COMPUTER VISION-DRIVEN CLASSIFICATION OF PARKINSON'S DISEASE SEVERITY VIA MOBILE POSE ESTIMATION AND AI MODELS

Lee Teng Hong[1], Ezreen Farina Shair[2]*, Muhammad Hazwan Adlin Jumaris[3], Nur Zawani Saharuddin[4], Raja Rina Raja Ikram[5], Siti Anom Ahmad[6]

ABSTRACT

Parkinson's disease (PD) is becoming increasingly prevalent because of global population aging, while the high cost of treatment and limited access to specialist care underscore the need for accessible diagnostic solutions. This study presents a smartphone-based application for PD detection and severity classification using computer vision and artificial intelligence. A custom video dataset comprising healthy individuals and patients with mild and severe PD was collected. Human pose keypoints were extracted using MediaPipe Pose, with Y-axis coordinates selected to capture vertical motion patterns. Deep learning models, including 1D Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) were evaluated alongside traditional machine learning methods using TSFEL-extracted features. GRU, GRU-LSTM, and Random Forest achieved the best performance, with classification accuracies exceeding 80%. A Flutter-based mobile application was developed for real-time video capture and pose estimation using Google ML Kit. Keypoint data are transmitted to a cloud-hosted Flask API for inference using the best-performing model. The proposed system demonstrates the potential of smartphone-based, non-invasive, and cost-effective tools for accessible PD screening and severity assessment.

Keywords: Parkinson's disease, artificial intelligence, machine learning, deep learning, computer vision, mobile health application, pose estimation

1. INTRODUCTION

The prevalence of PD is growing globally and there are insufficient resources to cater to the increasing number of patients. According to the Global Burden of Disease Study 2021 (GBD 2021), an estimated 11.77 million individuals worldwide were living with PD, representing a dramatic 274% increase from 3.15 million cases in 1990. Projections suggest that the global number of PD cases will reach 25.2

[1]Student, Department of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malaysia, Email: leetenghong06@gmail.com
[2]Senior Lecturer, Department of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malaysia, Ph. +6019-3946175, Email: ezreen@utem.edu.my
[3]Student, Department of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malaysia, Email: hazwanadlin@gmail.com
[4]Senior Lecturer, Department of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malaysia,, Email: nurzawani@utem.edu.my
[5]Senior Lecturer, Department of Software Engineering, Universiti Teknikal Malaysia Melaka, Malaysia, Email: raja.rina@utem.edu.my
[6] Professor, Department of Engineering, Universiti Putra Malaysia, Malaysia, Email: sanom@upm.edu.my.

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million by 2050 [1]. The healthcare cost of the PD is high over the long term because there is no disease–modifying treatment for PD. Due to ageing population, the economic burden of PD will increase [2]. It is reported that the cost of PD reached $52 billion per year. It is very important for the PD to be detected at an early stage which allows early intervention which in turn can cause reduction in symptoms and slow down disease progression. It is also reported that early treatment can reduce the treatment costs over the long term [3].

The current diagnosis system of PD has the limitation of being prone to error due to subjectiveness of the physiotherapists and the technology being used in the diagnosis system is often invasive. Researchers explored non–invasive diagnostic techniques for PD to overcome the limitations of current diagnosis method which are invasive and require empirical testing as well as incurring exorbitant costs. The non-invasive techniques mainly involve artificial intelligence, deep learning, machine learning and neuroimaging. There are many digital biomarkers that potentially can be used in the diagnosis of PD which include voice, electroencephalogram (EEG) signal and gait [4], [5]. Gait dysfunction is one of the motor symptoms of the PD, so gait analysis provides important subclinical information for the classification of PD and its severity level [6]. It is reported that patients with PD display decreased gait speed, increased cadence, decreased stride length and decreased swing time when they walk [7]. The gait acquisition techniques that are used by the researchers can be categorized broadly into two major groups which are vision–based and sensor–based. The vision–based gait acquisition technique has become a popular approach by researchers because it is non-invasive and low cost [8]. Current state–of–the–art for gait analysis includes the use of marker–based motion capture systems and instrumented gait maps which are hardly accessible due to cost and the tremendous amount and time needed for setup.

The rapid advancement of human pose estimation algorithms and computer vision techniques has enabled markerless gait and motor assessment using ordinary RGB cameras, smartphones, and tablets, eliminating the need for expensive marker-based motion capture systems. Recent studies have demonstrated that pose estimation frameworks integrated with artificial intelligence provide objective, non-invasive, and cost-effective approaches for evaluating PD in both clinical and home environments [9], [10]. Kondo et al. developed a continuous video-based postural tracking system by combining MediaPipe Pose and DeepLab semantic segmentation using videos captured with an iPad. The proposed system achieved excellent agreement with manual clinical measurements, reporting intraclass correlation coefficients of 0.98 for lumbar trunk flexion and 0.96 for thoracic trunk flexion, demonstrating the feasibility of reliable markerless posture assessment in patients with PD [9]. Similarly, Zhang et al. proposed an explainable video-based assessment framework that automatically quantifies motor impairments from standard clinical videos, reducing the subjectivity associated with neurologist-based evaluations while improving the consistency and interpretability of PD assessment [10]. Furthermore, Zuo et al. introduced a unified skeleton-based framework incorporating robust 3D human pose estimation and an Adaptive Graph Topology Modeling Network (AGTM-Net) for PD classification. Their method achieved an accuracy of 88.1% and an F1-score of 89.8%, while identifying clinically relevant body joints such as the spine, hips, and chest that contribute most significantly to disease classification [11]. These recent developments demonstrate that markerless vision-based systems are increasingly capable of providing accurate, objective, and interpretable assessment of PD using low-cost consumer devices, making them promising tools for large-scale screening, telemedicine, and continuous disease monitoring.

The mobile devices have become sophisticated and are able to capture the image sequence of the user for gait analysis [12]. However, there is a lack of integration of diagnosis of PD in the mobile devices. Advanced customized mobile application for classification of PD is helpful for the caretakers to check on the gait of the elderly without direct intervention from the medical practitioners. Frequent medical check–up using mobile application at home makes early treatment of PD possible.

This research paper explores the development of the mobile application that can record the keypoints of the recorded person to be classified into healthy people and patients with PD of the severity level that includes mild severity and the high severity with the use of Google’s ML Kit Pose Detection package. This research also compares the use of machine learning and deep learning in the classification process in parallel. The walking videos of the healthy people and the patients with PD are collected from Mendeley Data [13]. MediaPipe Pose is used to extract the keypoints from the collected videos. Then, the features are derived from the Y-axis coordinates of the keypoints using Time Series Feature Extraction Library (TSFEL) and are fed into random forest, SVM and KNN for comparison. In parallel, the Y-axis coordinates are then fed directly into various combinations of 1D–CNN, LSTM and GRU for comparison. The reason the Y-axis coordinates are chosen is because the videos collected include the subject walking in two different directions horizontally from right to left and left to right which cause differences in X-axis. These two videos can be considered as two different sets of data if only Y-axis coordinates are used. Also, the direction of the recorded person walking is perpendicular to the view of the camera which causes the value of Z-axis coordinates close to 0. MediaPipe Pose and Google's ML Kit Pose Detection can be used interchangeably because they extract the same keypoints.

2. RESEARCH METHODOLOGY

The pipeline for Y – axis coordinate extraction from MediaPipe keypoints to AI model input and the research methodology of this research are as shown in **Figure 1** and **Figure 2** respectively. The research methodology starts with the extraction of the walking videos of the healthy walking people, patients with PD of mild severity and high severity from Mendeley Data.

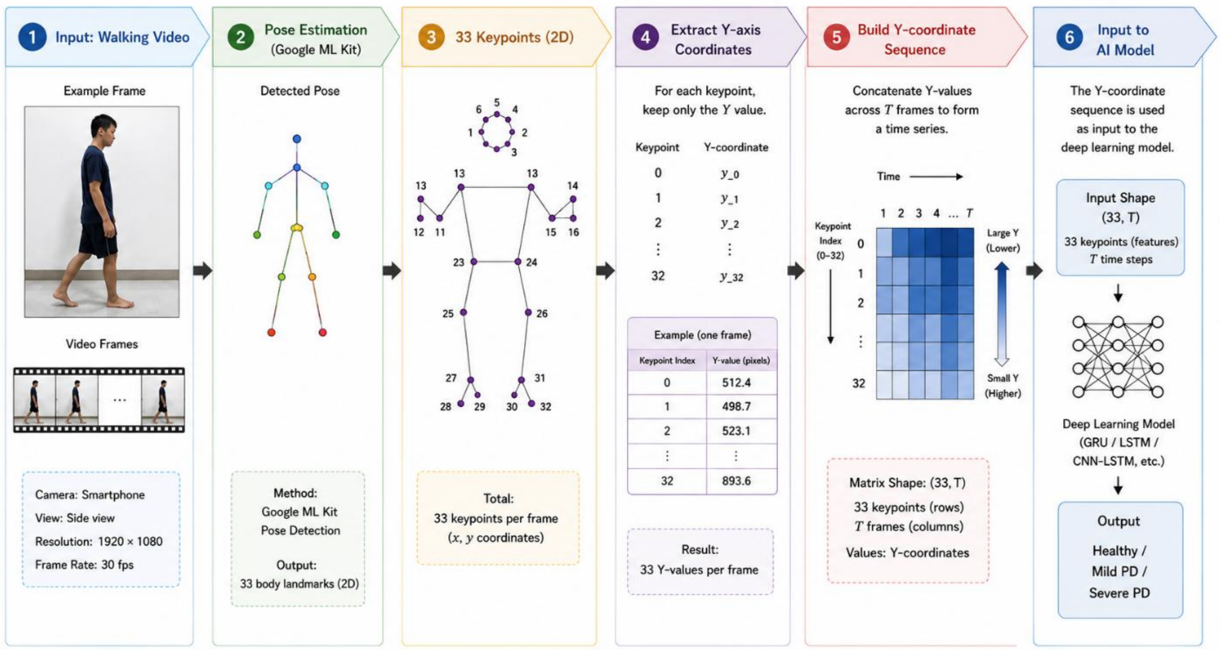

Figure 1. Pipeline for Y-axis coordinate extraction from MediaPipe keypoints to AI model input

Then, through MediaPipe, the three dimensional joint coordinates of body movement are computed and extracted. Then, the Y-axis coordinates are fed into deep learning methods, 1D-CNN, LSTM and GRU for classification. In parallel, the features are derived from the Y – axis coordinates by using TSFEL python package. The features are then fed into SVM, KNN and random forest. The classification performance is then compared. The best deep learning method is incorporated into smartphone mobile application for classification of subjects. **Table 1** shows the demographics of the collected data. The data are collected from the experiment conducted by N. Kour et al [13].

Figure 3 shows the flowchart design of the mobile application. The mobile application was developed using the Flutter framework which is a cross platform framework which can be incorporated into IOS and Android platform. The best deep learning model is identified and is hosted in Render by using Flask Application Program Interface (API). Render is a cloud platform that allows developers to build, deploy and scale applications with ease.

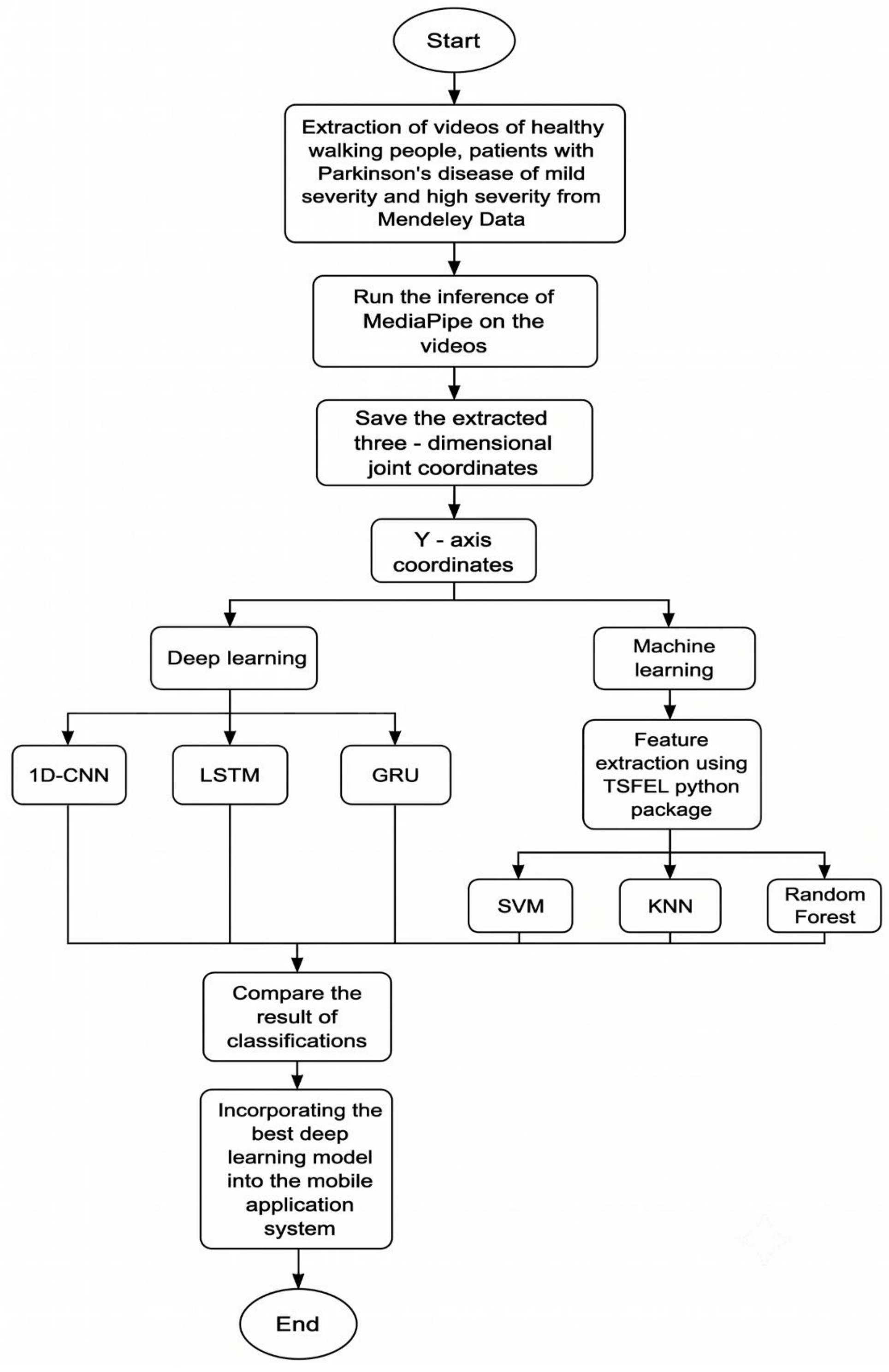

Figure 2. The overall flowchart of the research methodology

Flask is a popular lightweight web framework for Python. The mobile application involves a person taking video of a patient walking from right to left or left to right perpendicular to the direction of the smartphone camera as shown in **Figure 4** for about 10s. Note that the keypoints are extracted using Google's ML Kit Pose Detection instead of MediaPipe Pose Detection due to faster performance.

Deep learning is chosen to be incorporated into the mobile application as shown in **Figure 4** because of ease of system design which can make the system perform significantly faster compared to the machine learning as shown in **Figure 5** where there is a need to extract features from the Y-axis coordinates of 33 landmarks. This task is more time-consuming than using a deep learning model.

Table 1. The demographics of the collected data

Class of Subject	Number of Male Subjects	Number of Female Subjects	Average age	Average height (m)
Healthy/Normal	13	17	43.77	1.60
Parkinson's disease of mild severity	6	0	66.50	1.67
Parkinson's disease of high severity	2	1	70.00	1.66

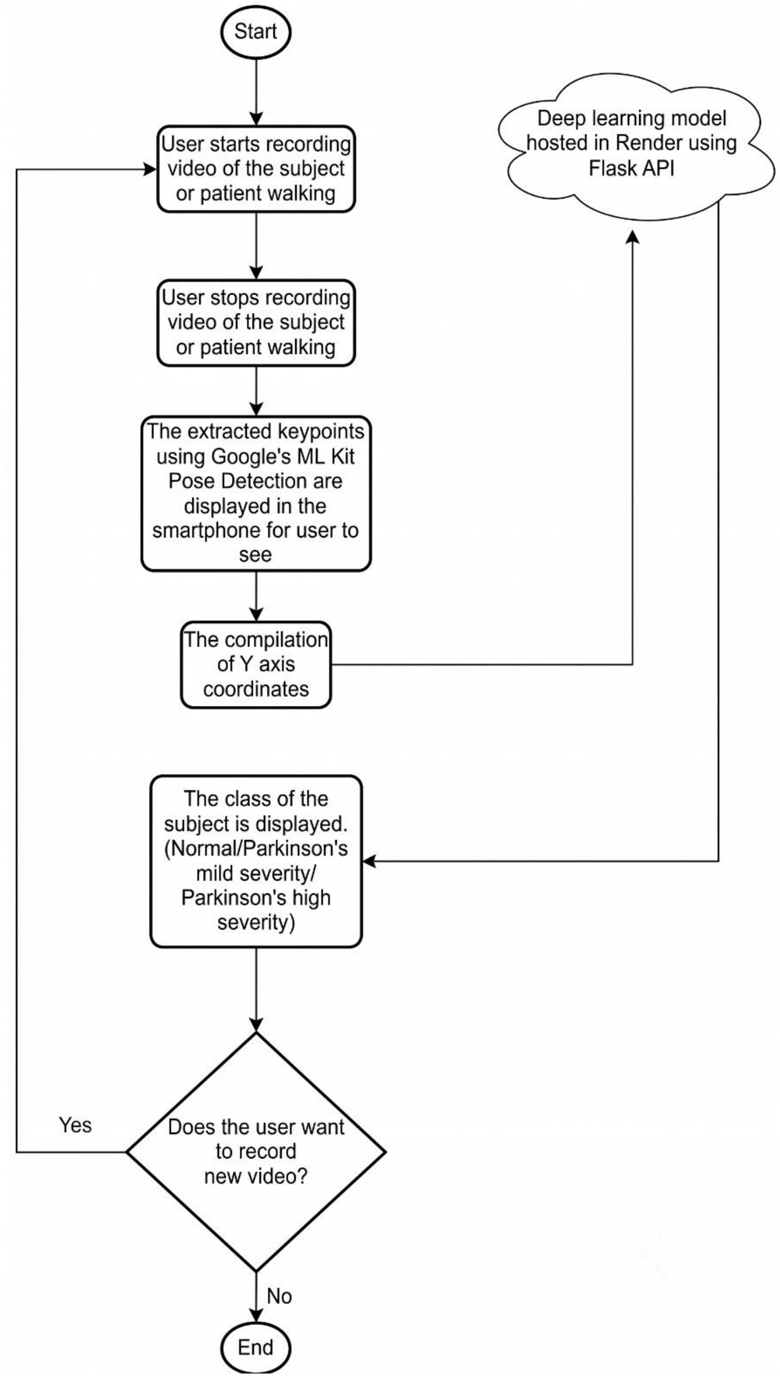

Figure 3. The flowchart design of the mobile application

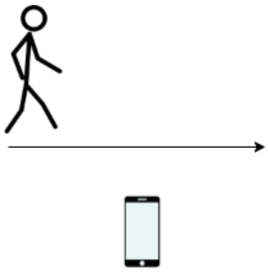

Figure 4. The diagnosis setup of a person walking using smartphone camera

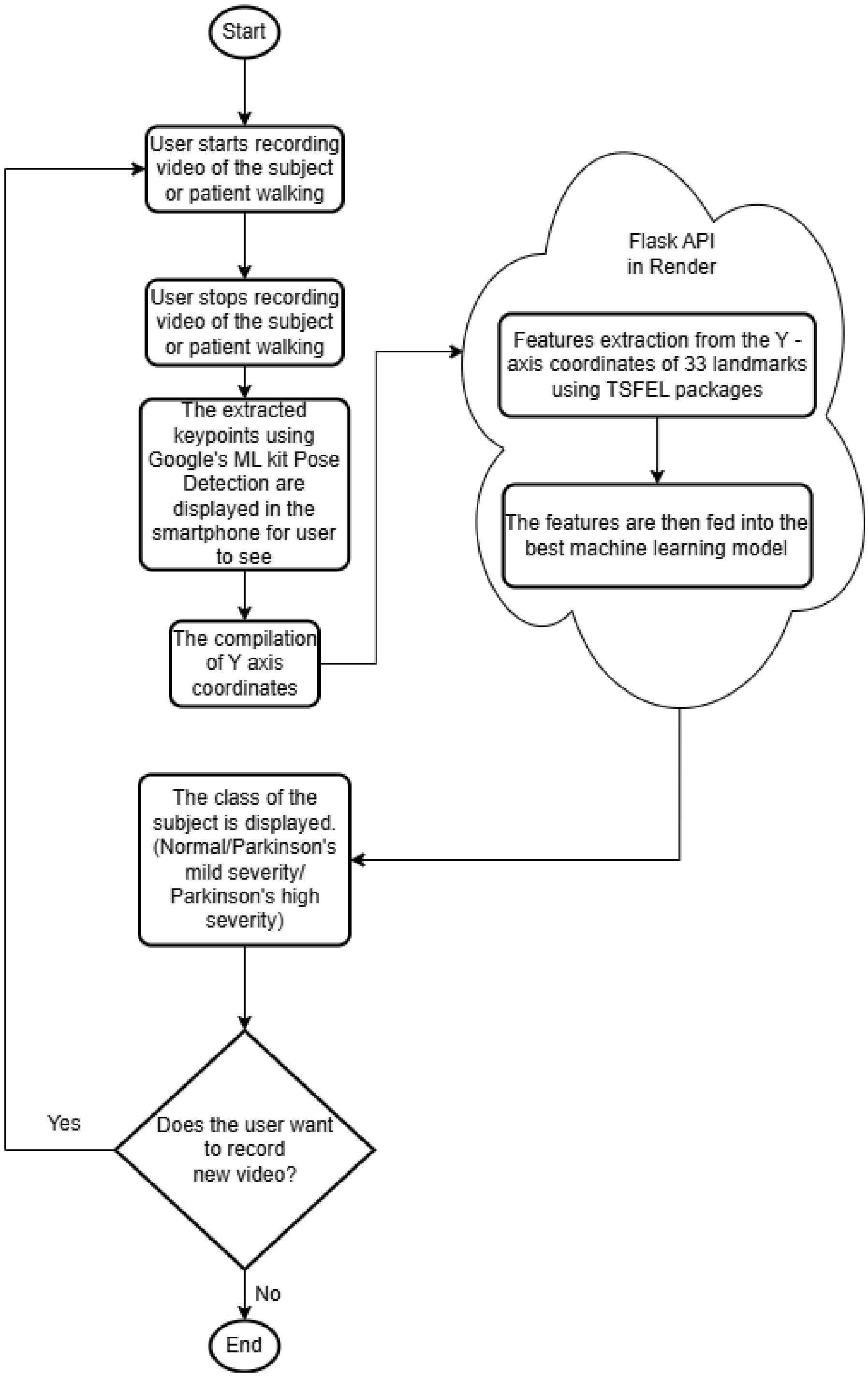

Figure 5. The flowchart design of the mobile application with the incorporation of machine learning model

Nevertheless, the performance of machine learning is compared to the deep learning model for future development. The reason the 1D–CNN, GRU and LSTM were selected in this research paper is because the Y-axis coordinates are readily available in the form of sequential data.

2.1 MediaPipe Pose Estimation & Google's ML Kit Pose Detection

MediaPipe Pose was developed by Google to estimate 2D human joint coordinates in the image or video. It was built on top of BlazePose which is a lightweight machine learning model that can extract 33 2D landmarks that can run on low-power devices like mobile phones and personal computers as shown in **Figure 6**.

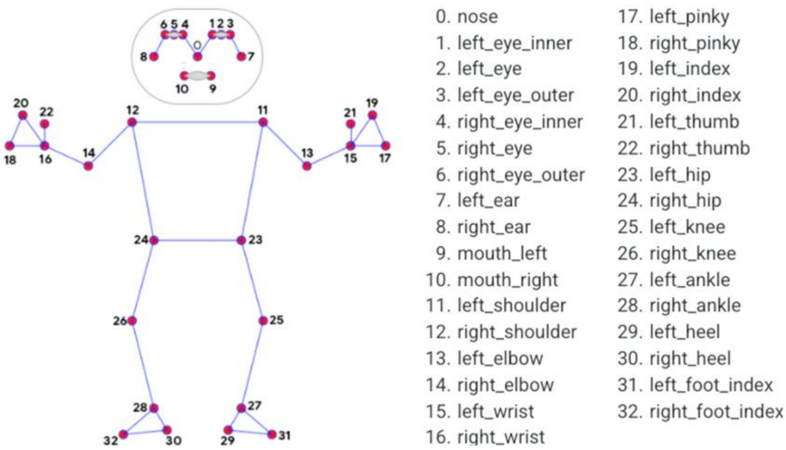

Figure 6. The 33 2D landmarks that are extracted by MediaPipe Pose

Figure 7 shows the inference of MediaPipe Pose on the video frame of one of the healthy walking people. The inference of MediaPipe Pose consists of points which represent the keypoints and lines which represent the lines between keypoints. The collected data includes three groups of people which are healthy normal people, patients with PD of mild severity and patients with PD of high severity.

Figure 7. The inference of MediaPipe Pose on the video of healthy walking person

2.2 TSFEL

TSFEL is a Python package that is developed to provide support for automating the process of feature extraction on multidimensional time series. In TSFEL, the time series data are divided into fixed length time windows which are defined by the users in which the features are extracted. In this research, the fixed length time windows are not defined which means that the features will be extracted from the entire length of the data by default. There are four categories of features which are extracted from

TSFEL which are temporal, statistical, spectral and fractal [14]. Below are the list of features extracted by TSFEL under the categories of statistical domain, temporal domain, spectral domain and fractal domain.

Statistical Domain: This category summarizes the distribution and amplitude characteristics of the signal. The extracted features include absolute energy, average power, empirical cumulative distribution function (ECDF), ECDF percentile, ECDF percentile count, entropy, histogram, interquartile range, kurtosis, maximum, mean, mean absolute deviation, median, median absolute deviation, minimum, root mean square, skewness, standard deviation, and variance.

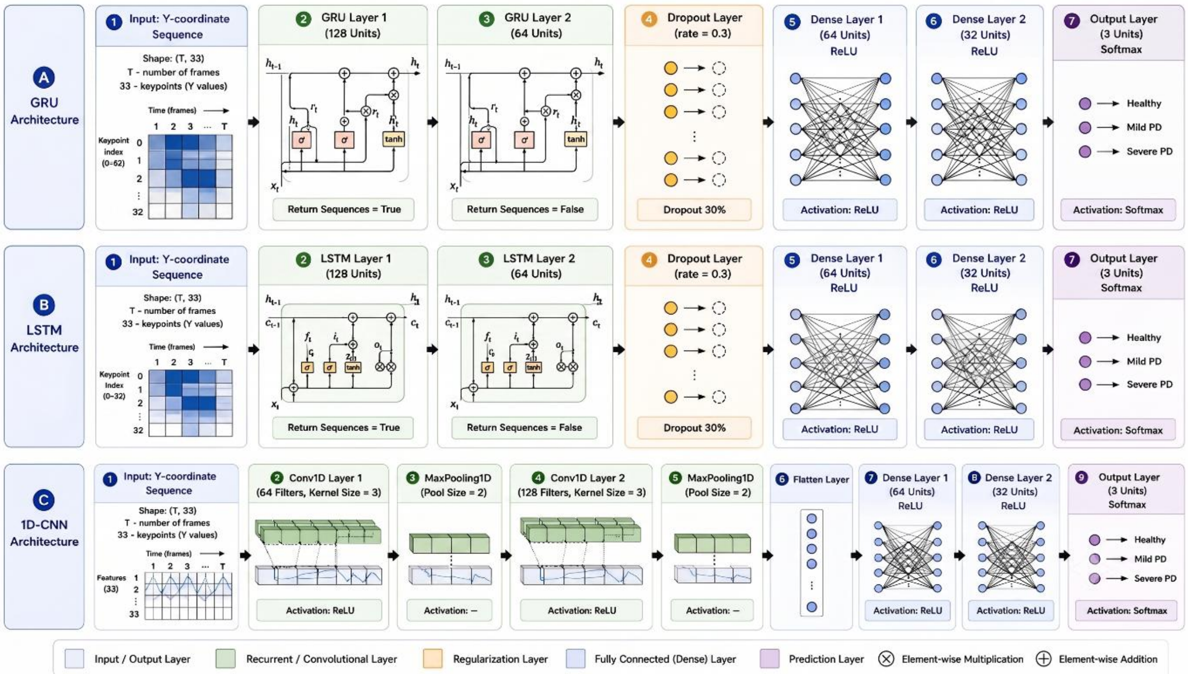

Figure 8. The architecture of GRU, LSTM and 1D-CNN Used for classification in this research

Temporal Domain: These features describe the signal behavior in the time domain by capturing its dynamic and structural characteristics. The extracted features comprise area under the curve, autocorrelation, centroid, Lempel-Ziv complexity, mean absolute difference, mean difference, median absolute difference, median difference, negative turning points, peak-to-peak distance, positive turning points, signal distance, slope, sum absolute difference, zero-crossing rate, and neighborhood peaks.

Spectral Domain: Frequency-domain descriptors are extracted to represent the spectral characteristics of the gait signal. The extracted features include Fast Fourier Transform (FFT) mean coefficient, fundamental frequency, human range energy, linear predictive cepstral coefficients (LPCC), Mel-frequency cepstral coefficients (MFCC), maximum power spectrum, maximum frequency, median frequency, power bandwidth, spectral centroid, spectral decrease, spectral distance, spectral entropy, spectral kurtosis, spectral positive turning points, spectral roll-off, spectral roll-on, spectral skewness, spectral slope, spectral spread, spectral variation, wavelet absolute mean, wavelet energy, wavelet standard deviation, wavelet entropy, and wavelet variance.

Fractal Domain: Fractal-based descriptors measure the complexity and self-similarity of the gait signal across multiple scales. The extracted features include detrended fluctuation analysis (DFA), Higuchi fractal dimension, Hurst exponent, maximum fractal length, multiscale entropy (MSE), and Petrosian fractal dimension.

In this research, TSFEL is used to extract the features from the Y-axis coordinates to be fed into the machine learning models. **Figure 8** shows the architecture of GRU, LSTM and 1D-CNN used for the classification in this research.

3. RESULTS & DISCUSSIONS

3.1 Design of the Mobile Application

The designed mobile application includes four pages which are shown as A, B, C and D in **Figure 9**. In A, the user initiates the recording of the video of the subject walking by pressing the button '1'. Then, the user records the subject in 'B' for about 10 seconds and stops recording by pressing the button '1'. Next, the user will be directed to the printed extracted keypoints which include the X and Y coordinates as shown in C. After a few seconds, the user will be directed to the result of the deep learning model and the printed class of the recorded subject as shown in D. This mobile application outputs three classes which are normal, PD of mild severity and PD of high severity.

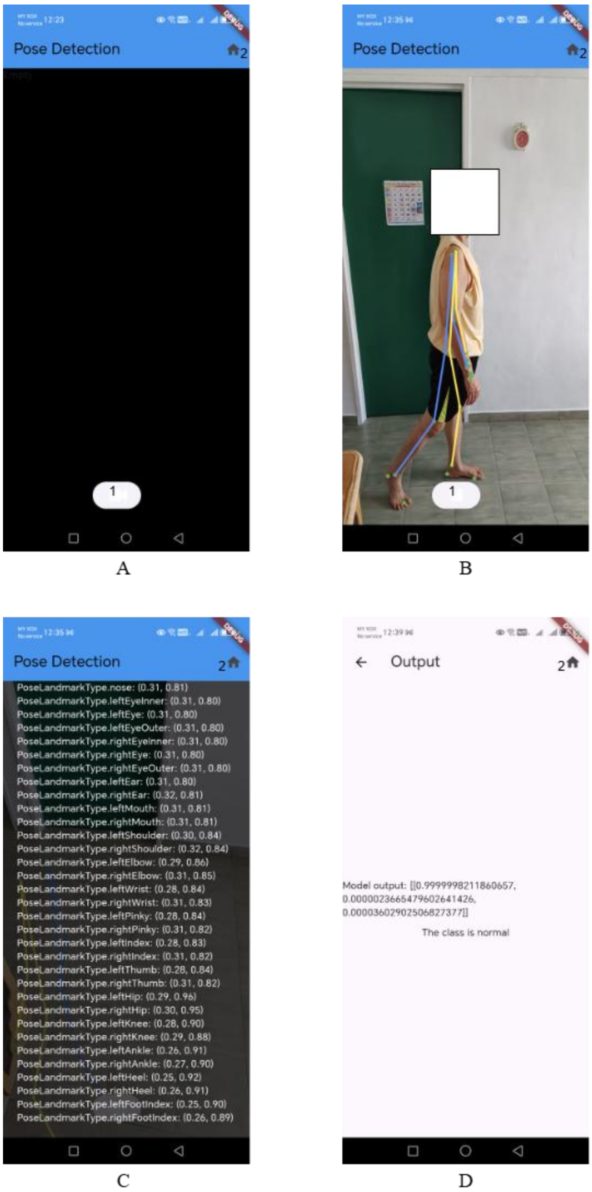

Figure 9. The user interface of the mobile application

Based on D, the output model comes in the form of [[x,y,z]]. x represents the probability of the class of the recorded person is normal or healthy person. y represents the probability of the class of the recorded person is PD of mild severity and z represents the probability if the class of the recorded person is PD of high severity.

This mobile application has the limitation of diagnosing the subject only if the subject can walk with or without walking assistance tool. If the subject is assisted to walk by another person, the mobile application cannot extract the keypoints correctly. Future work may include the combination of You Only Look Once (YOLO) algorithms and MediaPipe Pose to extract the keypoints of the subject.

Besides, the standard protocol to assess the severity and progression of the PD is Unified Parkinson's Disease Rating Scale (UPDRS). The class of the collected data is labelled as PD of mild severity and Parkinson's disease of high severity but is not linked to UPDRS. To improve the deep learning and the machine learning model, the model should be trained according to UPDRS so that the mobile application can be used in the clinical setting. The mobile application is not tested thoroughly because volunteers with PD cannot be accessed. Even though Google's ML Kit Pose Detection extracts the keypoints from the same 33 landmarks as the MediaPipe Pose and has the faster inference time, the mobile application needs to be tested on real patients to study the compatibility of Google's ML Kit Pose Detection and MediaPipe Pose.

Gait dysfunction is just one of the symptoms of the PD. The mobile application can be developed further to track eye movement, hand tremor and speech from the subjects to allow a more integrated diagnosis of PD and its severity.

3.2 Deep Learning & Machine Learning Performance

Table 2 shows the result of different deep learning and machine learning techniques in classifying the class of the patients based on **Table 1**. Group 0 represents the healthy normal walking people. Group 1 represents the patients with PD of mild severity while Group 2 represents the patients with PD of high severity. Support is the number of occurrences of each group in the testing of the machine learning models and deep learning models.

Table 2. The compilation of precision, recall & F1-score using different deep learning and machine learning techniques

Method	Group	Precision	Recall	F1 - score	Support
GRU	0	1.00	0.91	0.95	11
	1	1.00	1.00	1.00	2
	2	0.80	1.00	0.89	4
LSTM	0	1.00	0.91	0.95	11
	1	0.50	0.50	0.50	2
	2	0.60	0.75	0.67	4
1D-CNN	0	0.65	1.00	0.79	11
	1	0.00	0.00	0.00	2
	2	0.00	0.00	0.00	4
1D-CNN & GRU	0	1.00	0.91	0.95	11
	1	0.50	0.50	0.50	2
	2	0.60	0.75	0.67	4
1D-CNN & LSTM	0	0.85	1.00	0.92	11
	1	0.00	0.00	0.00	2
	2	0.50	0.50	0.50	4
	0	1.00	0.91	0.95	11

GRU - LSTM	1	1.00	1.00	1.00	2
	2	0.80	1.00	0.89	4
Random Forest	0	0.91	1.00	0.95	10
	1	1.00	0.75	0.86	4
	2	1.00	1.00	1.00	3
SVM	0	0.92	1.00	0.96	12
	1	0.00	0.00	0.00	2
	2	0.67	0.67	0.67	3
KNN	0	0.86	1.00	0.92	12
	1	0.50	0.00	0.50	2
	2	0.00	0.50	0.00	3

Table 2 shows that out of the machine learning techniques, random forest performs the best with accuracy of over 80%. The reason is because the dataset that is fed to machine learning is huge in which there are 69 features from each Y-axis coordinates of 33 landmarks totaling 2277 data. Random forest is capable of handling large datasets with high dimensionality compared to SVM and KNN. This shows that SVM and KNN are lacking in performance when dealing with heterogeneous datasets with complex, non-linear relationships and noisy features. Out of all deep learning methods, LSTM and GRU–LSTM perform the best with accuracy of over 80% just like random forest.

There is a problem with the lack of data for the PD of mild severity and PD of high severity. Nevertheless, even with the problem of insufficient data, GRU and GRU-LSTM classify three classes with accuracy of 80% and above. Another limitation of this mobile application is that the architecture to train the deep learning model continuously with new data is not set up.

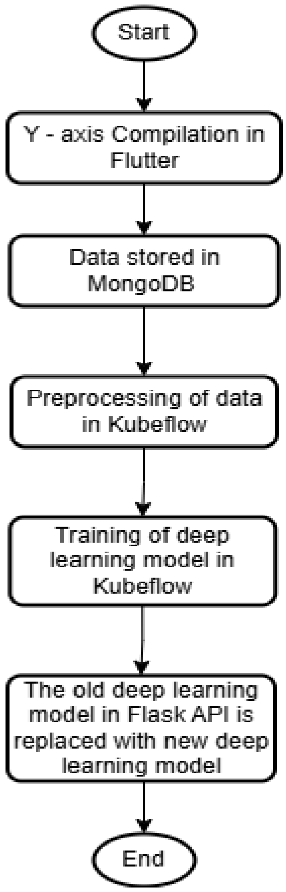

Figure 10. The integration of MongoDB and Kubeflow into Flask API

The capability of taking in new data to train the deep learning model can be easily added to the mobile application by integrating MongoDB and Kubeflow into Flask API. The role of MongoDB is to store large amounts of data to allow easy management of datasets that will be used to train deep learning model. MongoDB enables real–time data update to allow the continuous data collection and integration into training pipeline. Kubeflow retrieves new data from MongoDB, preprocess the data for training and train the deep learning model. Finally, Kubeflow updates the deep learning model deployed through the Flask API. This architecture is illustrated in **Figure 10**.

Compared with previous studies summarized in **Table 3**, this research offers several distinctive contributions. While recent studies mainly focus on remote symptom monitoring, digital biomarkers, or smartphone-based assessment of PD, they generally do not provide an end-to-end mobile diagnosis system capable of automatically classifying disease severity. The proposed work integrates Google ML Kit Pose Detection, Flutter, and cloud-based deep learning into a single smartphone application that performs real-time gait acquisition, markerless pose estimation, and automatic classification of healthy individuals, patients with mild PD, and patients with severe PD. Furthermore, this study performs a comprehensive comparison between traditional machine learning algorithms (Random Forest, SVM, and KNN) and deep learning models (1D-CNN, LSTM, GRU, CNN-LSTM, CNN-GRU, and GRU-LSTM) using the same gait dataset, providing valuable insights into their relative performance. Another distinguishing feature is the use of only the Y-axis coordinates of MediaPipe keypoints for classification, resulting in a computationally efficient approach suitable for mobile deployment. Finally, the proposed cloud-based architecture using Flask API, together with the proposed MongoDB-Kubeflow continual learning framework, provides a practical pathway for future large-scale deployment and continuous model improvement, features that are largely absent from existing smartphone-based PD diagnosis studies.

Table 3. The summary of recent research articles related to diagnosis of Parkinson's disease using smartphone

Researchers	Year	Research Outcome
Y. Zhang et al [15]	2024	Developed a mobile application, PDMotion which introduced tapping test as well as drawing test via on – screen interactions and collection of motion along with spatiotemporal data via accelerometer of the smartphone
I.H.J Willemse et al [16]	2024	Conducted study on smartphone applications for movement disorders which concluded that the Parkinson's disease is classified by using various sensors such as gyroscope, accelerometer and magnetometer
A. Stergioulas at al [19]	2024	Collect motion features from the captured videos that consists of four categories which are leg agility, arising from chair, posture and gait using MediaPipe Pose Detection
M. G. Di Cesare et al [17]	2024	Apply machine learning to the voice recording collected by the smartphone which achieved accuracy of 92.3% in the classification of Parkinson's disease
L. Bart et al [18]	2024	Demonstrated the ability of the smartphone's mobile application to monitor the gait metrics of the post – stroke patients before, during and after a rehabilitation program in terms of regularity, symmetry and walking speed using accelerometer

4. CONCLUSION

This study presents a novel, smartphone-based system for the detection and severity classification of PD using computer vision and artificial intelligence techniques. By leveraging pose estimation through MediaPipe and analyzing Y-axis gait features, both deep learning and machine learning models were evaluated for their effectiveness in classifying healthy individuals and patients with varying degrees of Parkinson's severity. Among the models tested, GRU, GRU–LSTM, and Random Forest demonstrated superior performance with classification accuracies exceeding 80%. The integration of these models into a mobile application developed using Flutter, with real-time keypoint extraction via Google's ML Kit and cloud-based inference using Flask API, illustrates the potential of accessible and scalable healthcare solutions. This approach addresses the need for cost-effective, non-invasive diagnostic tools, especially in resource-limited settings. Future work may focus on expanding the dataset, enhancing model robustness across diverse populations, and incorporating additional features to further improve classification accuracy and clinical applicability.

5. ACKNOWLEDGEMENT

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AUTHORS' PROFILES

Lee Teng Hong *received his B.Sc (Hons.) in Electrical and Electronic Engineering from KDU Penang, University College. He the received his M.Sc. in Electrical Engineering from Universiti Teknikal Malaysia Melaka. Currently, he is working as an engineer in Penang, Malaysia. His research interests are in deep learning and machine learning for the rehabilitation purpose.*

Ezreen Farina Shair *received her B.Eng in Electrical - Control & Instrumentation and M.Eng in Electrical - Mechatronics & Automatic Control from Universiti Teknologi Malaysia (UTM) in 2009 and 2011, respectively, and a Ph.D. in Electronics Engineering from the Universiti Putra Malaysia in 2019. She is currently a senior lecturer at Universiti Teknikal Malaysia Melaka and Treasurer of the IEEE-EMBS Malaysia Chapter. She also serves onthe editorial boards of the International Journal of Human and Technology Interaction (IJHaTI), and the Asian Journal of Medical Technology (AJMedTech). Her research focuses on biomedical signal processing, artificial intelligence, machine learning, deep learning, and IoT.*

Muhammad Hazwan Adlin Jumaris *received his B.Sc. in Electrical Engineering in 2025 from Universiti Teknikal Malaysia Melaka (UTeM). He is currently a postgraduate student under the Advanced Digital Signal Processing (ADSP) Research Lab in the Faculty of Electrical Technology and Engineering, UTeM. He is registered with the Board of Engineers Malaysia (BEM) and the Malaysia Board of Technologists (MBOT) as an Engineering Technologist. His research interests are biomedical signal processing, artificial intelligence, machine learning, deep learning, and IoT.*

Nur Zawani Saharuddin *received her diploma in Electrical Engineering and B.Eng. degree in Electrical Engineering (Industrial Power) from Universiti Teknikal Malaysia Melaka, Malaysia in 2005 and 2008, respectively. She then received her M.Eng. degree in Electrical Engineering from University of Malaya, Malaysia, and Ph.D. degree from Universiti Tenaga Nasional, Malaysia, in 2020.Currently she serves as senior lecturer at the Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka. Her research interests are focused on power system analysis, power system islanding, energy management, and renewable energy.*

Raja Rina Raja Ikram *is an academician at Universiti Teknikal Malaysia Melaka (UTeM) specialising in TVET educational technology, healthcare informatics, software engineering, and software testing optimisation. Her work focuses on developing sustainable software engineering algorithms, advancing health informatics research, leading professional certifications, and driving EdTech initiatives at national and international levels.*

Siti Anom Ahmad *is a Professor in the Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia. She received her Ph.D. and M.Sc. in Electronic Engineering from the University of Southampton, United Kingdom. Her research interests include biomedical engineering, artificial intelligence, control systems, signal processing, and gerontechnology. She previously served as Director of the Malaysian Research Institute on Ageing (MyAgeing™) and currently leads the Control System and Signal Processing Research Centre. She is a Chartered Engineer (CEng), Professional Engineer (PEng), and Senior Member of IEEE.*