONMENT

1. Early Diagnosis and Prevention

By analyzing handwriting, the system makes it possible to detect Parkinson's disease early on, before significant symptoms manifest. This enables prompt medical intervention, improving patients' quality of life and slowing the progression of their diseases.

2. Accessibility in Remote Areas

Even in places without neurologists or sophisticated diagnostic tools, NeuroSense offers an inexpensive, AI-based screening technique. This encourages underprivileged and rural communities to have equal access to healthcare.

3. Non-Invasive Screening

The solution is a straightforward handwriting-based assessment that takes the place of expensive and intrusive clinical testing. Using a stylus or digital pen, patients can complete the test with ease, guaranteeing comfort and lowering the stress associated with diagnosis.

4. Healthcare Support Tool

By providing precise, data-driven insights into neuromotor function, the system helps physicians. It improves decision-making, lessens the subjectivity of diagnosis, and facilitates ongoing patient progress monitoring. This enables physicians to concentrate on analyzing the information for prompt action and improved patient care.

5. Awareness and Education

promotes self-awareness of early Parkinson's disease symptoms by encouraging people to use technology to monitor their neuromotor health. An earlier diagnosis can result from this emphasis on education and early screening, which can help detect the illness before significant symptoms manifest.

6. Empowering Patients

Provides ongoing feedback and progress monitoring to assist families in better managing care. Through entertaining chatbot reminders, the project also hopes to assist users in seeking early consultation and maintaining routine checkups.

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