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Pattern identification of different human joints for different human walking styles using inertial measurement unit (IMU) sensor

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Abstract

A bipedal walking robot is a kind of humanoid robot. It is suppose to mimics human behavior and designed to perform human specific tasks. Currently, humanoid robots are not capable to walk like human being. To perform the walking task, in the current work, human gait data of six different walking styles named brisk walk, normal walk, very slow walk, medium walk, jogging and fast walk is collected through our configured IMU sensor and mobile-based accelerometers device. To capture the pattern for six different walking styles, data is extracted for hip, knee, ankle, shank, thigh and foot. A total six classes of walking activities are explored for clinical examination. The accelerometer is placed at center of the human body of 15 male and 10 female subjects. In the experimental setup, we have done exploratory analysis over the different gait capturing techniques, different gait features and different gait classification techniques. For the classification purpose, three state of art techniques are used as artificial neural network, extreme learning machine and deep neural network learning based CNN mode. The model classification accuracy is obtained as 87.4%, 88% and 92%, respectively. Here, WISDM activity data set is also used for verification purpose.

Keywords Clinical gait · Connectionist learning · Biometrics · Human activities recognition · Motion analysis · Deep learning

1 Introduction

Gait assessment refers to the study of human locomotion (Semwal 2017; Semwal and Nandi 2015), which plays a significant role in clinical examination for the identification of gait abnormality for neurological disorder person (Semwal et al. 2015b; Sivakumar et al. 2016). This can also be used in biometrics as it is unique and difficult to hide. Tables 1 and 2 show the important comparative study of gait biometrics (Bovi et al. 2011; Patil et al. 2019). The human gait can be utilized for wide number of applications

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Table 1 Different physiological based biometric characteristics (Patil et al. 2019)

Biometric traits	Universality	Distinctiveness	Permanence	Collectabilty	Circumvention
Face	High	Medium	Medium	High	Low
Iris	High	High	High	Medium	Low
Palm print	High	High	Medium	Medium	Medium
Fingerprint	High	High	Medium	Medium	High
Retina	High	High	High	Low	Low

Table 2 Different behavior based biometric characteristics (Patil et al. 2019)

Biometric traits	Universality	Distinctiveness	Permanence	Collectability	Circumvention
Gait	Low	Medium	Low	High	Low
Speech	High	Medium	High	Medium	Medium
Signature	High	Medium	Low	Medium	Low
Keystroke	High	Medium	Low	Medium	Low
Device uses	Low	Medium	Low	High	Low

e.g., surveillance (Kusakunniran et al. 2009), forensics (Zhang et al. 2011), biometric identification (Chaki et al. 2019), rehabilitation (Yang et al. 2017), clinical assessment (Gallow and Heiderscheit 2016) and prosthesis development (Nandi et al. 2009). Real-time tracking of human walking provide important information about individual's gait biometric through which one can investigate different clinical analysis for gait abnormality (Semwal et al. 2018) and reconstruction of gait (Semwal and Nandi 2016). The human gait is the coordination of two limbs with forward propulsion of Center of Mass (CoM). The inherent nature of human gait is bipedal & biphasic i.e., swing & stance phase (Semwal et al. 2013a, 2015c). The gait signatures are captured by changes in the joints angle of hip, knee, ankle, shank, thigh and foot of left and right human legs (Raj et al. 2018a).

1.1 Problem description and motivation

Gait disorder is the most common clinical problem of stroke survivors patients; thus, it is a major targeted area for the research of post-stroke rehabilitation. Human gait analysis, study of human locomotion & push recovery (Semwal et al. 2013b), is very useful in diagnosing the patients of neurological disorders, post-stroke hemiparetic patients, rehabilitation of patients, analysis of sports-person patterns, unique biometric identification and other focused research areas. The popularly known human motion capture systems for gait analysis are vision-based in which markers are positioned on the human body with multiple Infrared (IR) sensors, thus, system is accurate but very cost expensive and should need a specific controlled environment (Chan et al. 2018). Force plates are also used for gait analysis but, these devices are very expensive and need specific clinical labs environment also, it is used to measure the dynamics of lower limbs only (Weiss et al. 2012a).

1.2 Author's contribution

The major contribution of this work is to analyze the six different walking activity using gait analysis. To achieve the objective following tasks are performed.

- The gait data of 25 subjects using IMU based wearable sensors is captured. These sensors are placed to various parts of the body and capture the real time data for different walking activities.
- The mobile phone based accelerometer is used for walking activities tracking. The 9-degree IMU sensor consists of 3-degree of freedom (dof) accelerometer sensor (ax, ay & az), 3-dof gyroscope sensor (gx, gy & gz) and 3-degree of magnetometer sensor (mx, my & mz).
- In the experimentation, the 6-dof IMU sensor (IMU BWT61CL) is used for accelerometer data. The walking trajectories of 6 joins, namely, Hip, Knee, Ankle, Foot, Shank and Thigh for gait analysis is also being calculated (Gouwanda et al. 2016).
- Finally, the 6 features of raw data named subject-id, time stamp, ax, ay, az, and activities name is being provided as input for machine learning (ML) algorithm. The ANN (Nandi et al. 2016), ELM (Semwal et al. 2019) and DNN (Semwal et al. 2017b) based ML algorithm is being applied for classification.

From the obtained results, better accuracy is achieved as compared to previous work. The walking pattern of different joints can be utilized for the assessment & recovering of rehabilitation of individuals with abnormal gait. The muscular activity pattern of a healthy subject is compared with rehabilitation walk. The proposed technique is very robust & accurate in clinical analysis. We have reported 87.84%, 88% and 92% accuracy using ANN, ELM and CNN model respectively for clinical walking data.

1.3 Organization of research article

The remainder section of this paper is divided as follows. The second section is literature review about gait analysis techniques and comparison of different biometric identification. This selection also, presents the study of various gait capturing techniques and various gait classification techniques. Section 3, describes about data collection and prepossessing of raw data. This section also, describes data set description and different human walking activities recognition tasks. The fourth section is methodology and proposed algorithm. The fifth section is about results and analysis of different joints angle analysis. This section also, presents the classification of human gait using neural network, deep learning based CNN model and ELM. The fifth and final section describes our conclusion and future scope.

2 Literature review of related work

There are three popularly known techniques to capture the gait data using Kinect sensor, IMU sensor and force plate sensor based approach for gait analysis. The Kinect sensor extract 3D virtual skelton data of human being and joint position information data is being extracted from the stick model. This system analyzes the spatio-temporal features such as gait cycle time, stride length, left & right steps length, and kinematic features like hip, knee, ankle joints angle. The kinect based technique is further categorized into 2 parts, model based approach and model free approach. The model based approach is view and scale invariant but required a lot of parameters. Whereas, IMU & accelerometer sensor based technique is noninvasive and less parameters. Table 3 present the comparison of all gait data collection techniques.

Hsu et al. (2018) proposed the multiple wearable sensors based technique to analyzing and classifying the gait data of neurological disorders patients. They have collected gait data for patience suffering from freezing of gait, multiple sclerosis, cerebral palsy and stroke (Hsu et al. 2018). The seven sensor were placed on 20 subjects to collect features. They applied many machine leaning for classification out of which Multi-layer Perceptron (MLP) outperform others. Clinical gait assessment can also be utilized for early diagnosis of gait abnormality in neurological disorder subjects. Lau et al. (2009) applied support vector machine (SVM) for analyzing of walking conditions of stroke survive patient with dropped foot. In Patil et al. (2019), used different types of classification techniques to identify the patients suffering from neurological disorders and stroke patients. The performance of the ELM classifier was found to be the best in terms of accuracy and performance time. In Adil et al. (2016) proposed surface electromyography (sEMG) signal in order to recognize drop foot of the stroke patients and provide a therapy as they needed for rehabilitation. They used ELM classifier to classify the healthy and weak muscles of the human leg and the performance was also compared with the SVM and ANN. The performance of the ELM can be further increased by eliminating sensitivity of its hyper parameters by considering a variable length optimization using particle swarm algorithm (Ekinci 2006). This technique was also used to optimize the hidden layers neurons of ELM corresponding to input weights and biases. Another approach was proposed by Guo et al. (2019) to identify gait disorders in Parkinson's disease by using machine learning algorithms in 2019. This model was used to classify four different types of gait abnormality. Another novel approach was proposed by Mekruksavanich and Jitpattanakul (2019) where wearable sensors on smartphones were used to collect data. The study was made to classify gait patterns for three different activities like walking upstairs, walking downstairs and walking on floor (Mekruksavanich and Jitpattanakul 2019) using different types of learning techniques.

Gait can also be used as a biometric characteristic which can find its application in various fields like surveillance and forensics (Connor and Ross 2018; Semwal et al. 2017a; Chellappa et al. 2007; Anusha and Jaidhar 2019). A number of techniques have been proposed like utilizing mutual information obtained from a query and gallery sample. This method uses the region of interests (ROI) extracted from gait energy image to perform classification and identification. In another approach Li et al. (2019), proposed a method in which subject is identified from extracting skeleton information obtained from single depth sensors. Another application of gait analysis is in clinical and medical purposes where the patients suffering

Table 3 Different technique to acquire the human gait data

Data acquisition technique	References
IMU sensor based	Semwal et al. (2017b), Akdoğan and Yilmaz (2014), Sivakumar et al. (2018)
Computer vision	Chellappa et al. (2007), Anusha and Jaidhar (2019)
Model free approach using kinect	Guo et al. (2019), Akdoğan and Yilmaz (2014)
Model based approach using kinect	Bovi et al. (2011), Milovanovic (2008)

from neurological disorders can analyze their gait abnormalities and can design personalized treatment (Papavasileiou et al. 2017). Human gait classification is also an important area of research interest where a number of techniques are implemented to study and analyze the gait pattern for different human locomotion activities like walking, running, climbing, etc (Bovi et al. 2011). Chen et al. (2018) proposed deep convolutional neural networks (DCNNs) based on multistatic radar micro-Doppler signatures for gait classification. A new gait based gender classification method based on kinect sensor was proposed by Ahmed and Sabir (2017) and Blumrosen et al. (2016).

Bayat et al. (2014) proposed the mobile based accelrometer for data capturing of different human activity (Bayat et al. 2014). Lockhart et al. (2011, 2012) presented smart phone based sensor mining architecture for capturing different human activity walking, sitting, jogging, stand up, stand down and running for total six activities. Later they have used neural network and deep learning based CNN model for classification (Weiss and Lockhart 2012b; Lockhart et al. 2011). The other previously used gait features are listed in Table 4 and classification approach are listed in Table 5.

3 Preliminaries

In this section, we are providing the full 3- link manipulators Inverse kinematics (IK) solution:

In this solution, manipulator is of R–R–R type is considered, whose rotations are restricted within the following ranges:

- Here, Eq. 1 represents the joint angle range of different joints and Fig. 1 shows a simple structure of a planar 3-link robotic arm.
- The manipulator, in our case consists of three movable links that can move limited to a plane only. The Human leg is considered as 3-link manipulator.
- The links of above manipulator are linked by rotational joints whose axis of rotation are perpendicular to the planes of the joints.
- We will use some extra constraints in our model so that we can restrict our sample space in first quadrant only. We have done so, because in most of the practical cases robot will have to work only in the first quadrant.

$$\theta_1 \in [0, \pi], \theta_2 \in [-\pi, 0], \theta_3 \in [-\pi/2, \pi/2] \tag{1}$$

$$\begin{cases} l_1 cos(\theta_1) + l_2 cos(\theta_1 + \theta_2) > 0 \\ l_1 sin(\theta_1) + l_2 sin(\theta_1 + \theta_2) > 0. \\ 0 < \theta_1 + \theta_2 + \theta_3 < \pi/2 \end{cases} \tag{2}$$

3.1 Forward kinematics

The forward kinematic equations are given in Eqs. 3 and 4. Where x_e and y_e are the cartesian coordinate and θ_1, θ_2 & θ_3 are joints coordinate.

$$x_e = l_1 cos(\theta_1) + l_2 cos(\theta_1 + \theta_2) + l_3 cos(\theta_1 + \theta_2 + \theta_3) \tag{3}$$

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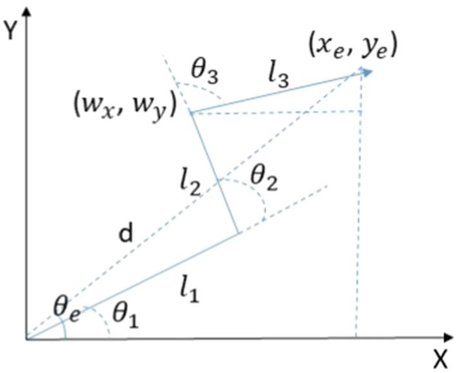
Table 4 Different gait feature for data acquisition techniques

Different features category	Name of features	References
Time domain feature	Mean absolute value root mean square, wave from length, zero crossing, variance	Lau et al. (2009), Prakash et al. (2018), Sabir et al. (2019)
Gait spatio-temporal features	Gait cycle time, stride length, left & right s teps length	Yang et al. (2017)
Kinematics features	Hip, knee, ankle, foot, shank & thingh joints angle	Semwal et al. (2013a)
Combined features (gait temporal and time domain)	Average, SD, average absolute difference, average resultant acceleration time between peaks, binned distribution	Semwal et al. (2015b), Dua et al. (2021)

Table 5 List of state of art machine learning algorithm for Gait identification

Classification technique	References
Adaboost, decision tree, random forest	Semwal et al. (2017b), Ahmed et al. (2018a, b), Chiu et al. (2019)
SVM, ELM, MLP	Semwal et al. (2017b), Huan et al. (2018b), Raj et al. (2018b), Gupta et al. (2014, 2020)
Dynamic Bayesian, RBF-Kernal	Milovanovic (2008), Akdoğan and Yilmaz (2014), Huan et al. (2018a, 2019)
Self-organizing map	Zhang et al. (2019), Semwal et al. (2015a)
CNN, RBM, DNN	Semwal et al. (2017b), Chiu et al. (2019), Raj et al. (2019), Mahfouf et al. (2018)

Fig. 1 Solution to 3-link problem



$$y_e = l_1 sin(\theta_1) + l_2 sin(\theta_1 + \theta_2) + l_3 sin(\theta_1 + \theta_2 + \theta_3). \tag{4}$$

Here, Eqs. 3 and 4 are not sufficient to locate the end effector completely within the plane. Its orientation is also required. Therefore, position can be given by Eqs. 3 and 4 and the orientation is represented by Eq. 5.

$$\theta = \theta_1 + \theta_2 + \theta_3. \tag{5}$$

Hence, it is completely clear from aforementioned equations that they can be solved easily. Therefore, extra efforts is not required for forward kinematic solutions. Now, we will try to get inverse kinematic solutions using the Eqs. 3–5.

3.2 Analytical approach

We can find the inverse kinematics solution by simply solving the forward kinematics equations for the joint angles. In this section, firstly, simple 2-link manipulator inverse kinematics solution is derived and presented in Sect. 3.2.1. Afterwards, using the 2-link solution, 3-link manipulators inverse kinematic solution is derived and presented in Sect. 3.2.2.

3.2.1 Inverse kinematics solution for 2-link manipulator

$$W = \psi(\Theta) \tag{6}$$

$$\begin{bmatrix} x_e \\ y_e \end{bmatrix} = \begin{bmatrix} l_1 cos(\theta_1) + l_2 cos(\theta_1 + \theta_2) \\ l_1 sin(\theta_1) + l_2 sin(\theta_1 + \theta_2). \end{bmatrix} \tag{7}$$

From Fig. 1, we can derive the following equations:

$$d^2 = x_e^2 + y_e^2 = l_1^2 + l_2^2 - 2l_1 l_2 cos(\theta_2) \tag{8}$$

$$cos(\alpha) = \frac{l_1^2 + l_2^2 - x_e^2 - y_e^2}{2l_1 l_2} \tag{9}$$

But also, $\theta_2 = \pi - \alpha$

$$cos(\theta_2) = cos(\pi - \alpha) = -cos(\alpha) = \frac{l_1^2 + l_2^2 - x^2 - y^2}{2l_1 l_2} \tag{10}$$

$$\theta_2 = \begin{Bmatrix} \pi - cos^{-1}\left(\frac{l_1^2+l_2^2-x^2-y^2}{2l_1 l_2}\right) \\ \cos^{-1}\left(\frac{l_1^2+l_2^2-x^2-y^2}{2l_1 l_2}\right). \end{Bmatrix} \tag{11}$$

Using tangent rule:

$$\tan(\theta_1 + \beta) = \frac{y}{x} \tag{12}$$

$$\theta_1 = tan^{-1}\left(\frac{y}{x}\right) - \beta \tag{13}$$

And also,

$$\beta = tan^{-1}\left(\frac{l_2 sin(\theta_2)}{l_1 + l_2 cos(\theta_2)}\right) \tag{14}$$

Hence,

$$\theta_1 = tan^{-1}\left(\frac{y}{x}\right) - tan^{-1}\left(\frac{l_2 sin(\theta_2)}{l_1 + l_2 cos(\theta_2)}\right). \tag{15}$$

Note Now, we can easily expand this concept for higher order complex problems.

3.2.2 Inverse kinematics solution for 3-link manipulator

Let's consider solving 3-link manipulator problem using the results obtained from the 2-link manipulator.

In Fig. 1, positions (w_x, w_y) are estimated from simple trigonometric equations as follows:

$$w_x = x_e - l_3 cos(\theta_3) \tag{16}$$

$$w_y = y_e - l_3 sin(\theta_3). \tag{17}$$

Now, the problem reduces like that of a simple 2-link manipulator. And we can do this for any number of links.

The formulation of 3-link solutions by considering Fig. 1 as follows:

$$D^2 = w_x^2 + w_y^2 = l_1^2 + l_2^2 - 2l_1 l_2 cos(\theta_2) \tag{18}$$

$$cos(\theta_2) = (w_x^2 + w_y^2 - l_1^2 - l_2^2)/2l_1 l_2 \tag{19}$$

$$sin(\theta_2) = \pm\sqrt{1 - (cos(\theta_2))^2} \tag{20}$$

$$\theta_2 = atan2(sin(\theta_2), cos(\theta_2)). \tag{21}$$

From Eqs. 3–5

$$w_x = (l_1 + l_2 cos(\theta_2))cos(\theta_1) - l_2 sin(\theta_1)sin(\theta_2) \tag{22}$$

$$w_y = (l_1 + l_2 cos(\theta_2))sin(\theta_1) - l_2 cos(\theta_1)sin(\theta_2) \tag{23}$$

$$sin(\theta_1) = (l_1 + l_2 cos(\theta_2))w_y - l_2 sin(\theta_2)w_x)/\triangle \tag{24}$$

$$cos(\theta_1) = (l_1 + l_2 cos(\theta_2))w_x - l_2 sin(\theta_2)w_y)/\triangle \tag{25}$$

$$\theta_1 = atan2(sin(\theta_1), cos(\theta_1)) \tag{26}$$

And,

$$\theta_3 = \theta_e - \theta_1 - \theta_2. \tag{27}$$

Thus, we can find the joint angles from the aforementioned equations.

4 Proposed methodology

The entire research work involves the two majors steps. Figure 2 represents the detailed flow chart of our working methodology. The first step involves following steps: data acquisition through IMU sensor, pre-processing of data, feature extraction for human activities recognition using different learning algorithm. The next working hypothesis is joints angle calculation from accelerometer's raw data (Raj et al. 2018b). We have solved the inverse kinematics (Raj et al. 2019) to extract the joints angles value using Algorithm 1. The detailed solution of 2-link and 3-link manipulator's inverse kinematics has been provided in Sect. 3.

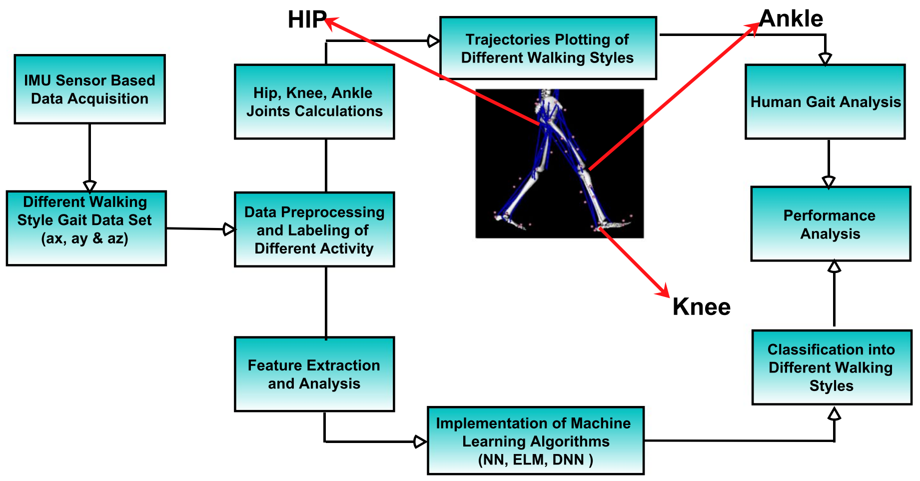


Fig. 2 Flow chart of detailed working

4.1 Data representation

4.1.1 Data acquisition and calibration

Figure 3 represents the data collection technique of different subjects using IMU sensor and mobile based accelerometer. Total 25 subjects was considered, out of which 15 were male and 10 were female. We have also collected data for pregnant women. The sensor was placed on 6 joints and CoM position of each subjects. It was asked to each subjects to perform the 6 different walking styles. Figure 4 shows the number of samples collected for different walking styles. The data was collected on frequency 100 Hz.

Fig. 3 Different subject(s) data collection using IMU sensor

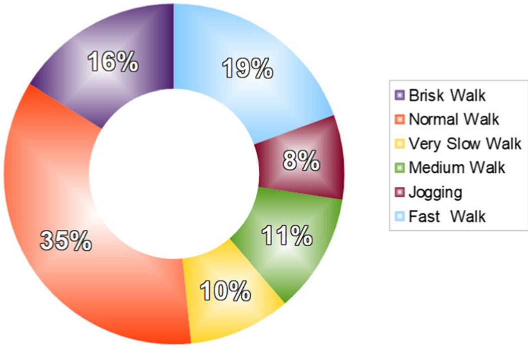


Fig. 4 Distribution of different walking activities samples

4.1.2 Data set description

The data set is collected for 25 subjects using wearable accelerometer (6-Degree IMU sensors) for six different walking activities named: brisk walk, normal walk, very slow walk, medium walk, jogging and fast walk for clinical examination purpose. We have considered the subject from different age group, gender and also collected data for pregnant woman data. Each data file is having following column: time(s) stamp, activities name, acceleration, angular velocity and joint angles. The details of all the columns are presented in Table 6.

4.2 Feature engineering

4.2.1 Feature extraction and processing

We have used 6 features for our data set. All the data was labeled into 6 different walking style as given in Fig. 4. We have used subject id, time stamp, activities name, ax, ay, az. The data is processed by providing label to each samples.

4.2.2 Proposed algorithm to calculate the joint angles

Algorithm 1: describes the way how we have calculated joint angles value?. In Algorithm 1, L1, L2 and L3 represents thigh length, shank length and foot length respectively, and current position coordinates of foot when placed on ground is represented by X and Y.

Table 6 Description of data

Notation	Description
Time (s)	It shows the time stamp
ax (g), ay (g), az (g)	Represents the acceleration about x, y and z axis
wx (deg/s), wy (deg/s), wz (deg/s)	Show the angular velocity about x, y, & z axis
Angle X (deg), Angle Y (deg), Angle Z (deg)	Various joint angle value in degree

Algorithm 1: Calculation of joints trajectories for Shank, Thigh, Hip, Knee, Ankle and foot using Inverse Kinematic

Result: Joint angle trajectories for Shank,Thigh, Hip, Knee, Ankle & Foot

Input: Raw data collected through accelerometer X, Y, L1, L2, L3;

Output: Joint Angles;

Procedure;

Step 1 Solve the inverse kinematic for co-ordinate(X,Y);

1.1 Estimate X and Y coordinates as follows;

$$X = L_1 cos(\theta_1) + L_2 cos(\theta_1 + \theta_2) + L_3 cos(\theta_1 + \theta_2 + \theta_3) \tag{28}$$

$$Y = L_1 sin(\theta_1) + L_2 sin(\theta_1 + \theta_2) + L_3 sin(\theta_1 + \theta_2 + \theta_3) \tag{29}$$

Step 2 Calculate the Joint Angle values ;

2.1 Calculate the joint angle for Knee (θ_2)

$$\theta_2 = \begin{Bmatrix} \pi - cos^{-1}(\frac{L_1^2+L_2^2-X^2-Y^2}{2L_1L_2}) \\ \cos^{-1}(\frac{L_1^2+L_2^2-X^2-Y^2}{2L_1L_2}) \end{Bmatrix} \tag{30}$$

2.2 Calculate the joint angle for Hip (θ_1)

$$\theta_1 = tan^{-1}(\frac{Y}{X}) - tan^{-1}(\frac{L_2 sin(\theta_2)}{L_1 + L_2 cos(\theta_2)}) \tag{31}$$

2.3 Calculate the joint angle for Ankle (θ_3)

$$\begin{aligned} \theta_e &= \theta_1 + \theta_2 + \theta_3 \\ \theta_3 &= \theta_e - \theta_1 - \theta_2 \end{aligned} \tag{32}$$

Step 3 Finally Plot the curve;

4.2.3 Model fitting and classification

This section present the parameters used by ELM, ANN & deep learning architecture. The proposed architecture of neural network includes three hidden layer with 100 neurons, 6 inputs neurons (represents Hip, Knee, Ankle, Thigh, Shank & Foot) and 6 output neurons corresponds 6 walking activities.

Illustration of Table 7: It represents the learning parameter used by ANN model. The optimizer used by ANN model was ‘adam’ and cross entropy considered as loss function for 50 epochs. The hidden layer activation function was ‘relu’ and output layer activation function was ‘softmax’.

The next classifier was ELM and all the set of parameters used by ELM are reported in Table 8. Table 9 shows the parameters used by CNN model.

Table 7 Set of parameter for ANN

Parameter	Value
No. of hidden layer	3
Hidden layer neurons	100
Hidden layer activation function	relu
Output layer activation function	softmax
Solver	'Lbfgs'
Alpha	0.0001
Momentum	0.9
Epoch	50

Table 8 Set of parameter for ELM

Parameter	Value
Hidden neurons	100
Activation function	'multiquadric'
Rbf-width	0.4

Table 9 Set of parameter for DNN

Parameter	Value
No. of convolution layers	4
Activation function of hidden layers:	'relu'
No. of output layer neuron	6
Activation function of output layer	Soft max
Sub sampling	Max pooling

5 Results and discussions

To evaluate the performance of proposed methodology, experiments were conducted using GPU machine with a Intel 2.50-GHz, i7 CPU and 32.0-GB RAM. The code was executed on Google colab using GPU. The grid search was preformed to find the best set of parameters for each of the classifiers. Next, tenfold cross validation is performed to reduce validation error. Finally, all the classifiers i.e., ANN, ELM and DNN were implemented using TensorFlow-Keras Python libraries.

5.1 Experiment outcome condition and discussion

First step for the experimentation is the data collection. In this process, IMU sensor was placed at six different positions, namely, shank, thigh, hip, knee, ankle and foot for capturing the six different activity.

The IMU sensor has given accelerometer value which is converted into joint angle(degree). This objective is achieved using the inverse kinematics algorithm solution which considers Center of Mass(CoM) at reference points. The detail description of inverse kinematic solution is provided in Sect. 3 (preliminaries).

Illustration of Fig. 5: It shows the 6 joint angle trajectories for five different walks. In Fig. 5, hip, shank, knee, ankle, thigh, & foot joint trajectories are represented by (a), (b), (c), (d) and (e) respectively. In this figure, jogging is excluded due to it required more prepossessing.

5.2 Model validation and training accuracy

The classification of different walking activities were preformed using three different classifiers named ANN, ELM and Deep learning model CNN. The ANN has reported testing accuracy 87.84% whereas ELM and DNN based model has reported 88% & 92% respectively.

Illustration of Figs. 6 and 7: In Fig. 6, the obtained overall classification accuracy percentage using ANN, ELM and CNN is presented. In Fig. 7, different testing accuracy percentage of each class output is provided.

5.3 Performance analysis and discussion

In this section, we have provided the obtained results of various performance matrix such as accuracy, precision, recall, f-score and support value to classify the individual walking activity.

Illustration of Tables 10 and 11: it was observed from Table 10, obtained accuracy of CNN is better than remaining tested classifiers. In precision, ANN obtains the highest value. In recall, ELM outperforms over others. Finally, in F1-score, ANN shows the superior performance. Table 11 shows the different performance of different classifier as individual and combined for classifying the different walking activities.

5.4 Data-set validation

In the comparative analysis, the proposed data-set is compared with the existing data-set WISDM in terms of classification accuracy. The classifier models, namely, ANN, ELM and DNN are applied on both the data-set.

Illustration of Table 12: From the obtained results, it was observed that the obtained classification accuracy of WISDM data-set is 87% in ANN, 85% in ELM & 90% in DNN. In the proposed data-set, 87%, 88% and 92% classification accuracy was achieved in ANN, ELM and DNN. Hence, the proposed data-set shows the variety of data and also obtains the better results in both ELM and DNN classifiers. It shows the validity of collected data-set correctly. This data-set can be considered as a benchmark data-set for the future research.

6 Conclusion and future research direction

This section consists of conclusion of this research article and future research direction.

6.1 Conclusion

In this paper, walking problem of humanoid robot was addressed using the deep learning models, namely, ANN, ELM, and DNN. To achieve the objective, firstly, six different

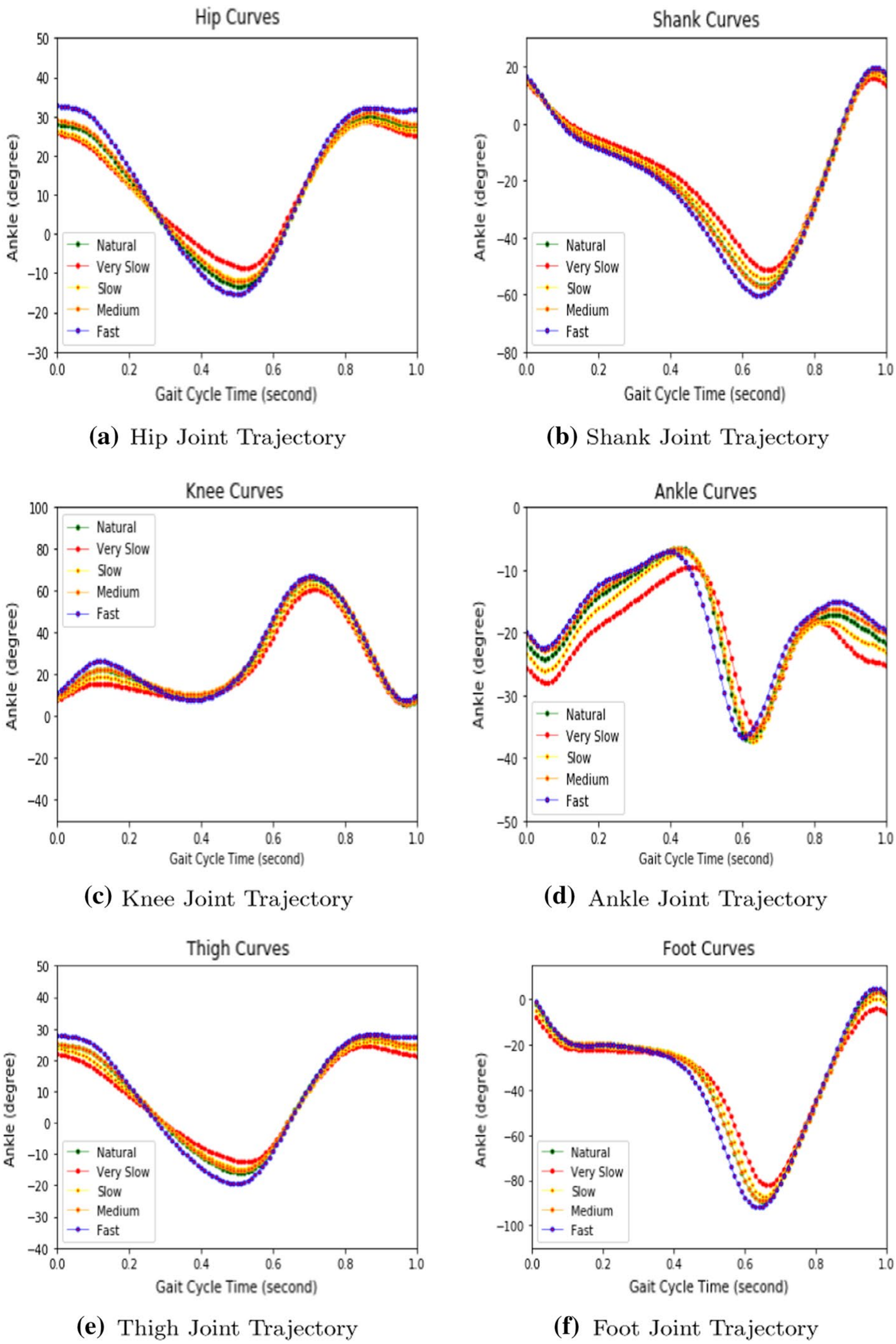


Fig. 5 Different joints angle curves. **a** Hip joint, **b** shank joint, **c** knee joint, **d** ankle joint, **e** thigh joint, **f** foot joint

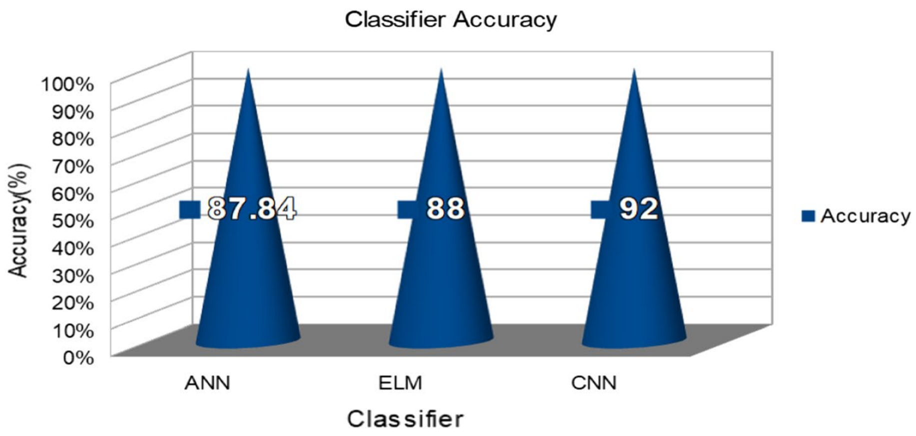


Fig. 6 Accuracy percentage of different classifier

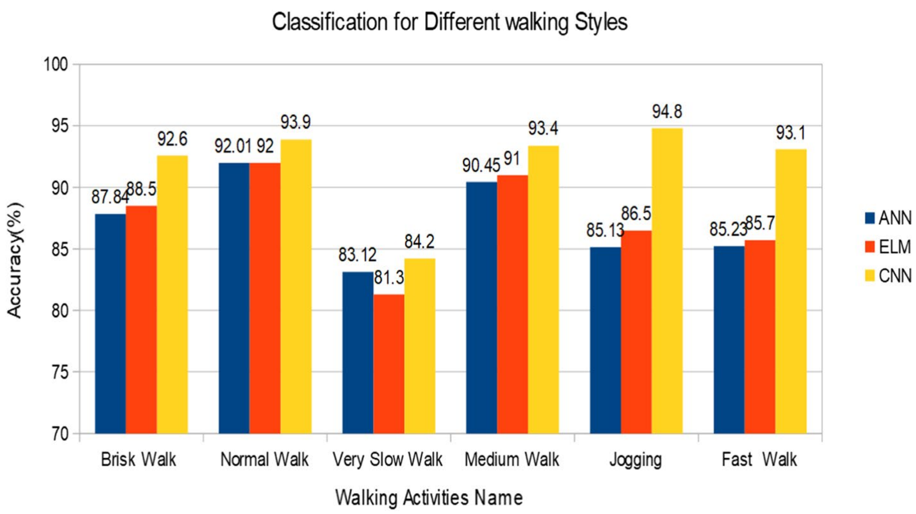


Fig. 7 Different activity classification percentage

Table 10 Metrics showing combined results

Model	Accuracy	Precision	Recall	F1-Score	Support
ANN	0.87	1.00	0.99	0.99	459
ELM	0.88	0.99	1.00	0.99	459
CNN	0.92	0.96	0.97	0.96	459

walking activities were explored for clinical examination purpose, namely, (1) brisk walk, (2) normal walk, (3) very slow walk, (4) medium walk, (5) jogging & (6) fast walk. From the aforementioned activities, we have collected data for 25 subjects using 6-degree IMU sensor and mobile-based accelerometers. In the next step, joint trajectories pattern of hip,

Table 11 Metrics showing individual results

Model	Walking style	Slow walk	Brisk walk	Natural walk	Medium walk	Jogging	Fast walk
ANN	Accuracy	0.87	0.92	0.83	0.90	0.85	0.85
	Precision	0.96	0.96	0.77	0.67	0.66	0.69
	Recall	0.96	0.96	0.76	0.68	0.67	0.70
	F1	0.96	0.96	0.77	0.67	0.66	0.69
	Support	117	120	120	120	120	120
ELM	Accuracy	0.88	0.92	0.81	0.91	0.86	0.85
	Precision	0.89	0.95	0.78	0.69	0.71	0.75
	Recall	0.88	0.94	0.79	0.68	0.72	0.76
	F1	0.98	0.94	0.78	0.68	0.71	0.75
	Support	117	120	120	120	120	120
CNN	Accuracy	0.92	0.94	0.84	0.93	0.95	0.93
	Precision	0.85	0.86	0.71	0.73	0.72	0.72
	Recall	0.83	0.87	0.71	0.73	0.74	0.73
	F1	0.83	0.86	0.71	0.73	0.72	0.72
	Support	117	120	120	120	120	120

Table 12 Comparison with WISDM & our data set

Model	WISDM (Kwapisz et al. 2011)	Collected dataset
ANN	0.87	0.87
ELM	0.85	0.88
DNN	0.90	0.92

ankle, knee, shank, foot and thigh were compared for five walking activities. Finally, deep learning models have been applied, namely, ANN, ELM and DNN for the classification of different walking activities. From the obtained results, it was observed that 87.84%, 88% and 92% accuracy was achieved using ANN, ELM and DNN respectively. Hence, DNN is the most suitable deep learning model for the different walking activities classification. This research work can be utilized for the generation of robot walking trajectories and can be adopted for various applications such as clinical patient monitoring, surveillance, forensic application. In addition, the collected data set for 25 subjects is made available publicly for research purpose.

6.2 Future research direction

In the future, this work can be extended for more varieties of human activities and collection for better features. In addition, the computer vision based technique will be explored in future.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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