# DETECTING PARKINSON'S DISEASE USING GAIT ANALYSIS

**A PROJECT REPORT**

***Submitted by***

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# BONA FIDE CERTIFICATE

Certified that this project report titled **'DETECTING PARKINSON'S DISEASE USING GAIT ANALYSIS'** is the bona fide work of **ADITYA RAJ (2020179001)** who carried out project work under my supervision. Certified further that to the best of my knowledge and belief, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or an award was conferred on an earlier occasion on this or any other candidate.

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# ABSTRACT

Many neurological diseases like Parkinson's impair movement, which limits people's function. Quantitative assessment of motion is critical to medical decision-making but is currently possible only with expensive motion capture systems and highly trained personnel. The ineffectiveness of clinical rating scales makes the Parkinson's Disease diagnosis a very complicated task. Thus, more efficient systems are required to perform an automated evaluation of PD for its earlier detection and to enhance the life expectancy rate.

Gait-based clinical diagnosis can provide useful indications regarding the presence of PD. In the existing system, wearable technologies and IoT devices are used to detect PD, this system requires lots of time ,cost and professi onals to place devices and operate them. Both normal and abnormal people have to follow the steps to check their PD. The person can't check PD at home.

So, Proposed a video GAIT analysis system for predicting clinically relevant motion parameters from a patient's video, and a Machine learning model to analyze GAIT parameters and predict Parkinson's disease. If PD is detected then need to check Freezing of Gait & Hoehn and Yahr scale which are used for analysis of PD. The advantages of proposed work is it can reduces lots of time and cost of people and they can check their PD very easily from Home and don't need any professionals to guide for getting the results. Various gait parameters such as step length, joints angle,etc. can be effectively utilized in order to measure differences among individuals.The walking characteristics of an individual vary to a larger extent as compared to a normal one such as slow speed, increased cadence, gait abnormality, etc. Thus the Gait Analysis provides decisive clues regarding abnormal motion pattern of a PD subject to better classify an affected gait from a healthier one.

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**ADITYA RAJ**

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# LIST OF SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| $2D$ | Two-Dimensional |
| $3D$ | Three-Dimensional |
| $PD$ | Parkinson's Disease |
| $FOG$ | Freezing of Gait |
| $GDI$ | Gait Deviation Index |
| $PAF$ | Part Affinity Fields |
| $CNN$ | Convolutional Neural Network |
| $LANK$ | Left Ankle |
| $LKNE$ | Left Knee |
| $LHIP$ | Left Hip |
| $LBTO$ | Left Big Toe |
| $RANK$ | Right Ankle |
| $RKNE$ | Right Knee |
| $RHIP$ | Right Hip |
| $RBTO$ | Right Big Toe |

# CHAPTER 1

# INTRODUCTION

Over past years, the unique characteristics of the human body known as biometric(e.g. handwriting speech, gait, etc.) have been enormously analyzed to make excellent progress in clinical diagnosis. Each individual has an idio syncratic style of walking that occurs due to coordinated and collaborated actions of the musculoskeletal and nervous system. This makes the gait biometric a powerful indicator to determine pathological behavior. These internal and external factors directly affect the motion and action of the body and results in gait impairment. The alterations in a person's gait (e.g. freezing of gait (FOG), severity levels, short steps, etc.) provides significant clues regarding the presence of Parkinson's Disease (PD). The subjective diagnosis of PD at early stages using clinical rating scales is very challenging as the symptoms appear more with increased age due to which several cases go unrecognized. Therefore, effective and automated analysis of an individual gait parameter's is required to differentiate PD and normal subjects and to provide them rehabilitation.

## 1.1 PARKINSON'S DISEASE

Parkinson's disease is a brain disorder that causes unintended or un controllable movements, such as shaking, stiffness, and difficulty with balance and coordination. Symptoms usually begin gradually and worsen over time. As the disease progresses, people may have difficulty in walking and talking. They may also have mental and behavioral changes, sleep problems, depression, memory difficulties, and fatigue. In Parkinson's, the cells of the substantia nigra start to die. When this happens, dopamine levels are reduced. When they have

dropped 60 to 80 percent, symptoms of Parkinson's start to appear.

### 1.1.1 Characteristics and stages of PD

The characteristics of PD are Slow moving than expected, stooped-lean posture, small and shuffling steps,freezing of gait etc...

**The five stages of PD are as follows:**

1. Symptoms at this stage are mild and do not interfere with daily activities
    - Mild problems with posture and balance
    - Slight difficulty walking
    - Mild changes in facial expressions
2. Symptoms at this stage become worse, making daily activities more difficult. The person is, however, able to look after themselves.
    - Difficulty in walking
    - Difficulty in balancing
3. Symptoms at this stage (mid-stage) are more severe than those of stage II. However, the person is still independent.
    - Daily activities such as eating, bathing and dressing are significantly impaired
    - Freezing of GAIT
4. Independent living is almost impossible at this stage due to limitations in daily activities such as eating, bathing, dressing, sleeping, and waking.

5. Symptoms at this debilitating stage become so severe that standing on one's own may be impossible. The person becomes bedridden and needs a wheelchair to be moved around.

### 1.1.2 Causes of PD

The exact cause of Parkinson's is unknown. It is caused by a loss of nerve cells in the part of the brain called the substantia nigra. It's not known why the loss of nerve cells associated with Parkinson's disease occurs, although research is ongoing to identify potential causes.

Currently, it's believed a combination of genetic changes and environ mental factors may be responsible for the condition.. Some scientists believe that viruses can trigger Parkinson's as well.

### 1.1.3 Diagnosis of PD

No tests can conclusively show that you have Parkinson's disease. Your doctor will base a diagnosis on your symptoms, medical history and a detailed physical examination.Your general practitioner will talk to you about the problems you're experiencing and may ask you to perform some simple mental or physical tasks, such as moving or walking around, to help with the diagnosis.In the early stages, your GP may find it difficult to say whether you definitely have the condition because symptoms are usually mild. There are currently no blood or laboratory tests to diagnose non-genetic cases of Parkinson.

### 1.1.4 Treatments for PD

There's currently no cure for Parkinson's disease, but treatments are available to help relieve the symptoms and maintain your quality of life.These treatments include supportive therapies, such as physiotherapy,medication,surgery (for some people). You may not need any treatment during the early stages of Parkinson's disease as symptoms are usually mild, But you may need regular appointments with your specialist so your condition can be monitored.

## 1.2 GAIT Analysis

Human gait depends on a complex interplay of major parts of the nervous, musculoskeletal and cardiorespiratory systems.The individual gait pat tern is influenced by age, personality, mood and sociocultural factors.The pre ferred walking speed in older adults is a sensitive marker of general health and survival. Safe walking requires intact cognition and executive control. Gait disorders lead to a loss of personal freedom, falls and injuries and result in a marked reduction in the quality of life [1].

**Gait** - the manner or style of walking.

**Gait Analysis** - Gait analysis is the study of human locomotion. In order to analyze and quantify how someone walks, it is necessary to isolate the shortest, unique, repeatable task during gait. This task is called the gait cycle. A single gait cycle can be measured from any gait event to the same subsequent event on the same foot, but the conventional tacit model considers gait cycle is measured from one foot strike to the subsequent foot strike of the same foot.

### 1.2.1 Phases of the Gait Cycle

The gait cycle can be broken down into two primary phases (shown in Figure.1.1), the stance and swing phases, which alternate for each lower limb[2].

1. Stance phase: Consists of the entire time that a foot is on the ground. The stance phase is 60 percent of the gait cycle and can be subdivided into double-leg and single-leg stance.In double-leg stance, both feet are in contact with the ground. At an average walking speed, it represents 10 percent of the entire gait cycle, but decreases with increased walking speed and ultimately disappears as one begins to run. At slower walking velocities the double-leg support times are greater . Single-leg stance comprises up to 40 percent of the normal gait cycle . The muscles that are active during the stance phase act to prevent buckling of the support limb. These include the tibialis anterior, the quadriceps, the hamstrings, the hip abductors, the gluteus maximus, and the erector spinaer[3].

2. Swing phase: Consists of the entire time that the foot is in the air. The swing phase is described when the limb is not weight bearing and represents 40 percent of a single gait cycle. It is subdivided into three phases: initial swing (acceleration), midswing, and terminal swing (deceleration). Acceleration occurs as the foot is lifted from the floor and, during this time, the swing leg is rapidly accelerated forward by hip and knee flexion along with ankle dorsiflexion . Midswing occurs when the accelerating limb is aligned with the stance limb . Terminal swing then occurs as the decelerating leg prepares for contact with the floor and is controlled by the hamstring muscles[3].

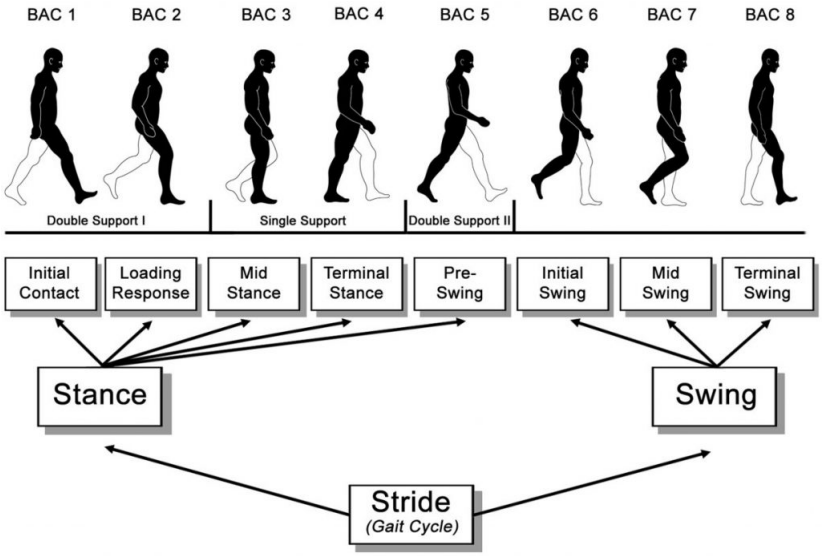


**Figure 1.1: Breakdown of the gait cycle into phases based on the work of Perry and Burnfield**

### 1.2.2 Gait Disorders

Gait disorders - altered gait pattern due to deformities, weakness or other impairments eg loss of motor control or pain [3].Causes of gait disorders include Neurological, orthopedic, and psychiatric conditions and multifactorial etiology becomes more common with advancing age, making classification and management more complex.

### 1.2.3 Parkinsonian Gait

Parkinson's disease results from lesions of the basal ganglia affecting motor control and function bilaterally.It is characterized by a paucity of move ment of the facial, trunk, and upper and lower limb muscles. This results in a gait that is slow and shuffling with short rapid steps described as being festinating .The trunk is flexed forward and the person may have difficulties with stops and turns, appearing to chase after his or her COM [4]. Joint motion is reduced due to rigidity and there is usually little or no arm swing to help in balancing the

individual, with falls being a common result.

### 1.2.4 GAIT Deviation Index

The Gait Deviation Index (GDI) is a score derived from three dime nsional gait analysis .The GDI provides a numerical value that expresses overall gait pathology (ranging from 0 to 100 [5].GDI aims at providing a comprehen sive, easy to interpret, and clinically meaningful metric of overall gait function. It has been used as an outcome measure to study gait in several conditions such as cerebral palsy (CP), post-stroke hemiparetic gait, and Parkinson's disease among others.The GDI provides a numerical value that expresses overall gait where 80 + indicates the absence of PD in gait pathology. Below 80 the freezing of gait occurs[6].

## 1.3 ORGANIZATION OF REPORT

**Chapter 2:** This chapter explains about the literature survey made on existing system,issue with the existing system.

**Chapter 3:** This chapter consists System design of the project with its preliminary design and descriptive details about the modules.

**Chapter 4:** This chapter consists Algorithm and project design related to the models with their outcomes.

**Chapter 5:** This chapter consists Result and Analysis of the model with Interface and generation of summary overview.

**Chapter 6:** Concludes the thesis by summarizing the result and purpose possible enhancement that can be done in future.

# CHAPTER 2

# LITERATURE SURVEY

## 2.1 GAIT ANALYSIS

Roiz et al. [7] proposed a study to analyze the differences among gait parameters of subjects with 12 idiopathic PD and 15 healthy controls using 3D human motion analysis system with six IR cameras and eighteen active markers. The study outcomes demonstrated notable differences between PD patients and healthy subjects and gait variables shown correlation with clinical measures

Amardeep Kaur et al. [8] proposed a Study of Gait Analysis Methods with automatic support. Motion Capture is one of the measurement techniques used for gait analysis. The measurement is done using cameras, markers(passive as well as active) which are placed on the target and the processing system. Key Findings - Human skeleton model is generated by the help of markers, which produces a cloud of points. Mocap systems are quite accurate along with its limitations of high expense and the need of a specialised laboratory.

Abdullah S. el at. [9] proposed a Study of Deep Learning to track HumanGait. The gait data was recorded using wearable sensors(WS). With the help of Convolutional NeuralNetwork the extracted spatiotemporal gait features were utilized. Two “Long-Short Term Memory models” were accustomed: the first model processed the CNN output while the second extracted features from gait using the Wearable sensor. Then “Grey Wolf Optimizer” was accustomed to merge the outputs by LSTMs.

## 2.2 FOG DETECTION/PREDICTION

Aich et al. [10] proposed a study to compare the gait features obtained via wearable and a 3D Mocap system for freezing of gait (FOG) assessment in PD. Five spatiotemporal gait features i.e. step time, stride time, step length, stride length and walking speed were estimated using initial contact. The results obtained using support vector machines (SVM) provided 80 percent accuracy and less than 10 percent mean error rate between the two systems showing the effectiveness of wearable sensors for prediction of FOG. In another study by Shaw [11] considered gait image sequences were considered to detect patients with PD using hidden Markov model (HMM). Initially, the silhouette images was extracted from input video frames and a boundary box was built enclosing the subject's silhouette for measuring a number of spatiotemporal gait features such as cadence, step length, stride length, height, width, gait cycle length. Study outcomes showed the potential of the proposed model for PD diagnosis.

Tripoliti el at. [12] proposed a study to detect freezing of gait (FoG) events in patients suffering from Parkinson's disease (PD) using signals received from wearable sensors (six accelerometers and two gyroscopes) placed on the patients' body. For this purpose, an automated methodology has been developed which consists of four stages. In the first stage, missing values due to signal loss or degradation are replaced and then (second stage) low frequency components of the raw signal are removed. In the third stage, the entropy of the raw signal is calculated. Finally (fourth stage), classification algorithms have been tested in order to detect the FoG events.

Li el at. [13] implemented a novel FOG detection system using deep learning technology. The system takes multi-channel acceleration signals as input, uses one-dimensional deep convolutional neural network to automatically learn feature representations, and uses recurrent neural network to model the

temporal dependencies between feature activations. In order to improve the detection performance, they introduced squeeze-excitation blocks and attention mechanism into the system, and used data augmentation to eliminate the impact of imbalanced datasets on model training.

## 2.3 PARKINSONS DETECTION/PREDICTION

Khan et al.[14] proposed a markerless computer-vision based system to note the deviations in PD gait. The used approach proved to be feasible but was limited by the color segmentation method. So the future work can be directed towards the development of enhanced and effective pre-processing techniques that can handle such concerns and can perform robust background modeling for improved PD inquiry. They also presents a computer-vision based marker-free method for gait-impairment detection in Patients with Parkinson's disease (PWP). The system is based upon the idea that a normal human body attains equilibrium during the gait by aligning the body posture with Axis-of-Gravity (AOG) using feet as the base of support. In contrast, PWP appear to be falling forward as they are less-able to align their body with AOG due to rigid muscular tone. A normal gait exhibits periodic stride-cycles with stride-angle around 45o between the legs, whereas PWP walk with shortened stride-angle with high variability between the stride-cycles. In order to analyze Parkinsonian-gait (PG), subjects were videotaped with several gait-cycles. The subject's body was segmented using a color-segmentation method to form a silhouette. The silhouette was skeletonized for motion cues extraction. The motion cues analyzed were stride-cycles (based on the cyclic leg motion of skeleton) and posture lean (based on the angle between leaned torso of skeleton and AOG). Cosine similarity between an imaginary perfect gait pattern and the subject gait patterns produced 100 percent recognition rate of PG for 4 normal-controls and 3 PWP. Results suggested that the method is a promising tool to be used for PG assessment in home-environment.

Alissa el at. [15] Proposed a study of PD diagnosis process by using a convolutional neural network, a type of deep neural network architecture, to differentiate between healthy controls and PD patients. Their approach focuses on discovering deviations in patient's movements with the use of drawing tasks. In addition, this work explores which of two drawing tasks, wire cube or spiral pentagon, are more effective in the discrimination process. With 93.5% accuracy, our convolutional classifier, trained with images of the pentagon drawing task and augmentation techniques, can be used as an objective method to discriminate PD from healthy controls.

Eltoukhy et al. [16] presented a study to scrutinize and compare the gait variables of older adults suffering from PD and having no such disease. The gait data was gathered using Kinect v2, a Mocap system (BTS) and reflective markers concurrently. The study results demonstrated the correlation among both the systems, reflecting the potential of Kinect v2.

Galna et al. [17] tried to explore the capability of Kinect in diagnosing the movement of 9 PD and 10 healthy subjects. The experiment was conducted by initially collecting the gait data using 3D Vicon system along with markers as a benchmark and a Kinect system. Comparison among computed gait variables via both modalities manifested high correlation (r¿0.8) proving the reliability of the Kinect sensor for PD inspection.

# CHAPTER 3

# SYSTEM DESIGN

This module consists system design of the project as overall Architecture diagram and process flow diagram which tells about the modules integration in the project.

## 3.1 SYSTEM ARCHITECTURE

The proposed work of the system architecture is shown in Figure 3.1.

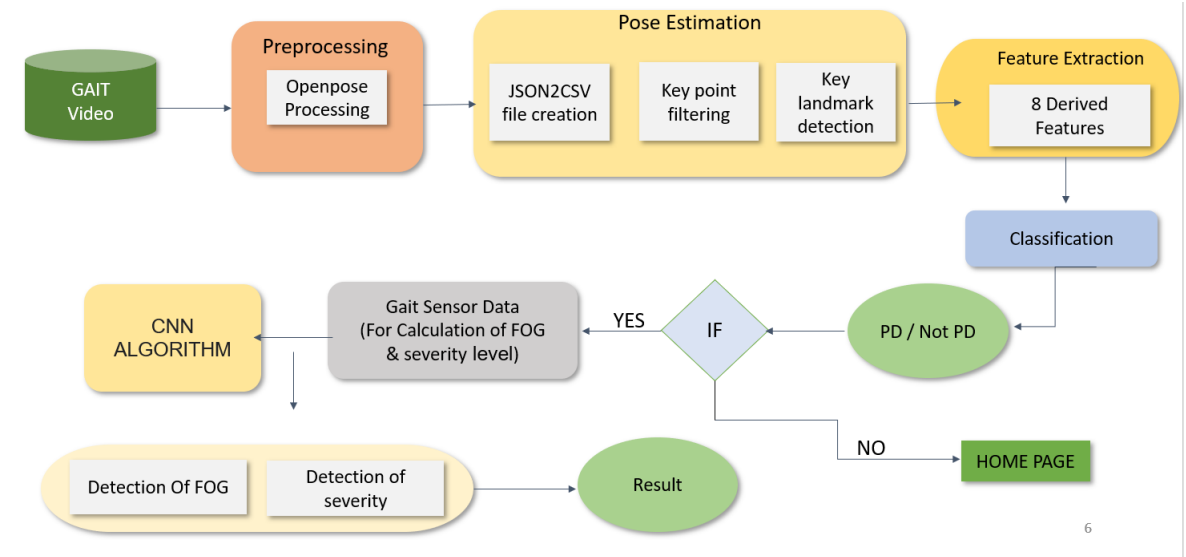


**Figure 3.1: System Architecture**

## 3.2 SYSTEM ARCHITECTURE OVERVIEW

The project is set up to take video or Openpose Processed Video file path as input.In Pre-processing, Input video data may be of any dimensions, so first re-scaling the video in required dimensions. Pose estimation is performed on the clip to obtain a sequence of skeleton which contains location of body joints. In feature extraction and gait classification stage, extracted gait and postural parameters and employed time series analysis to classify if the gait is normal or abnormal. After this,applying pose estimation on each frame of the video. The output of the pose estimation is a sequence of 25 anatomical joint coordinates in each frame. If the gait is classified as abnormal, it means the gait has deviated from their normal gait. To better analyze the gait,also extracting gait and postural features to help understand how the gait has changed in PD patients. Based on gait metrics results,If found abnormal gait and found symptoms of PD , then patients have to check FOG and severity level.

## 3.3 SYSTEM DESIGN DETAILS

### 3.3.1 Data Gathering

These are three datasets used in proposed model.

1. video-gait-v1 Dataset
2. Daphnet Dataset
3. Physionet Dataset

**video-gait-v1 Dataset** : This dataset contains Total Record of 3000 procssed Video trajectories of body keypoints extracted using OpenPose and

corresponding labels derived from optical motion capture or annotated by physicians, including speed, cadence, GDI, surgerical decisions.

**Daphnet Dataset** : This dataset comprises of recordings of 3D acceleration at 64 Hz from 3 acceleration sensors. The sensors are placed at the ankle (shank), on the thigh, and on the hip as shown in Figure 3.2. The dataset was recorded in the lab with emphasis on generating many freeze events. Users performed three kinds of tasks: straight line walking, walking with numerous turns, and finally a more realistic activity of daily living (ADL) task, where users went into different rooms while fetching coffee, opening doors, etc. The meaning of the annotations of the samples are as follows:

1. No Freeze
2. Freeze

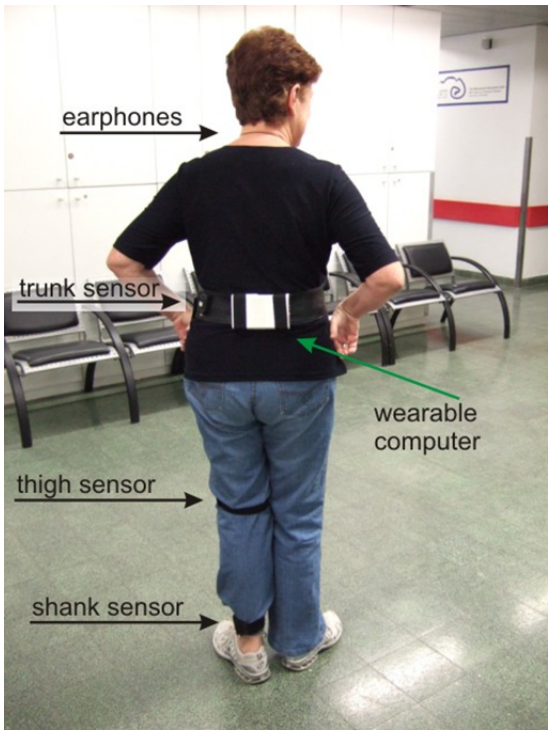


**Figure 3.2: Daphnet Sensor Position**

**Physionet Dataset** : This database contains 93 patients with PD (mean age: 66.3 years; 63% men), 73 healthy controls (mean age: 66.3 years; 55% men)measures of gait. The database includes the vertical ground reaction force records of subjects as they walked at their usual, self-selected pace for approximately 2 minutes on level ground. The output of each of these 16 sensors has been digitized and recorded at 100 samples per second, and the records also include two signals that reflect the sum of the 8 sensor outputs for each foot as shown in Figure 3.3 The database includes the vertical ground reaction force records of subjects as they walked at their usual, self-selected pace for approximately 2 minutes on level ground. Underneath each foot were 8 sensors.

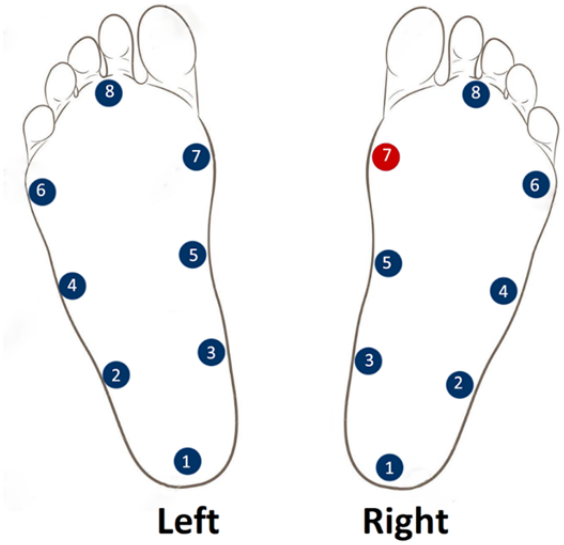


**Figure 3.3: Physionet Sensor Position**

### 3.3.2 Data Pre-Processing

The pre-processing of data is a method for preparing and adapting raw data to a model of learning. This is the first and significant step to construct a machine learning model. Real-world data generally contain noise, missing values and may not be used in an unusable format especially for machine

learning models. Data pre-processing needs to be performed in order to purify data and adapt it to the machine learning model of a system which also makes a machine learning model more accurate and efficient. The first thing for data preprocessing is to collect the required data set, and then check the missing values once the data set is imported. Correcting missed values is necessary, or else the data would be difficult to access and maintain. This data is unclean and contain many errors as well as bugs. Correcting missed values is necessary, or else the data would be difficult to access and maintain. Then calculate the mean of the column containing missing values to rectify the missed values, and substitute it with the measured mean. Now, this data set can be used to train a machine learning algorithm to predict values.

## 3.4 Pose Estimation and Skeleton Extraction

OpenPose library is used in the project to extract joint coordinates in the frame. OpenPose is an open-source real-time human 2D pose estimation method. It introduces a novel bottom-up approach to pose estimation using Part Affinity Fields (PAFs) to learn to associate body parts of a person in images or videos.Overall pipeline of OpenPose is shown in Figure 3.4 [18].

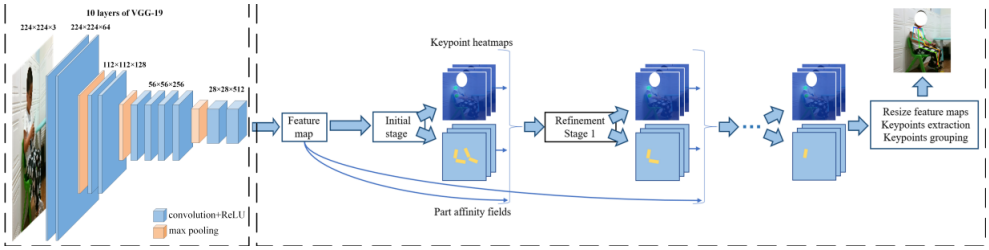


**Figure 3.4: Overall pipeline of OpenPose**

### 3.4.1 The architecture of OpenPose

The system takes a color image/video as input, then analyzes it with a CNN initialized and fine-tuned base on the first 10 layers of VGG-19 [19]. A set of feature maps generated from CNN are fed into another multi-stage CNN. The first set of stages predicts and refines PAFs, which is a set of 2D vector fields that encode the degree of association between body parts. The last set of stages generate confidence maps of body part locations. Finally, the confidence maps and the PAFs are parsed by bipartite matching to obtain 2D keypoints for each person in the image.

### 3.4.2 Part Affinity Fields for Part Association

PAFs [20] contain location and orientation information across the region of support of the limb. It is a set of flow fields that encodes the unstructured pairwise relationship between body parts. Each pair of body parts have one PAF. PAFs are represented as set $L = (L_1, L_2, ...L_c)$ where $L_c \, \varepsilon \, \mathbb{R}^{w \times h \times 2}, c \, \varepsilon \, \{1...c\}$ C denotes the number of pairs of body parts, $w \times h$ is the size of the input image. Each image location in $L_c$ encodes a 2D vector, if it lies on the limb c between body parts $j_1$ and $j_2$. The value of PAF at that point is a unit vector that points from $j_1$ to $j_2$; otherwise, the vector is zero-valued. The ground truth PAF $L^*_{c,k}$ at a point **p** for person p is shown in Eq. 3.1

$$L^*_{c,k}(p) = \begin{cases} \frac{x_{j_2,k} - x_{j_1,k}}{||x_{j_2,k} - x_{j_1,k}||_2} \end{cases} \tag{3.1}$$

### 3.4.3 Confidence Map for Part Detection

Each confidence map is a 2D representation of the belief that a particular body part can be located in any given pixel. Each body part has one corresponding confidence map. Confidence maps are represented as set

$S = (S1_1, S_2, ...S_j)$ where $S_j \varepsilon \mathbb{R}^{w \times h}$, $j \varepsilon \{1...j\}$ and J denotes the number of body parts.

Individual confidence maps $S^*_{j,k}$ for each person k is defined in Eq. 3.2

$$S^*_{j,k}(p) = \exp\left\{ -\frac{||p - x_{j,k}||^2_2}{\sigma^2} \right. \tag{3.2}$$

where $x_{j,k}$ is the ground truth position of the body part j of person k.The ground truth confidence map is an aggregation of individual confidence maps is shown in Eq. 3.3

$$S^*_j(p) = \max S^*_{j,k}(p) \tag{3.3}$$

### 3.4.4 Multi-stage CNN

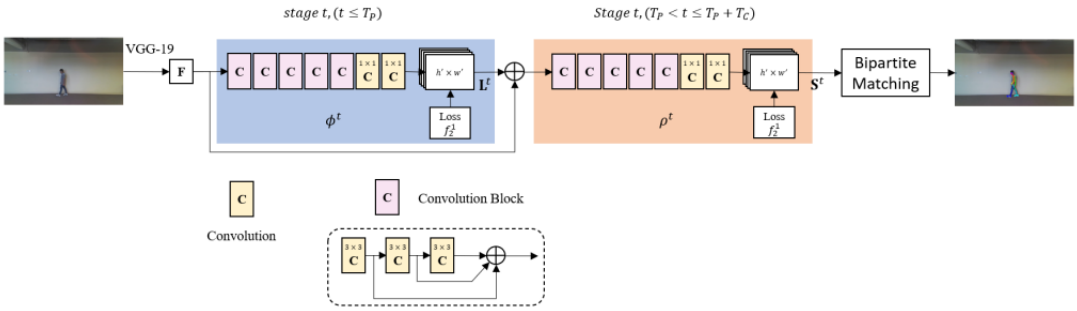


**Figure 3.5: Architecture of the multi-stage CNN**

Stage t = 1: Given the feature maps **F** generated from VGG-19, the network computes a set of part affinity fields,$L^1 = \Phi^1(F)$ where $\Phi^1$ refers to the CNN at stage 1[18].

Stage $2 \leq t \leq T_p$ : Original feature maps **F** and the PAF prediction from previous stage are concatenated to refine the prediction as shown in Eq.

3.4

$$L^t = \Phi^t(F, L^{t-1}), \forall 2 \leqq t \leqq T_P \tag{3.4}$$

$T_P$ refer to the number of PAF stages, $\phi^t$ is the CNN at stage t.

Stage $T_p \leq t \leq T_p + T_c$ : After $T_p$ iterations, starting from the most updated PAF prediction $L^{T_P}$, the process is going to be repeated for $T_c$ iterations to refine confidence map detection as shown in Eq. 3.6

$$S^{T_P} = \rho^t(F, L^{T_P}), \forall t = T_P \tag{3.5}$$

$$S^t = \rho^t(F, L^{T_P}, S^{t-1}), \forall T_P < t \leqslant T_p + T_c \tag{3.6}$$

$T_c$ refer to the number of confidence map stages,$\rho^t$ is the CNN at stage t.

An $L_2$ loss function is applied at the end of each stage; it is specially weighted to tackle the case when people in some images are not completely labeled. Loss function at PAF stages $t_i$ is shown in Eq. 3.7

$$F_L^{ti} = \sum_{c=1}^{c} \sum_{p} w(p).||L_c^{ti}(p) - L_c^*(p)||_2^2 \tag{3.7}$$

where $L_c^*$ is the ground truth PAF, W s a binary mask. If pixel p is not labeled, W(p) = 0.Loss function at confidence map stages $t_k$ is shown in Eq. 3.8

$$F_S^{tk} = \sum_{j=1}^{j} \sum_{p} w(p).||S_j^{tk}(p) - S_j^*(p)||_2^2 \tag{3.8}$$

where $S_j^*$ is the ground truth part confidence map. The overall objective is to minimize the total loss is shown in Eq.3.9

$$f = \sum_{t=1}^{T_p} f_L^t + \sum_{t=T_p+1}^{T_P+T_c} f_S^t \tag{3.9}$$

To evaluate f in Eq. (3.9) during training, openpose generate the groundtruth confidence maps S from the annotated 2D keypoints. Each confidence map is a 2D representation of the belief that a particular body part can be located in any given pixel. Ideally, if a single person appears in the image, a single peak should exist in each confidence map if the cor-responding part is visible.

### 3.4.5 Person Parsing using PAFs

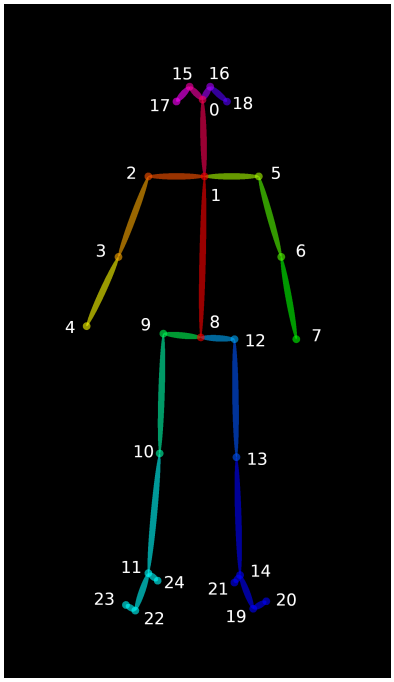


**Figure 3.6: BODY_25 skeleton output**

Person Parsing is performed by following steps. First, obtain a set of part candidate locations from confidence maps. Then find the pairs of body parts that connect limbs using PAF. Finally, assemble limbs that belong to the same person into full body poses. The output of the OpenPose is BODY-25

output format as figure 3.6 shows, it consists of an (x, y) coordinate pair and confidence score for each of 25 joints [21].

## 3.5 Time Series Analysis

After getting pose estimation of each frame in the videos,Gait Deviation Index (GDI) has to be calculated. GDI aims at providing a comprehensive, easy to interpret, and clinically meaningful metric of overall gait function. It has been used as an outcome measure to study gait in several conditions: cerebral palsy (CP), post-stroke hemiparetic gait, and Parkinson's disease among others. The GDI provides a numerical value that expresses overall gait where 80 + indicates the absence of PD in gait pathology. Below 80 the freezing of gait occurs . GDI is calculated with eight features derived from openpose keypoints video frame.The features used for calculating GDI are "LHip" (Keypoint 12),Left lower leg: "LKnee" (keypoint 13),"LAnkle" (keypoint 14) and "LToe" (keypoint 19),"RHip" (Keypoint 9) Right lower leg: "RKnee" (keypoint 10),"RAnkle" (keypoint 11) and ("RToe" keypoint 22) as Table 3.1 and Table 3.2 shows

**Table 3.1: List of body part angles**

| *AngleName* | *Joints* |
|---|---|
| ankle knee hip Left | LANK(keypoint 14), LKNE(keypoint 13), LHIP(Keypoint 12) |
| toe ankle knee Left | LBTO(keypoint 19), LANK(keypoint 14), LKNE(keypoint 13) |
| ankle knee hip Right | RANK(keypoint 11), RKNE(keypoint 10), RHIP(Keypoint 9) |
| toe ankle knee Right | RBTO(keypoint 22), RANK(keypoint 11), RKNE(keypoint 10) |

**Table 3.2: List of body part Distance**

| *Distance* | *Joints* |
|---|---|
| toe ankle dist right | RBTO(keypoint 22), RANK(keypoint 11) |
| toe ankle dist left | LBTO(keypoint 19), LANK(keypoint 14) |

Angles of each lower leg respect to the vertical axis in each frame has to be calculated.Gait Deviation Index (GDI) could be feasible to characterize gait in patients with Parkinson's disease (PD) and evaluate outcomes of levodopa treatment.Each video has two corresponding time series representing the angles mentioned above.

- The first time series model is the difference between the x-coordinates (horizontal image-plane coordinates) of the left and right ankles
  throughout time, which approximated the 3D distance between ankle centers.
- The second time series model is the image-plane angle formed by the ankle, knee, and hip keypoints. computed the angle between the vector from the knee to the hip and the vector from the knee to the ankle

## 3.6 Freezing of Gait

Freezing of gait (FoG) affects over half the population with advanced Parkinson's disease (PD) [22]. This highly disabling symptom is defined as "brief episodes of inability to step or by extremely short steps that typically occur on initiating gait or on turning while walking.Freezing of gait is an ab normal gait pattern that can accompany Parkinson's disease (PD) as well as other parkinsonian disorders in which there are sudden, short and temporary episodes of an inability to move the feet forward despite the intention to walk. In a sense, you're stuck. This results in the characteristic appearance of the feet making quick stepping movements in place. However, while the feet remain in place, the torso still has forward momentum which makes falls unfortunately common in the context of freezing of gait. For some, these episodes can simply

be frustrating, annoying and perhaps embarrassing; for others freezing of gait can become incredibly disabling and lead to injury.

Freezing of gait episodes tend to occur least often when walking on an unobstructed, straight path. Any deviation from that can induce freezing – for example, when you first try to start walking, when you go to make a turn, or try to navigate around obstacles or through narrow spaces – any of these can cause you to get "stuck."

The particular triggers for one person may be different than for another. An episode is typically very brief, often lasting only 1-2 seconds, although they can last longer. Freezing of gait can be affected by anxiety, so if a person feels rushed (e.g. under a time constraint to board an elevator before the doors close), freezing may be particularly prominent.

## 3.7 Hoehn Yahr Severity Scale

Hoehn and Yahr was originally published in 1967 in the journal Neu rology by Margaret Hoehn and Melvin Yahr and included stages 1 through 5. In 1983 Pandey et al.[23] published an article entitled "Theoretical and practical issues in assessment of deficits and therapy in Parkinsonism," wherein they included a modification of the original Hoehn and Yahr scale. They added some minor alterations which did not substantially change the basic classification published in 1967. This scale is used along with Unified Parkinson's Disease Rating Scale for a better assessment of Parkinson's disease. The scale has been used for the staging of the functional disability associated with Parkinson's disease. It helps in describing the progression of the disease through various stages, thus allowing us to measure the severity of the case. The modified Hoehn and Yahr scale is as follows :

- Stage 0: No signs of disease
- Stage 1.0: Symptoms are very mild; unilateral involvement only
- Stage 1.5: Unilateral and axial involvement
- Stage 2: Bilateral involvement without impairment of balance
- Stage 2.5: Mild bilateral disease with recovery on pull test
- Stage 3: Mild to moderate bilateral disease; some postural instability; physically independent
- Stage 4: Severe disability; still able to walk or stand unassisted
- Stage 5: Wheelchair bound or bedridden unless aided

In next chapter,Algorithm , Pseudo code and explanation of the various modules used in the project are described.

# CHAPTER 4

# ALGORITHM AND PSEUDO CODE

This section explains in detail the various modules in the system. Each module includes the input for the module, process flow for the module and output for the module in detail.

## 4.1 GAIT DEVIATION INDEX CLASSIFICATION USING DECISON TREE

The goal of using a Decision Tree is to create a training model that can use to predict the class or value of the target variable by learning simple decision rules inferred from prior data(training data). Classification is a two-step process, learning step and prediction step, in machine learning. In the learning step, the model is developed based on given training data. In the prediction step, the model is used to predict the response for given data. Decision Tree is one of the easiest and popular classification algorithms to understand and interpret.Decision trees represent rules, which can be understood by humans and used in knowledge system such as database. A decision tree is a hierarchical model for supervised learning whereby the local region is identified in a sequence of recursive splits in a smaller number of steps. A decision tree is composed of internal decision nodes decision node and terminal leaves. Each decision node m implements a test function fm(x) with discrete outcomes labelling the branches. Given an input, at each node, a test is applied and one of the branches is taken depending on the outcome. This process starts at the root and is repeated recursively until a leaf node is hit, at which point the value written in the leaf constitutes the output. A decision tree is also a nonparametric model in the sense that we do not assume any parametric form for

the class densities and the tree structure is not fixed a priority but the tree grows, branches and leaves are added, during learning depending on the complexity of the problem inherent in the data.ecision tree is a classifier in the form of a tree structure which consists of:

- Decision node: specifies a test on a single attribute.
- Leaf node: indicates the value of the target attribute.
- Edge: split of one attribute
- Path: a disjunction of test to make the final decision.

### 4.1.1 ID3 Algorithm

ID3 stands for Iterative Dichotomiser 3 and is named such because the algorithm iteratively (repeatedly) dichotomizes(divides) features into two or more groups at each step.The ID3 follows the Occam's razor principle.Attempts to create the smallest possible decision tree.

**The Process :** Take all unused attributes and calculates their entropies then Chooses attribute that has the lowest entropy is minimum or when information gain is maximum Makes a node containing that attribute

**Entopy and Information gain :** Entropy can be said to be the amount of randomness that exists in a particulat set of data, while information gain is a measure of reduction in entropy due to a feature, or, how well does a feature separate the "target feature". Entropy is defined as Eq. 4.1 shows.

$$Entropy(s) = -\sum p_i * \log_2(p_i)\, i = 1\, to\, n \tag{4.1}$$

Formula for entropy. $p_i$ is the fraction of the dataset whose target feature/attribute is 'i', and 'n' is the total possible values that the target

feature/attribute can have.

Information Gain is defined as Eq. 4.2 shows.

$$IG(S,A) = Entropy(s) - \sum((|S_v| \,/\, |S|) * Entropy(S_v) \tag{4.2}$$

Formula for Information Gain for a particular feature/attribute. $S_v$ is the fraction of the dataset where the feature 'A' is 'v', and —S— is the number of entries in the dataset.

## 4.2 Algorithm of Decision Tree using ID3

1: ID3 (Examples, Target Attribute, Attributes)
2: Create a root node for the tree
3: If all examples are positive, Return the single-node tree Root, with label = +.
4: If all examples are negative, Return the single-node tree Root, with label = -.
5: If number of predicting attributes is empty, then Return the single node tree Root,
6: with label = most common value of the target attribute in the examples.
7: Otherwise Begin
8: A ← The Attribute that has maximum Information gain
9: Decision Tree attribute for Root = A.
10: For each possible value, vi, of A,
11: Add a new tree branch below Root, corresponding to the test A = vi.
12: Let Examples(vi) be the subset of examples that have the value vi for A
13: If Examples(vi) is empty
14: Then below this new branch add a leaf node with label = most common target value in the examples
15: Else below this new branch add the subtree ID3 (Examples(vi), Target Attribute, Attributes – A)
16: End
17: Return Root

**Methodology :** Split the dataset which involves iterating over each row, checking if the attribute value is below or above the split value and assigning it to the left or right group. From dataset,must check every value

on each attribute as a candidate split, evaluate the cost of the split and find the best possible split. Once the best split is found, it can use as a node in decision tree. Build a tree recursively until get all the leaf nodes based on two criteria: Maximum tree depth and Minimum node record. Then, make predictions using the tree by navigating the tree upto its leaf node. Evaluate the accuracy of the algorithm using training test set and cross-validation set as shows in Algorithm 4.2

## 4.3 Pseudo Code

- Input : 8 Derived Features from video Keypoints.(Body joints angle and distance)
- Output : 0/1 (PD/Not PD)

```
1: from sklearn.model_selection import train_test_split
2: from sklearn.preprocessing import StandardScaler
3: sc_X = StandardScaler()
4: X_train = sc_X.fit_transform(X_train)
5: X_test = sc_X.transform(X_test)
6: from sklearn.tree import DecisionTreeClassifier
7: model = DecisionTreeClassifier(criterion="entropy",max_depth=5)
8: model = model.fit(X_train,y_train)
9: #prediction y_pred = model.predict(X_test)
10: from sklearn import metrics
11: print('Accuracy Score:', metrics.accuracy_score(y_test,y_pred))
```

**Explanation :** First of all Fit the model in the Decision Tree classifier and then Make predictions and check accuracy.The decision tree classifier gave an accuracy of 88%.

## 4.4 GAIT DEVIATION INDEX USING PRE-TRAINED MODEL USING CNN

CNN model is a parameterized mapping from a fixed-length time-series data (i.e.key points) to an outcome metric (eg. gdi). The key building block of model is a 1-D convolutional layer.The input to a 1-D convolutional layer consisted of a T × D set of neurons, where T was the number of points in the time dimension and D was the depth (the dimension of the multivariate time-series input into the model). Each 1-D convolutional layer learned the weights of a set of filters of a given length Each convolutional layer had 32 filters and a filter length of eight. We used the rectified linear unit (ReLU), defined as f(x) = max(0, x), as the activation function after each convolutional layer. Trained CNN on 124-frame segments from the videos.Augmented the time-series data using a method sometimes referred to as window slicing, which allowed us to generate many training segments from each video. From each input time series, X, with length 500 in the time dimension and an associated clinical metric (e.g., GDI) extract overlapping segments of 124 frames in length, with each segment separated by 31 frames.[24]

## 4.5 FREEZING OF GAIT DETECTION USING DEEP LEARNING MODEL

Based on the data from 3 acceleration sensors, the Freezing of GAIT Detection Model is shown in Figure 4.1. The output of this model is the detection of the presence of Freezing of GAIT (FOG) in the patients.

Dataset Used : Daphnet
Input : Sensor data
Output : 0/1 (No Freeze / Freeze)

Input data features = ['Time', 'ankle-x', 'ankle-y', 'ankle-z',

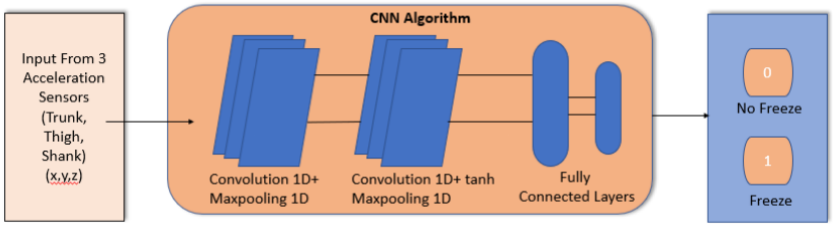


**Figure 4.1: FOG Detection Model**

'thigh-x', 'thigh-y', 'thigh-z', 'trunk-x', 'trunk-y', 'trunk-z', Annotations]

### 4.5.1 Data Format

Each file comprises the data in a matrix format, with one line per sample, and one column per channel [25]. The channels are as follows:

1. Time of sample in millisecond
2. Ankle (shank) acceleration - horizontal forward acceleration
3. Ankle (shank) acceleration - vertical
4. Ankle (shank) acceleration - horizontal lateral
5. Upper leg (thigh) acceleration - horizontal forward acceleration
6. Upper leg (thigh) acceleration - vertical
7. Upper leg (thigh) acceleration - horizontal lateral
8. Trunk acceleration - horizontal forward acceleration
9. Trunk acceleration - vertical
10. Trunk acceleration - horizontal lateral

11. Annotations

**Annotations** The meaning of the annotations are as follows:
0: not part of the experiment. For instance the sensors are installed on the user or the user is performing activities unrelated to the experimental protocol, such as debriefing
1: experiment, no freeze (can be any of stand, walk, turn)
2: freeze

### 4.5.2 CNN Algorithm For FOG Detection

CNN is a kind of deep neural network, that has the capability to work as a function extractor. These types of networks can be applied in temporary signals and images to work as a type of filter that automatically extracts discriminant characteristics. This type of network can group several convolutional operators to create some hierarchical and progressively more abstract features that are learned automatically. For the model based in fully connected neural networks and convolutional layers, two 1D-CNN layers with max-polling for automatic feature extraction were used, while three fully connected layers were used for classification.

The first convolutional layer has 128 filters and a kernel size of 3. The second layer has 128 filters and a kernel of 3, the pool size in the max-pooling layers was set 2 in all cases.The forth and fifth layer has 64 filters ,the pool size in the max-pooling layers were set to 2 and layers seventh and eighth has filter 32 and kernel of 3. In order to connect the convolutional to the fully connected layers, a flatten layer was used in between.

After the convolutional layers, two dense layers were connected. The first dense layer has 128 neurons , and the output layer uses 1 neuron. All layers

in the model use tanh as activation functions, except the last one that uses a softmax activation to output the probability of a FOG event.

The configuration that achieved the best performance in the training process was 27 epochs, batch size equal to 500. The loss function was the binary cross entropy with Adam optimizer.

## 4.6 PARKINSON'S DISEASE SEVERITY MODEL

Based on the data from 16 force sensors, the Parkinson's Disease Severity Classification model is shown in Figure 4.2. The output of this model is the classification of the severity of PD in the patients based on the Hoehn Yahr (HY) scale.

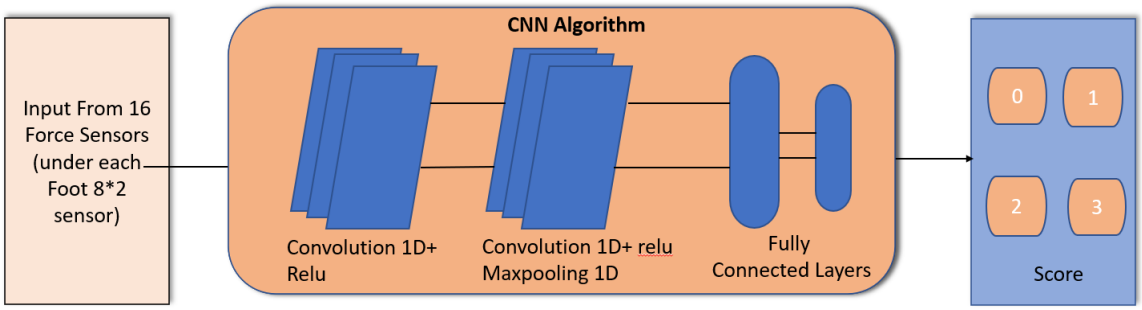


**Figure 4.2: PD Severity Model**

Dataset Used : Physionet
Input : Sensor data
Output : 0/1/2/3 (Severity Level)

features = ['Time', 'L1' , 'L2', 'L3', 'L4', 'L5', 'L6', 'L7', 'L8', 'R1', 'R2', 'R3', 'R4', 'R5', 'R6', 'R7', 'R8', 'Total_Force_Left', 'Total_Force_Right']

### 4.6.1 Data Format

Each line contains 19 columns.Column 1 consist of Time (in seconds). Columns 2-9 consist of Vertical ground reaction force (VGRF, in Newton) on each of 8 sensors located under the left foot. Columns 10-17 consist of VGRF on each of the 8 sensors located under the right foot. Column 18 and 19 consist of Total force under the left foot and right foot.

When a person is comfortably standing with both legs parallel to each other, sensor locations inside the insole can be described as lying approximately at the following (X,Y) coordinates, assuming that the origin (0,0) is just between the legs and the person is facing towards the positive side of the Y axis:

```
------Sensor coordinates------
    Sensor       X      Y
---------------------------
L1          -500   -800
L2          -700   -400
.
L8          -500    800

R1           500   -800
R2           700   -400
.
R8           500    800
```

The X and Y numbers are in an arbitrary coordinate system reflecting the relative (arbitrarily scaled) positions of the sensors within each insole. During walking, the sensors inside each insole remain at the same relative

position, but the two feet are no longer parallel to each other. Thus, this coordinate system enables a calculation of a proxy for the location of the center of pressure (COP) under each foot.The sampling rate was 100 Hz [26].

### 4.6.2 CNN Algorithm For PD Severity Model

The first convolutional layer has 64 filters and a kernel size of 3. The pool size in the max-pooling layers was set 2 in all cases.The second layer has 64 filters and a kernel size of 3 ,the pool size in the max-pooling layers were set to 2.In order to connect the convolutional to the fully connected layers, a flatten layer was used in between with a dropout of 0.5.

After the convolutional layers, two dense layers were connected. The first dense layer has 100 neurons , and the output layer uses 1 neuron. All layers in the model use relu as activation functions, except the last one that uses a softmax activation to output the probability of a FOG event.

The configuration that achieved the best performance in the training process was 13 epochs, batch size equal to 500. The loss function was the binary cross entropy with Adam optimizer.

In next chapter the result and analysis for each model along with the summary and graphical analysis is described.

# CHAPTER 5

# RESULTS AND ANALYSIS

This section includes the result and analysis for each model along with the summary and graphical analysis

## 5.1 RESULT

This section of the chapter shows all the results obtained from the system or applications:

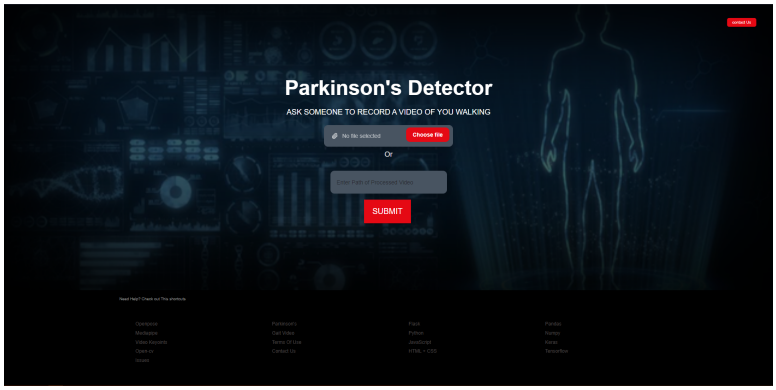


**Figure 5.1: HomePage**

### 5.1.1 Input

In (Figure 5.1) system take first input from user.There's 2 ways to take input First as Video File and Second as Openpose Processed Video File path.


**Figure 5.2: Parkinson's Result**

### 5.1.2 PD Result

In (Figure 5.2) system shows the results based on GAIT parameter (GDI). If the patient has no symptoms found, then the user is redirected to the homepage. but if patients have symptoms found then the app shows to check the FOG Severity Level.(Figure 5.3)

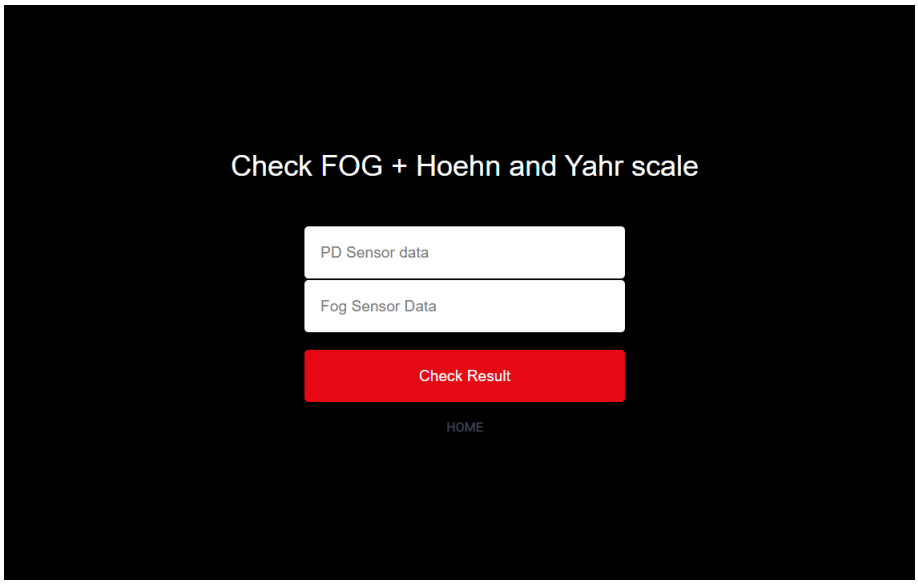


**Figure 5.3: FOG + Hoehn and Yahr scale Test**

### 5.1.3 Fog and Severity check

In (Figure 5.3) system take two input from user

1. Physionet Sensor Data

2. Daphnet Sensor Data

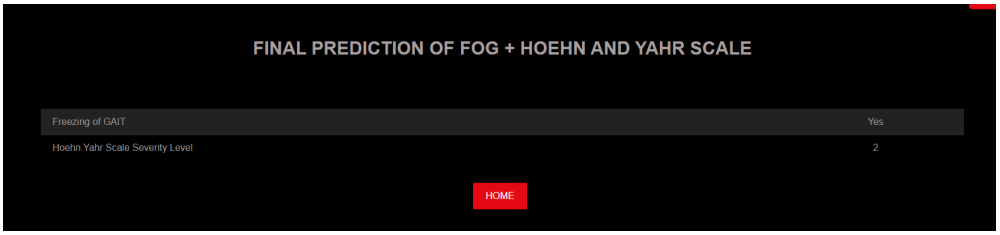


**Figure 5.4: Final Result**

### 5.1.4 Final Result

In (Figure 5.4) system shows the FOG as Yes or No and Severity Level between 0 to 3

## 5.2 ANALYSIS

### 5.2.1 Evaluation of Gait Deviation Index model

```
Accuracy: 0.875438596491228 = 88%
confusion Matrix :
array([[ 21, 111],
       [ 71, 937]], dtype=int64)
Classification Report
```

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.14 | 0.02 | 0.03 | 132 |
| 1 | 0.88 | 0.99 | 0.93 | 1008 |

```
    accuracy                           0.88      1140
   macro avg       0.51      0.50      0.48      1140
weighted avg       0.80      0.88      0.83      1140
```

Accuracy, Confusion Matrix and Classification of ID3 Model are shown and Evaluating model output

input: 8 Keypoints derived feature

Original Output : 1

```
model.predict([[2.8847466906306938,2.9376638011776786,
2.561574636308094,2.5676729208515265,0.38224499328243783,
0.36999847804478586,0.10507483363378983,-0.10507483363378983]])
```

predicted output : array([1], dtype=int64)

### 5.2.2 Evaluation of FOG detection Model

```
Accuracy for Test Data =  91.07029765674477

Classification Report
              precision    recall  f1-score   support

           0       0.92      0.99      0.95      2842
           1       0.71      0.18      0.29       316

    accuracy                           0.91      3158
   macro avg       0.81      0.59      0.62      3158
```

```
weighted avg       0.90      0.91      0.89      3158
```

Accuracy and Classification of FOG Model are shown.

### 5.2.3 Evaluation of PD Severity Model

```
Accuracy for Test Data =  89.67436263818907

Classification Report
              precision    recall  f1-score   support

           0       0.83      0.90      0.86      2862
           1       0.88      0.86      0.87      2708
           2       0.93      0.91      0.92      6720
           3       0.90      0.92      0.91      1007

    accuracy                           0.90     13297
   macro avg       0.89      0.90      0.89     13297
weighted avg       0.90      0.90      0.90     13297
```

Accuracy and Classification of PD Severity Model are shown and Evaluating Model Output of PD Severity FOG Model

```
for x in range(2):
    i = random.randrange(0, min(len(testX), len(fog_testX)))
```

```
    final_prediction(HY_model,FOG_model, testX[i],
        fog_testX[i], fog_testy[i])
```

Output:

```
ORIGINAL CLASS
Freeze
--------------------
PREDICTION
Freezing of GAIT
Hoehn Yahr Scale Severity: Healthy Control
_____________________________________________
ORIGINAL CLASS
No Freeze
--------------------
PREDICTION
No Freezing of GAIT
Hoehn Yahr Scale Severity: 2.5 severity
_____________________________________________
```

In this above block output is categorized into two parts. Original class and prediction. Original Class shows the Original category of the data and prediction shows the prediction on original class data with Hoehn Yahr Scale Severity level.

In next chapter, Conclusion and Future work of the project are described.

# CHAPTER 6

# CONCLUSION AND FUTURE WORK

## 6.1 CONCLUSION

In recent years, the number of people suffering from PD has increased substantially and is recorded as the deadly health issue worldwide. Making certain efforts,This thesis provides a video & sensor based gait analysis system to detect Parkinson's Disease and capture gait features non-invasively over time. Gait analysis and gait abnormality detection allow early intervention and treat ment to prevent underlying conditions develop and causing a fall. The system consists of three stages, First, the Openpose library converts the video frames into key points. pose estimation is applied to extract the sequence of skeleton and joints in the video.Then feature extraction and gait classification is performed to calculate gait parameters and classify if the gait is normal or abnormal and check for Parkinson's Gait abnormality from Derived features and predict PD from GDI. Second, if PD is detected then Freezing of gait (FOG) is one of the most incapacitating motor symptoms in Parkinson's disease Hoehn and Yahr scale (HY) the scale used for the staging of the functional disability associated with Parkinson's disease is Predicted from the sensor placed on patients foot and legs.

## 6.2 FUTURE WORK

This work can be extended by adding the most relevant set of PD gait features in order to enhance the classification accuracy. Human natural gait appearance can change due to many factors such as walking surface, footwear type, clothing variations, and carrying conditions, etc. for example in Indian

subcontinent women wear saree (traditional dress) which affects gait patterns as compared to women wearing short skirts, jeans. Hence, future work can be directed towards the development of enhanced and effective pre-processing techniques that can handle such concern and can perform robust background modeling for improved PD inquiry, to perform improved and more reliable PD analysis that can be useful for their rehabilitation.

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