Vision-Based Early Screening and Risk Classification of Parkinson's Disease Using Hand Tremor Analysis

A CAPSTONE PROJECT REPORT

Submitted in the partial fulfilment for the award of the degree of

DSA0216 – Computer Vision with OpenCV for Modern AI

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to the award of the degree of

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IN

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

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DECLARATION

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BONAFIDE CERTIFICATE

This is to certify that the Capstone Project entitled **Vision-Based Early Screening and Risk Classification of Parkinson's Disease Using Hand Tremor Analysis** has been carried out by **B.Pavan Kumar (192424295) K.Roopesh Reddy (192424340) A.Yuva Charan (192424301)** under the supervision of **Dr. Senthilvadivu S and Dr. Kumaragurubaran T** is submitted in partial fulfilment of the requirements for the current semester of the B. Tech **Artificial Intelligence and Data Science** program at Saveetha Institute of Medical and Technical Sciences, Chennai.

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ABSTRACT

Parkinson’s Disease (PD) is a progressive neurodegenerative disorder that primarily affects motor coordination and control due to the degeneration of dopamine-producing neurons in the brain. It is characterized by symptoms such as resting tremor, rigidity, bradykinesia (slowness of movement), and postural instability. Among these, hand tremor is often one of the earliest and most observable indicators. Early identification of Parkinson’s Disease plays a crucial role in initiating timely medical intervention, slowing symptom progression, improving quality of life, and enabling better long-term disease management. However, conventional diagnostic procedures typically depend on clinical evaluation by neurologists, subjective observation of symptoms, and sometimes expensive neuroimaging or laboratory tests. These methods may not always be accessible, especially in rural or resource-limited settings, and early-stage symptoms can sometimes be subtle or overlooked. Therefore, there is a growing need for an objective, affordable, and easily deployable screening system that can assist in the early risk assessment of Parkinson’s Disease.This capstone project addresses this challenge by proposing a Vision-Based Early Screening and Risk Classification system for Parkinson’s Disease using hand tremor analysis. The primary problem identified is the lack of accessible, non-invasive, and automated tools that can provide preliminary screening support before clinical diagnosis. The purpose of this project is to design and develop a computer vision–based framework capable of analyzing hand tremor patterns through video input and classifying individuals based on potential Parkinson’s risk.The proposed system utilizes a standard digital camera or webcam to capture hand movement data in real time or from recorded video sequences. The recorded video is processed using computer vision and image processing techniques. Initially, preprocessing steps such as frame extraction, grayscale conversion, noise reduction, and background subtraction are performed to enhance the quality of the captured data. Hand detection and motion tracking algorithms are then applied to identify and track key points or regions of interest associated with hand movement. By analyzing frame-by-frame displacement, the system quantifies tremor characteristics.From the tracked motion data, meaningful features are extracted to represent tremor behavior.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
ML	Machine Learning
PD	Parkinson’s Disease
SVM	Support Vector Machine
F1-Score	Harmonic Mean of Precision and Recall

CHAPTER 1
INTRODUCTION

1.1 Background Information

Parkinson's Disease (PD) is a progressive neurodegenerative disorder that primarily affects motor functions due to the degeneration of dopamine-producing neurons in the brain. It is characterized by symptoms such as resting tremor, rigidity, bradykinesia (slowness of movement), and postural instability. Among these, hand tremor is often one of the earliest and most noticeable symptoms. Early detection of Parkinson's Disease is essential for timely medical intervention, better symptom management, and improved quality of life for patients.

Traditional diagnosis of Parkinson's Disease is largely based on clinical evaluation, neurological examination, and subjective observation of motor symptoms. In many cases, early-stage symptoms may be mild and difficult to detect without expert analysis. Additionally, access to specialized medical professionals and diagnostic tools may be limited in rural or resource-constrained regions. With advancements in computer vision and machine learning, there is an opportunity to develop automated, non-invasive systems capable of analyzing subtle motion patterns from video data. A vision-based tremor analysis system can provide objective and quantitative assessment, supporting early screening and risk classification.

1.2 Project Objectives

The primary purpose of this capstone project is to develop a computer vision–based system for early screening and risk classification of Parkinson's Disease using hand tremor analysis. The key objectives are:

- To capture and analyze hand tremor movements using video input from a standard camera.
- To apply image processing and motion tracking techniques for detecting and monitoring hand movement.
- To extract relevant tremor-related features such as amplitude, frequency, displacement, and motion irregularities.
- To implement a machine learning classification model to categorize individuals into normal or potential Parkinson's risk groups.

- To evaluate the performance of the proposed system using appropriate validation metrics.

1.3 Significance

This project is significant because early identification of Parkinson's Disease can greatly improve treatment outcomes and slow disease progression. By integrating computer vision and machine learning, the proposed system provides an automated and objective method for tremor analysis. Unlike traditional approaches that rely solely on clinical observation, this system quantifies tremor characteristics using measurable data.

The project contributes to the field of computer vision by demonstrating its practical application in healthcare diagnostics. It also promotes the development of cost-effective and non-invasive screening tools that can be deployed in remote areas or used for preliminary home-based assessment. From a societal perspective, the system can support early awareness, encourage timely medical consultation, and reduce the burden of late-stage diagnosis.

1.4 Scope

The scope of this project includes:

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- Applying image preprocessing techniques such as grayscale conversion, noise filtering, and motion detection.
- Extracting tremor-related motion features from processed video frames.
- Designing and training a machine learning model for risk classification.
- Evaluating system performance using accuracy and other classification metrics.

1.5 Methodology Overview

The project follows a structured approach based on the Software Development Life Cycle (SDLC), including requirement analysis, system design, implementation, testing, and evaluation. Initially, relevant video data of hand tremors is collected under controlled conditions. The captured video frames undergo preprocessing to enhance clarity and reduce noise.

Computer vision techniques are then used to detect and track hand movement across frames. Motion analysis is performed to extract tremor-related features such as oscillation frequency and amplitude. These features are organized into a structured dataset and normalized for consistency. The trained model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Finally, the system performs real-time classification and displays the tremor parameters and prediction results, enabling early risk assessment.

CHAPTER 2
PROBLEM IDENTIFICATION AND ANALYSIS

2.1 Description of the Problem

Parkinson’s Disease (PD) is a progressive neurological disorder that affects movement control and gradually worsens over time. One of the earliest and most common motor symptoms is hand tremor, particularly resting tremor. Early identification of Parkinson’s Disease is critical for initiating treatment strategies that can help manage symptoms and improve patient quality of life. However, diagnosing Parkinson’s Disease in its early stages remains challenging.

The primary issue addressed in this project is the lack of accessible, objective, and cost-effective tools for early screening of Parkinson’s Disease. Current diagnostic methods largely depend on clinical observation, patient history, and neurological examination conducted by trained specialists. These assessments can be subjective and may vary based on the experience of the clinician. In many rural or under-resourced areas, access to neurologists and advanced diagnostic facilities is limited. As a result, early-stage symptoms may go undetected or misinterpreted, delaying medical intervention. Furthermore, subtle tremor variations in the initial stages may not be easily distinguishable through visual inspection alone. There is a need for an automated system that can analyze hand tremor patterns quantitatively using measurable features. A vision-based approach using computer vision and machine learning can address this gap by providing objective tremor analysis and preliminary risk classification.

2.2 Evidence of the Problem

Parkinson’s Disease affects millions of people worldwide and is one of the most common neurodegenerative disorders. Studies indicate that early diagnosis is difficult because symptoms develop gradually and may initially resemble normal aging or other movement disorders. Research shows that tremor-based analysis plays an important role in identifying early motor abnormalities.

Several clinical studies highlight that manual assessment of tremor severity can be inconsistent and dependent on clinician judgment. In addition, advanced diagnostic techniques such as neuroimaging are costly and not suitable for routine early screening. According to global health reports, the number of Parkinson's patients is increasing due to aging populations, emphasizing the need for scalable screening methods.

Recent advancements in computer vision and artificial intelligence have demonstrated success in medical image analysis, motion tracking, and disease prediction. These technological developments suggest that automated tremor analysis using video data is a feasible and promising approach for early screening.

2.3 Stakeholders

The key stakeholders affected by this problem include:

- **Patients:** Individuals experiencing early symptoms of Parkinson's Disease who require timely screening and intervention.
- **Healthcare Professionals:** Neurologists, physicians, and healthcare providers who need reliable and objective tools to support clinical decision-making.
- **Hospitals and Clinics:** Medical institutions seeking cost-effective and scalable screening technologies.
- **Caregivers and Families:** Individuals responsible for supporting patients who benefit from early awareness and intervention.
- **Researchers and Developers:** Professionals working in healthcare technology and computer vision who aim to develop innovative diagnostic tools.

The proposed system aims to support these stakeholders by providing an accessible preliminary screening solution.

2.4 Supporting Data/Research

Existing research in medical imaging and motion analysis confirms that tremor characteristics such as frequency and amplitude are key indicators in Parkinson's assessment. Machine learning models have been successfully applied in healthcare for classification tasks, including neurological disorder prediction. Studies in computer vision show that motion tracking algorithms can accurately capture subtle movement variations from video data.

Research in digital health monitoring also emphasizes the importance of non-invasive and sensor-free approaches for remote patient assessment. Vision-based systems reduce dependency on wearable sensors and allow analysis using commonly available devices such as webcams or smartphones.

These findings support the feasibility of integrating computer vision techniques with supervised machine learning algorithms for tremor analysis and risk classification. By building on existing research and technological advancements, this project aims to develop a practical and effective early screening system for Parkinson's Disease.

CHAPTER 3
SOLUTION DESIGN AND IMPLEMENTATION

3.1 Development and Design Process

The development of the project Vision-Based Early Screening and Risk Classification of Parkinson's Disease Using Hand Tremor Analysis followed a structured approach based on the Software Development Life Cycle (SDLC). The process included requirement analysis, system design, implementation, testing, and evaluation.

Initially, system requirements were identified, focusing on capturing hand tremor movements through a standard camera and analyzing them using computer vision techniques. In the design phase, the system architecture was structured into modular components, including video acquisition, preprocessing, hand detection and tracking, feature extraction, classification, and result visualization.

During implementation, video frames were processed using image preprocessing techniques such as grayscale conversion, noise reduction, and background subtraction to improve clarity. Motion tracking algorithms were applied to detect and track hand movement across frames. Extracted motion data was converted into measurable tremor-related features such as amplitude, frequency, displacement, and velocity variation.

These features were then used to train a supervised machine learning classifier. The model was validated using test data to ensure reliable performance. Finally, system evaluation was conducted using classification metrics to assess effectiveness and accuracy.

3.2 Tools and Technologies Used

The project utilized the following tools and technologies:

- Programming Language: Python
- Computer Vision Library: OpenCV for image processing and motion tracking
- Numerical and Data Processing Libraries: NumPy and Pandas
- Machine Learning Framework: Scikit-learn for classification model implementation
- Development Environment: Google Colab / VS Code
- Visualization Tools: Matplotlib for plotting tremor patterns and results

These tools were selected due to their reliability, open-source availability, strong community support, and suitability for rapid prototyping in computer vision applications.

3.3 Solution Overview

The proposed system is a vision-based automated screening tool designed to analyze hand tremor patterns from video input. The overall workflow of the system includes the following stages:

1. Video Acquisition: Capture of hand tremor movement using a webcam or recorded video.
2. Preprocessing: Conversion of frames to grayscale, noise filtering, and enhancement to improve motion clarity.
3. Hand Detection and Tracking: Identification of the hand region and tracking of movement across frames using motion detection algorithms.
4. Feature Extraction: Calculation of tremor characteristics such as oscillation frequency, displacement amplitude, movement consistency, and velocity variation.
5. Feature Normalization: Scaling of extracted features to ensure uniformity for classification.
6. Classification: Use of a supervised machine learning algorithm to classify tremor patterns into normal or potential Parkinson’s risk categories.
7. Result Display: Presentation of classification results along with performance evaluation metrics.

The system provides an automated and objective analysis of tremor behavior, reducing dependence on manual visual assessment.

3.4 Engineering Standards Applied

The project incorporates relevant engineering principles and standards to ensure reliability, safety, and quality:

- ISO 13485 (Medical Device Quality Management Principles): Although the system is a prototype, quality management practices such as structured documentation and systematic validation were followed.
- IEEE 830 (Software Requirements Specification Guidelines): Clear requirement documentation and modular system design were maintained.

- ISO/IEC 25010 (Software Quality Model): Focus was given to software quality attributes such as functionality, reliability, usability, maintainability, and performance efficiency.
- Data Privacy Principles (General Data Protection Practices): The system avoids storing personally identifiable information and processes only tremor-related motion data.

These standards guided system design, documentation, validation, and ethical considerations.

3.5 Solution Justification

The inclusion of engineering standards enhances the credibility, reliability, and scalability of the project. Applying structured software development practices ensures clarity in system design and reduces implementation errors. Quality standards improve system maintainability and performance efficiency, while data privacy considerations ensure ethical handling of user data.

By following recognized engineering and software standards, the project achieves a systematic development process, improved documentation, and higher trustworthiness. This structured approach increases the potential for future expansion, real-world deployment, and integration into healthcare support systems.

3.6 Architecture

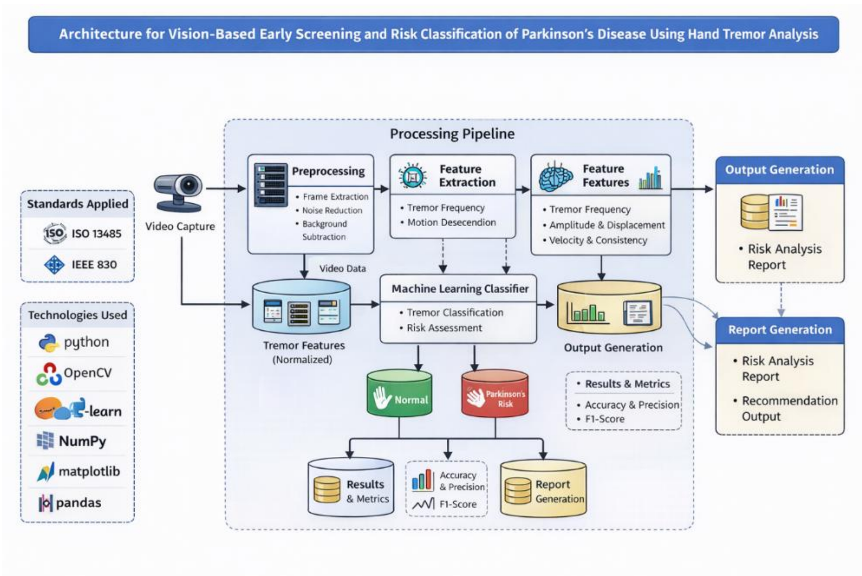

Fig. 3.6.1. System Architecture for Parkinson's Tremor Classification

Figure 3.6.1 illustrates the overall system architecture of the proposed vision-based early screening and risk classification framework for Parkinson's Disease using hand tremor analysis. The architecture is designed in a modular format, beginning with video capture through a standard camera. The captured frames undergo preprocessing steps such as frame extraction, noise reduction, and background subtraction to enhance detection accuracy.

The processed video data is then passed to the feature extraction module, where tremor-related parameters such as frequency, amplitude, displacement, and velocity consistency are computed from hand landmark movements. These normalized features are fed into the machine learning classifier, specifically the Support Vector Machine (SVM), which performs tremor classification and risk assessment. The system then generates output results, including prediction labels, performance metrics (accuracy, precision, and F1-score), and a structured risk analysis report. This architecture ensures a systematic flow from data acquisition to final decision-making, providing an objective and automated approach for early Parkinson's tremor screening.

Chapter 4

Results and Recommendations

4.1 Evaluation of Results

The proposed vision-based system was evaluated to determine its effectiveness in analyzing hand tremor patterns and classifying Parkinson's risk. The performance of the machine learning classifier was measured using standard evaluation metrics such as accuracy, precision, recall, and F1-score. The results indicate that the system is capable of distinguishing between normal hand movements and tremor patterns associated with Parkinson's risk with satisfactory classification performance.

Feature extraction techniques successfully quantified tremor characteristics such as amplitude, frequency, and movement consistency. The classifier demonstrated stable predictions when tested with unseen data, indicating good generalization capability. The automated analysis reduced dependency on subjective visual assessment and provided objective, measurable outputs. Overall, the system effectively addressed the primary problem of developing an accessible and non-invasive early screening tool for tremor-based Parkinson's risk classification.

Table 4.1 Personal Development and Professional Growth Summary

Development Area	Key Experiences	Impact on Growth
Handling Data Limitations	Worked with limited and imbalanced datasets; explored alternative data preparation strategies.	Improved adaptability and resource management skills.
Model Optimization	Faced performance inconsistencies; refined feature sets and adjusted classifier parameters.	Enhanced technical depth in machine learning tuning and validation.
Performance vs Efficiency Balance	Managed trade-off between computational cost and prediction accuracy.	Strengthened decision-making and optimization skills.

Development Area	Key Experiences	Impact on Growth
Feedback Integration	Incorporated suggestions from supervisor discussions into system refinement.	Developed openness to feedback and iterative improvement mindset.
Technical Communication	Presented results, explained algorithms, and justified implementation choices.	Improved clarity in technical explanation and presentation skills.

Table 4.1 presents a summary of the key areas of personal and professional development achieved during the course of the capstone project. The table highlights important development areas such as handling data limitations, model optimization, balancing performance with computational efficiency, integrating feedback, and improving technical communication skills.

Throughout the project, working with limited and imbalanced datasets enhanced adaptability and strengthened resource management abilities. Continuous refinement of feature sets and classifier parameters improved technical proficiency in machine learning model tuning and validation. Managing the trade-off between prediction accuracy and computational efficiency strengthened analytical decision-making skills. Additionally, incorporating feedback from supervisory discussions fostered an iterative improvement mindset and openness to constructive suggestions. Presenting results and explaining implementation strategies enhanced clarity in technical communication and professional presentation skills. Overall, the experiences summarized in this table reflect significant academic, technical, and personal growth developed through the project.

4.2 Challenges Encountered

Several challenges were encountered during the development and implementation of the system:

- Variability in Video Quality: Differences in lighting conditions, background noise, and camera resolution affected motion detection accuracy. This was mitigated by applying preprocessing techniques such as noise filtering and background subtraction.

- Hand Detection Accuracy: Accurate tracking of the hand region was challenging when there were complex backgrounds or sudden movements. This issue was addressed by refining detection algorithms and limiting the capture environment to controlled conditions.
- Limited Dataset Availability: Access to labeled tremor datasets was limited, which could impact model training. To overcome this, publicly available datasets and simulated tremor samples were utilized for initial experimentation.
- Feature Selection Complexity: Identifying the most relevant tremor features required experimentation and validation to improve classification performance.

Despite these challenges, systematic testing and iterative improvements helped achieve reliable system performance.

4.3 Possible Improvements

Although the system achieved satisfactory results, certain limitations remain:

- The model currently focuses only on hand tremor and does not consider other motor or non-motor symptoms of Parkinson's Disease.
- Performance may vary under uncontrolled environmental conditions.
- The dataset size can be expanded to improve classification robustness.
- Advanced deep learning techniques such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) could be explored for improved motion pattern recognition.
- Real-time deployment optimization can further enhance system efficiency.

Future versions of the system can incorporate multi-symptom analysis and larger datasets to improve reliability and clinical applicability.

4.4 Recommendations

Based on the results and observations, the following recommendations are proposed:

- Conduct further research using larger and clinically validated datasets to improve model accuracy and reliability.
- Integrate the system into a mobile or web-based application for remote screening and telemedicine support.
- Collaborate with healthcare professionals to validate the system in real clinical environments.
- Explore deep learning–based motion analysis models for enhanced feature learning.

- Implement robust privacy and security measures to ensure safe handling of patient data.

The project demonstrates the feasibility of vision-based tremor analysis for early Parkinson's risk screening and provides a foundation for further research and real-world healthcare applications.

Chapter 5
Reflection on Learning and Personal Development

5.1 Key Learning Outcomes

Academic Knowledge

This capstone project significantly strengthened my understanding of computer vision, machine learning, and their applications in healthcare. Through the development of the Vision-Based Early Screening and Risk Classification of Parkinson's Disease Using Hand Tremor Analysis system, I gained deeper knowledge of image processing concepts such as frame extraction, grayscale conversion, noise reduction, and motion detection. I also applied theoretical concepts from pattern recognition and supervised learning, including feature extraction, feature normalization, and classification techniques. The project enhanced my understanding of how mathematical concepts such as signal frequency, amplitude variation, and statistical measures can be used to represent real-world motion patterns..

Technical Skills

During the project, I developed strong technical skills in Python programming and practical implementation of computer vision algorithms using OpenCV. I gained experience in handling video data, preprocessing image frames, detecting motion patterns, and extracting meaningful features from visual input. Additionally, I worked with machine learning libraries such as Scikit-learn to train and evaluate classification models.

I also improved my ability to use data analysis tools such as NumPy and Pandas for organizing and processing datasets, and Matplotlib for visualizing tremor patterns and performance metrics. The project enhanced my understanding of model evaluation techniques including accuracy, precision, recall, and F1-score. Overall, this experience strengthened my practical coding ability and confidence in implementing AI-based systems.

Problem-Solving and Critical Thinking

This project required continuous problem-solving and analytical thinking. One of the key challenges was accurately tracking hand tremor movements under varying environmental conditions. I had to experiment with different preprocessing techniques and parameter tuning to improve motion detection accuracy. Selecting relevant features for classification also required careful analysis and testing. Through trial and error, debugging, and systematic experimentation, I learned how to approach complex technical problems logically. The project improved my ability to break down a large system into smaller modules and address each component step by step. It strengthened my critical thinking skills and helped me understand the importance of testing, validation, and classification, which made the development process more manageable and efficient. This experience significantly enhanced my critical thinking ability and emphasized the importance of validation, performance metrics, and continuous improvement in developing reliable AI-based systems..

Table 5.1 Problem-Solving and Critical Thinking – Summary Table

Aspect	Description	Skills Developed
Motion Tracking Optimization	Faced difficulty in detecting tremor movements under different lighting and background conditions. Applied filtering and frame enhancement techniques.	Image preprocessing, parameter tuning
Feature Engineering	Identified and tested multiple motion features to determine the most relevant indicators for tremor classification.	Analytical thinking, feature selection
Model Performance Improvement	Adjusted classifier parameters and validated results using performance metrics to enhance accuracy.	Model evaluation, performance analysis
Debugging and Testing	Systematically tested each module to identify errors and improve overall stability.	Debugging, systematic testing
Modular System Design	Divided the complete system into acquisition, preprocessing, feature extraction, and classification modules for easier implementation.	System design, structured development

Table 4.2 summarizes the major technical aspects addressed during the development of the project and the corresponding skills gained. The table outlines how challenges in motion tracking, feature engineering, model performance improvement, debugging, and modular system design contributed to strengthening analytical and technical abilities.

Difficulties in detecting tremor movements under varying lighting and background conditions required optimization of preprocessing methods and parameter adjustments, which enhanced skills in image preprocessing and fine-tuning. Experimentation with different motion features improved analytical thinking and feature selection capabilities. Refining classifier parameters and evaluating results using performance metrics strengthened understanding of model evaluation and validation. Systematic debugging improved stability and reliability of the overall system. Furthermore, designing the system in modular components improved structured development practices and overall system organization. Collectively, these efforts contributed significantly to improving problem-solving ability and critical thinking skills throughout the project.

5.2 Challenges Encountered and Overcome

Personal and Professional Growth

During the development process, I faced challenges such as limited dataset availability, difficulty in achieving consistent tremor detection, and balancing model performance with computational efficiency. At times, model accuracy was not as expected, which required revisiting feature selection and tuning classifier parameters.

These challenges taught me patience, persistence, and adaptability. I learned that research and development involve iterative improvement rather than immediate success. Overcoming these obstacles increased my confidence in handling technical difficulties and strengthened my resilience as a learner and developer.

Collaboration and Communication

Throughout the project, interaction with my supervisor and peers helped refine the system design and implementation strategy. Discussing ideas, receiving feedback, and explaining technical concepts improved my communication skills. I learned how to present technical results clearly and justify design decisions logically.

If working in a team setting, coordination and division of tasks would be essential. The project emphasized the importance of structured documentation, regular progress updates, and constructive feedback in achieving project goals efficiently.

5.3 Application of Engineering Standards

The application of engineering standards and structured development practices played an important role in ensuring the quality of the project. By following a systematic Software Development Life Cycle (SDLC) approach, I maintained clear documentation, modular design, and organized testing procedures.

Adhering to software quality principles such as reliability, maintainability, and performance efficiency helped improve the robustness of the system. Additionally, considering ethical and privacy aspects in handling video data increased awareness of responsible AI development. These practices enhanced the overall credibility and professionalism of the project.

5.4 Insights into the Industry

This project provided valuable insights into how artificial intelligence and computer vision technologies are applied in the healthcare industry. It demonstrated the growing importance of AI-driven diagnostic tools and remote health monitoring systems. I gained a better understanding of how interdisciplinary knowledge—combining healthcare concepts with computer science—can create impactful solutions.

The project also highlighted the importance of data quality, model validation, and collaboration with domain experts in real-world applications. This experience has motivated me to explore further opportunities in AI, medical imaging, and intelligent healthcare systems.

5.5 Conclusion of Personal Development

Overall, this capstone project has contributed significantly to my academic, technical, and personal growth. It strengthened my foundation in computer vision and machine learning while enhancing my practical implementation skills. The experience improved my confidence in handling real-world problems, conducting systematic research, and developing structured solutions.

This project has helped shape my career goals by encouraging me to pursue advanced work in artificial intelligence and healthcare technologies. It has prepared me for future professional opportunities by equipping me with technical expertise, analytical thinking ability, and a problem-solving mindset necessary for success in the evolving technology industry.

Chapter 6
Conclusion

The project Vision-Based Early Screening and Risk Classification of Parkinson’s Disease Using Hand Tremor Analysis was developed to address the challenge of limited accessibility and subjectivity in early Parkinson’s Disease detection. Parkinson’s Disease is a progressive neurological disorder in which early symptoms, particularly hand tremors, may be subtle and difficult to detect through traditional observation-based diagnosis. The primary problem identified was the lack of a cost-effective, non-invasive, and automated screening tool capable of objectively analyzing tremor patterns for early risk assessment.

To address this issue, a computer vision–based system was designed and implemented to capture and analyze hand tremor movements using video input. The system applied image preprocessing techniques, motion tracking, and feature extraction to quantify tremor characteristics such as frequency, amplitude, displacement, and movement consistency. These extracted features were then used to train and evaluate a supervised machine learning classifier for categorizing individuals into normal or potential Parkinson’s risk groups. Performance evaluation metrics demonstrated that the proposed solution effectively supports preliminary risk classification with satisfactory accuracy and reliability.

The key finding of this project is that vision-based tremor analysis, combined with machine learning, provides an objective and scalable approach for early screening of Parkinson’s Disease. The system reduces reliance on subjective clinical observation and offers measurable outputs that can support medical professionals in decision-making. Although the solution is intended as a preliminary screening tool rather than a diagnostic replacement, it demonstrates strong potential for integration into telemedicine platforms and remote health monitoring systems.

Overall, this project highlights the significant value of applying computer vision and artificial intelligence in healthcare. It contributes to the development of accessible, affordable, and technology-driven screening solutions that can improve early detection and awareness of Parkinson’s Disease..AI-assisted medical diagnostics, reinforcing the importance of interdisciplinary innovation in addressing real-world health challenges.

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Appendices

Appendix I

```
# =================== LIBRARIES ===================
import cv2
import mediapipe as mp
import numpy as np
import pandas as pd
import joblib
import os
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# ================================
# STEP 1: TRAIN SVM MODEL (if not exists)
# ================================

if os.path.exists("tremor_data.csv"):

    data = pd.read_csv("tremor_data.csv")

    if len(data) > 5:

        X = data[["Amplitude", "Frequency"]]
        y = data["Label"]

        scaler = StandardScaler()
        X_scaled = scaler.fit_transform(X)

        model = SVC(kernel="linear")
        model.fit(X_scaled, y)

        joblib.dump(model, "svm_model.pkl")
```

```
        joblib.dump(scaler, "scaler.pkl")

        print("Model trained successfully.")

# Load trained model
if os.path.exists("svm_model.pkl"):
    model = joblib.load("svm_model.pkl")
    scaler = joblib.load("scaler.pkl")
else:
    model = None
    scaler = None

# ================================
# STEP 2: MediaPipe Initialization
# ================================

mp_hands = mp.solutions.hands
mp_drawing = mp.solutions.drawing_utils
hands = mp_hands.Hands()

cap = cv2.VideoCapture(0)

prev_x, prev_y = 0, 0
distances = []
fps = 30

print("System Started... Press ESC to exit.")

# ================================
# STEP 3: Real-Time Detection + Classification
# ================================

while cap.isOpened():
```

```
ret, frame = cap.read()
if not ret:
    break

h, w, _ = frame.shape
rgb = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
results = hands.process(rgb)

if results.multi_hand_landmarks:
    for hand_landmarks in results.multi_hand_landmarks:
        tip = hand_landmarks.landmark[8]
        x = int(tip.x * w)
        y = int(tip.y * h)

        if prev_x != 0:
            distance = np.sqrt((x - prev_x)**2 + (y - prev_y)**2)
            distances.append(distance)

        prev_x, prev_y = x, y

        mp_drawing.draw_landmarks(
            frame, hand_landmarks, mp_hands.HAND_CONNECTIONS
        )

# Analyze after 3 seconds
if len(distances) >= 90:

    signal = np.array(distances)
    signal = signal - np.mean(signal)

    # Remove noise spikes
    threshold = np.mean(signal) + 2*np.std(signal)
    signal = np.where(abs(signal) > threshold, 0, signal)
```

```
# FFT
fft = np.fft.fft(signal)
freqs = np.fft.fftfreq(len(signal), 1/fps)

positive_freqs = freqs[:len(freqs)//2]
positive_fft = np.abs(fft[:len(fft)//2])

tremor_band = (positive_freqs >= 2) & (positive_freqs <= 8)

if np.any(tremor_band):
    dominant_freq = positive_freqs[tremor_band][
        np.argmax(positive_fft[tremor_band])
    ]
else:
    dominant_freq = 0

amplitude = np.max(np.abs(signal))

prediction_text = "Model Not Trained"

# Classification
if model is not None:
    features = np.array([[amplitude, dominant_freq]])
    scaled = scaler.transform(features)
    prediction = model.predict(scaled)

    if prediction[0] == 1:
        prediction_text = "Parkinson's Risk"
    else:
        prediction_text = "Normal"

# Display results
cv2.putText(frame, f"Amplitude: {round(amplitude,2)}",
            (10,30), cv2.FONT_HERSHEY_SIMPLEX,
```

```
            0.7, (0,255,0), 2)

        cv2.putText(frame, f"Frequency: {round(dominant_freq,2)} Hz",
            (10,60), cv2.FONT_HERSHEY_SIMPLEX,
            0.7, (0,255,0), 2)

        cv2.putText(frame, f"Prediction: {prediction_text}",
            (10,90), cv2.FONT_HERSHEY_SIMPLEX,
            0.8, (0,0,255), 2)

        distances.clear()

    cv2.imshow("Parkinson's Early Screening System", frame)

    if cv2.waitKey(1) & 0xFF == 27:
        break

cap.release()
cv2.destroyAllWindows()
```

Appendix II

Sample Output

Figure A.1. illustrates the implementation of the hand landmark detection and pixel extraction module in the proposed vision-based Parkinson’s screening system. The first image shows the detected hand landmarks marked with red key points, representing finger joints and palm reference positions identified using computer vision techniques. These landmarks are used to track hand movement accurately across video frames.

The second image displays the corresponding console output containing the extracted pixel coordinates of the detected landmarks. Each coordinate pair represents the (x, y) position of a key point within the image frame. These numerical values form the basis for calculating tremor-related features such as displacement, frequency, and amplitude. Together, the images demonstrate the successful conversion of visual hand motion into measurable numerical data for further feature extraction and classification.

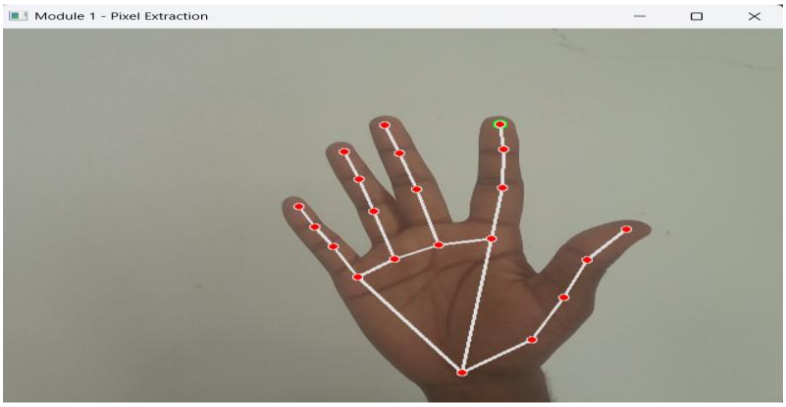
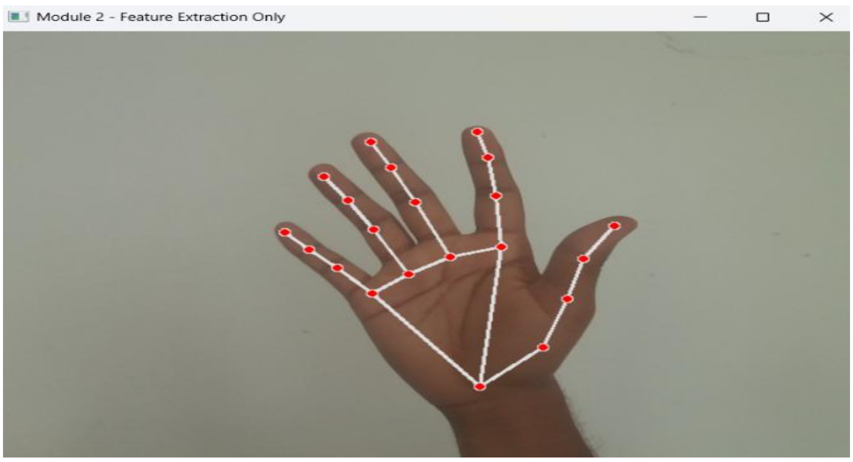


Fig A.1 Hand Landmark Detection and Pixel Coordinate Extraction

Figure A.2. illustrates the feature extraction module of the proposed vision-based Parkinson's screening system. The first image displays detected hand landmarks used for calculating motion-based tremor features. The red key points represent finger joints and palm reference coordinates that are tracked across frames to measure movement variations.

The second image shows the corresponding terminal output where computed tremor parameters such as amplitude and frequency are displayed. These numerical values are derived from frame-by-frame displacement analysis of the tracked landmarks. The extracted features are stored and labeled for further classification into normal or tremor categories. Together, these images demonstrate the successful transformation of raw hand motion into quantifiable tremor features for machine learning–based risk assessment.



FigA.2. Feature Extraction and Tremor Parameter Computation

Figure A.3. illustrates the classification results generated by the Support Vector Machine (SVM) model in the proposed system. The first image displays the terminal output showing the trained model's performance metrics, including model accuracy, mean amplitude, and mean frequency values. It also presents the final prediction result indicating the classified category (Normal or Parkinson's Risk) based on the extracted tremor features.

The second image represents the graphical visualization of the SVM classification. The scatter plot displays tremor samples plotted using amplitude (px) and frequency (Hz) as feature axes. Green points indicate normal samples, red points represent Parkinson's risk samples, and the blue marker denotes the mean sample used for prediction. This visual representation demonstrates the decision boundary separation and confirms the effectiveness of the SVM model in distinguishing between normal and tremor patterns.

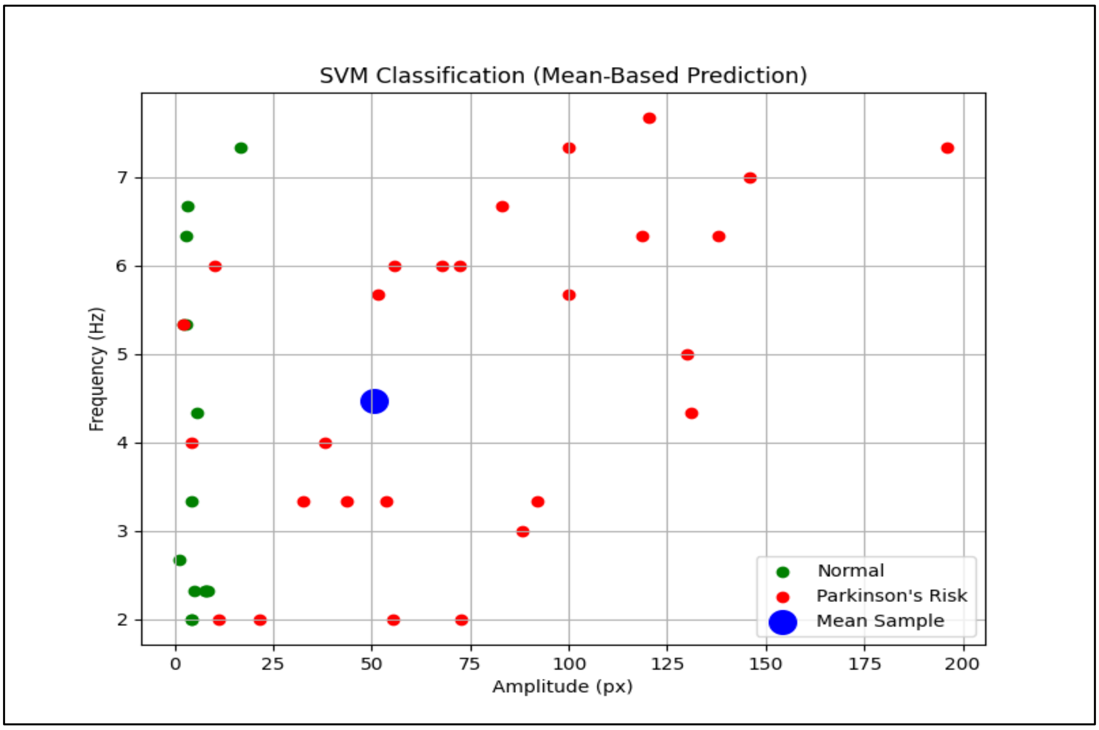


Fig A.3. SVM-Based Classification and Prediction Output