Identification of Gait data using machine learning technique to categorise human locomotion

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ABSTRACT

Human Gait is a model of movement while locomotion and it is known as behavioural characteristic of human. Gait recognition is a behavioural biometric method that includes human identification from afar i.e. in absence of human and this is achieved by analysing the behaviour of their walking. Main aim to make GAIT recognition system is to impart a best method to recognize risks in places where high security is required like in banking, parking, airports etc. or to detect disease like Parkinson's. In this paper we have shown the importance of gait recognition in order to detect whether a human GAIT is normal or abnormal, firstly the features of human gait is collected and then they are classified using neural network (Back propagation) and KNN classification technique. To test the proposed system the database contains 204 gaits and 16 different features were recognised, in which 3 datasets are crouch gait dataset and one normal gait dataset of 4 different humans is collected. We have obtained 100% of classification accuracy for a training data. Testing results shows 39.65% accuracy overall accuracy of system is 69.825%.

KEYWORDS

GAIT recognition; Back Propagation; KNN; Machine learning; supervised learning

1 INTRODUCTION

To verify/validate people identity is called as authentication. And now day's authentication is becoming very popular to check whether a person is authentic or not. Authentication is useful at various places and previously authentication is done with secret passwords or PIN codes. The main disadvantage to such authentication systems are anyone can crack the password or PIN codes so this method fails where very high security is needed.

So, biometric (in fig.1.) technology came to existence where authentication is done using a particular body part like fingers, iris etc. Lately biometric techniques are used to verify and validating the identity of some person. For authentication purposes biometrics are increasingly being used like fingerprint scanner, iris scanner etc. and one can say these are reliable too. But now days these biometrics are not user friendly as people dislike accessing finger print machine or avoid iris scanner as it may weaken or damage their vision. Therefore it is a good technique but consumes time as people are required to give their details to the authentication system [16]. So we can say using gait as biometric where a person don't have to be interactive will not cause any problem as it asks nothing other than walking by [23-34]. Therefore this system has more advantage over the previous one and it is very user friendly and has large user acceptance. The reasons for large user acceptance are as people do not need to interact or give time to the sensors which are applied to verify a person, so authentication becomes so natural. Secondly gait detection is a behavioural identity of a person which is used as biometric so it cannot be lost/stolen. Thirdly people don't have to waste time to give any details about them, as their gait identity is used in biometric verification [1].

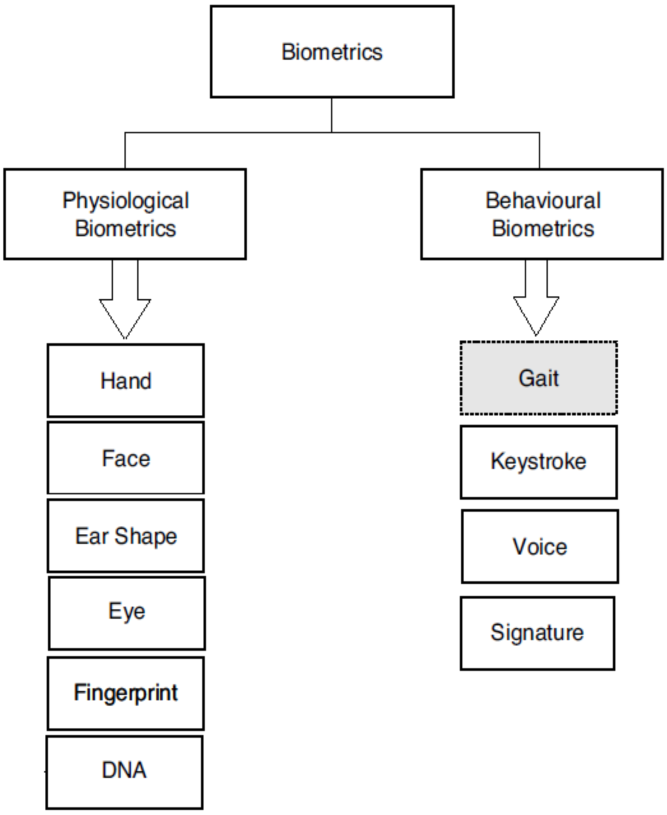


Fig. 1. Biometrics types (in this paper GAIT biometric classification is used)

So with this discussion we can say that all people walk so we can take gait as biometric identity in verification. As the walking of two persons always varies, biometric identification becomes very easier. So when the dataset of GAIT is collected one can classify into separate groups to know the normal behaviour of walking [2].

In this paper (fig.2.) we collect the human gait data from Human Motion Capture Device (HMCD). Then training and testing of GAIT data is done to get the maximum possible accuracy of the system. Then features of GAIT data is extracted and classified. Classification is done using Back Propagation technique and KNN, both are supervised learning technique. Comparison is done in both techniques and best technique is used to train and test the system.

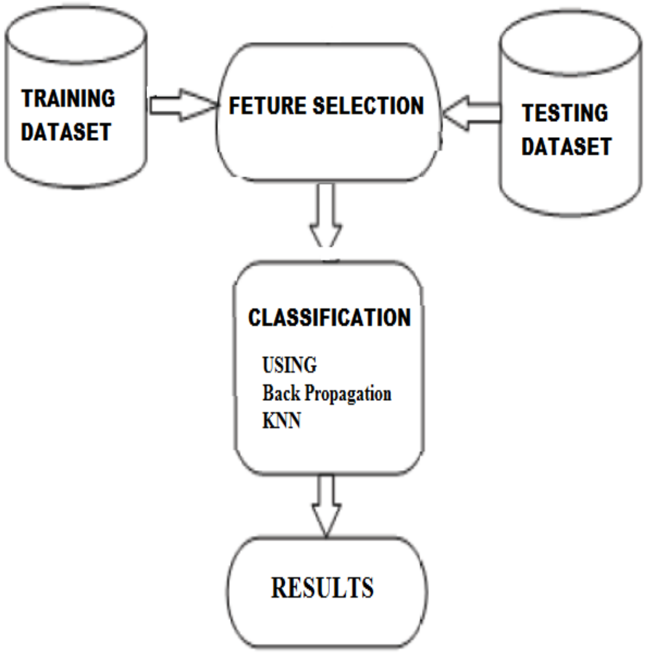


Fig. 2. **Block diagram of classification system**

2 PROPOSED SYSTEM

2.1 Human Gait Biomechanics

Gait cycle is defined as the periodic cycle/motion of human locomotion/walking. It consists of 8 phases shown in fig.3 [3].

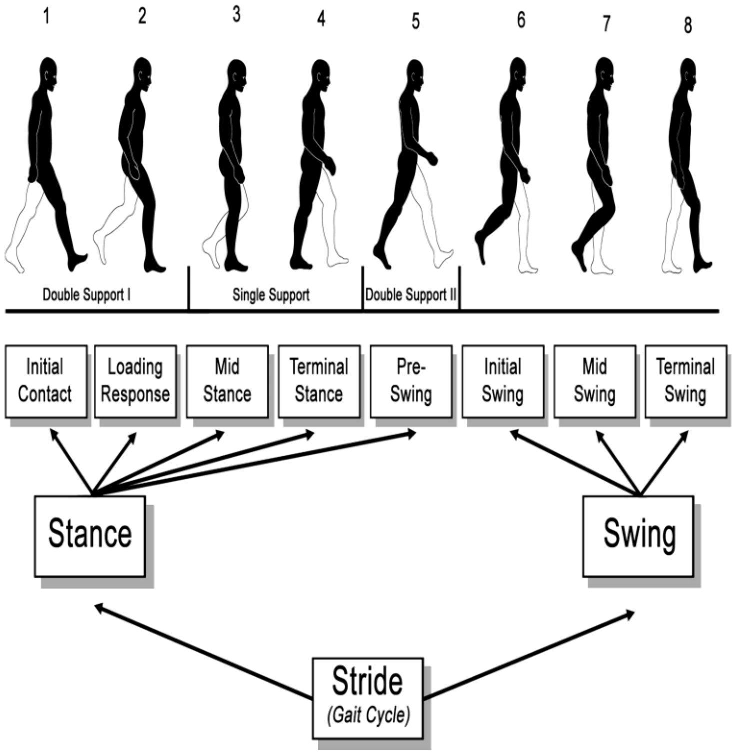


Fig. 3. **Eight phases of Gait cycle**

In *INITIAL CONTACT* phase foot of human contacts the ground. In *LOADING RESPONSE* phase the weight of body is shifted to leg. In *MID-STANCE* phase the human body moves over the leg. In *TERMINAL STANCE* phase the human body moves in front of the leg. In *PRE-SWING* phase leg pushes off the surface and opposite foot contacts the surface. In *INITIAL SWING* leg lifts off the surface [35-38]. In *MID-SWING* phase leg moves ahead of the human body. In *TERMINAL SWING* phase leg comes to the ground [4].

2.2 Proposed Work

Figure 4 states the methodology for proposed system. It classifies the human locomotion as normal or abnormal GAIT. The figure consists of training phase and testing phase. In the initial phase while doing training the dataset is fed with GAIT dataset (crouch2, crouch3, crouch4, normal) then the classification is done using neural network (back propagation) and KNN techniques [5]. Then these techniques are compared. In testing phase, the testing input is given to classifier and classification system tells that human locomotion is normal or abnormal [15].

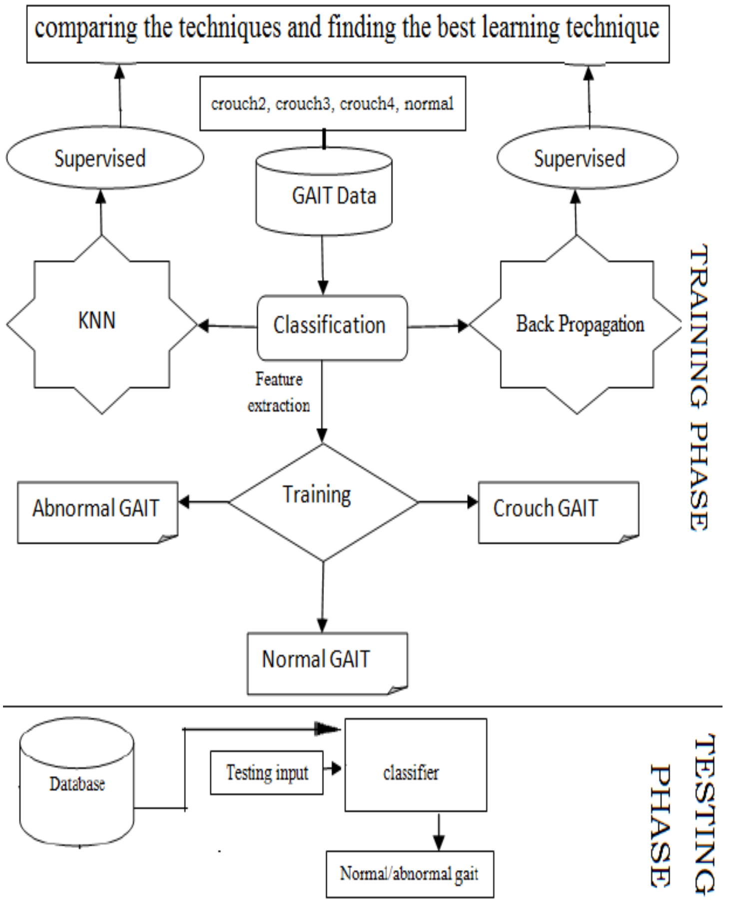


Fig. 4. **Proposed GAIT classification system**

3. METHODOLOGY

Firstly we collect the GAIT data then features are extracted and we classify the GAIT data. Training and testing of system is done. After the classification is done result is shown as normal or abnormal GAIT.

3.1 Data Set

To capture the human data we use HMCD. From this device different joint angles (knee, hip, and ankle) are captured to get the human GAIT data [6-8].

The data set used for proposed system contains four data set namely “crouch2”, “crouch3”, “crouch4”, and “normal”. Each data set has 51 gaits and 16 features. Therefore to the classification system we pass 51*4=204 gaits and train the classifier using machine learning techniques. Figure 5 shows the human GAIT of four different datasets. In figure5 ‘a’, ‘b’, ‘c’ shows some abnormalities in human locomotion whereas ‘d’ shows normal GAIT[9-11].

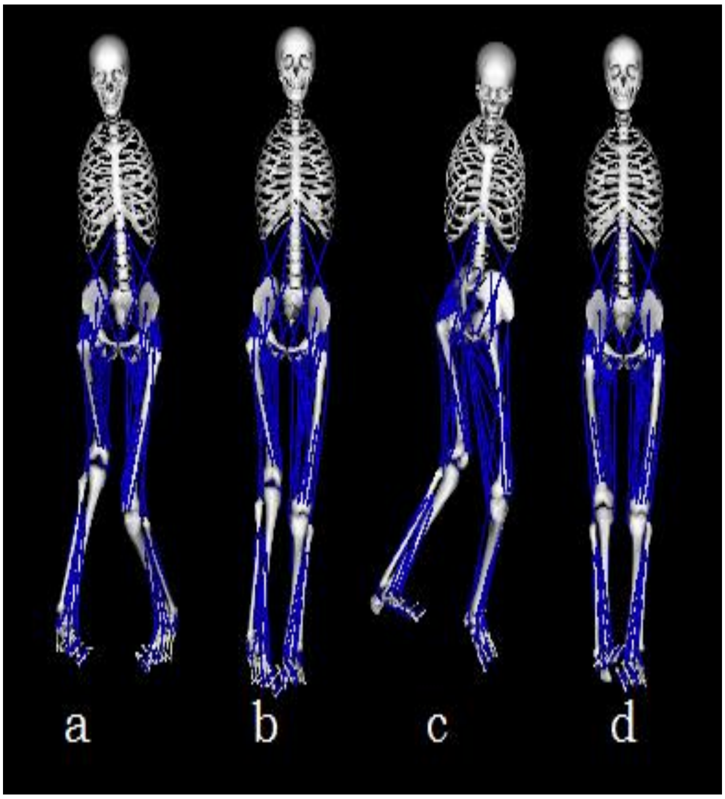
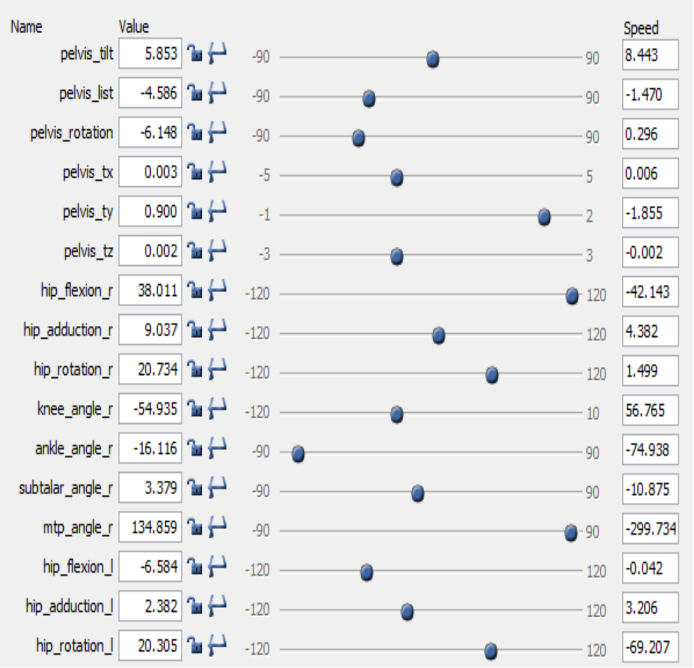
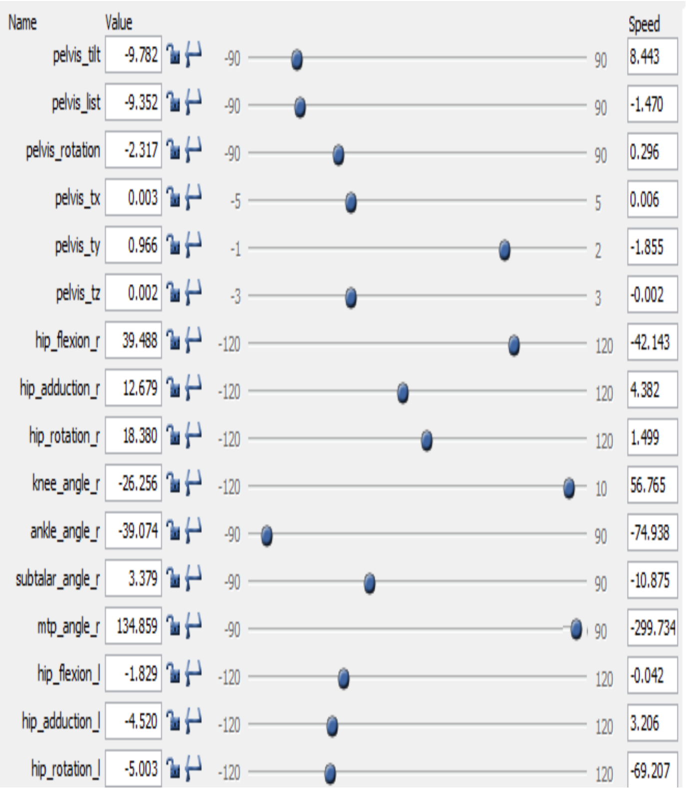


Fig. 5. **View of the human GAIT of four different data sets**



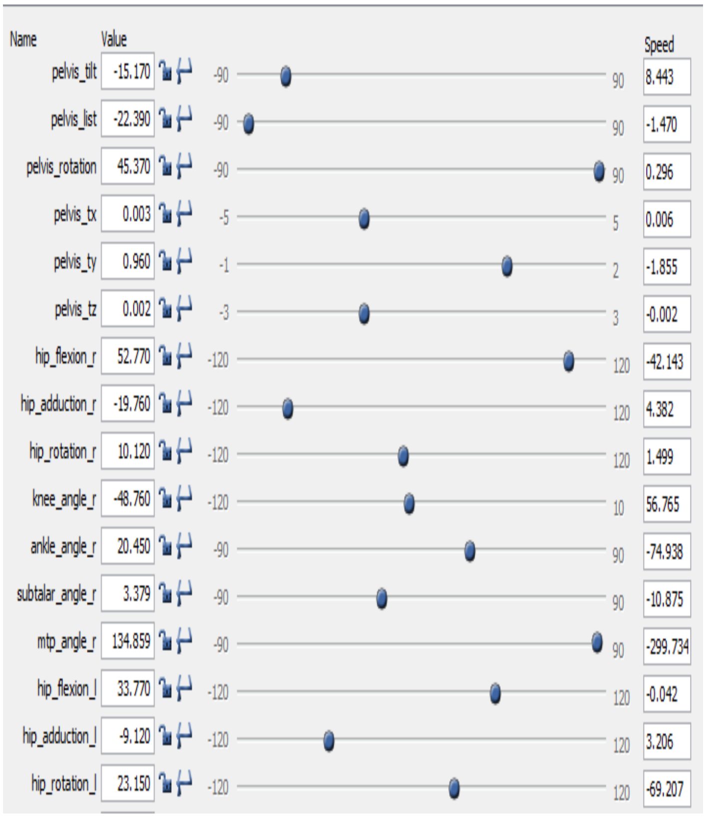
Name	Value			Speed
pelvis_tilt	5.853	-90	90	8.443
pelvis_list	-4.586	-90	90	-1.470
pelvis_rotation	-6.148	-90	90	0.296
pelvis_tx	0.003	-5	5	0.006
pelvis_ty	0.900	-1	2	-1.855
pelvis_tz	0.002	-3	3	-0.002
hip_flexion_r	38.011	-120	120	-42.143
hip_adduction_r	9.037	-120	120	4.382
hip_rotation_r	20.734	-120	120	1.499
knee_angle_r	-54.935	-120	10	56.765
ankle_angle_r	-16.116	-90	90	-74.938
subtalar_angle_r	3.379	-90	90	-10.875
mtp_angle_r	134.859	-90	90	-299.734
hip_flexion_l	-6.584	-120	120	-0.042
hip_adduction_l	2.382	-120	120	3.206
hip_rotation_l	20.305	-120	120	-69.207

Fig. 6. **Coordinates of crouch2 dataset**



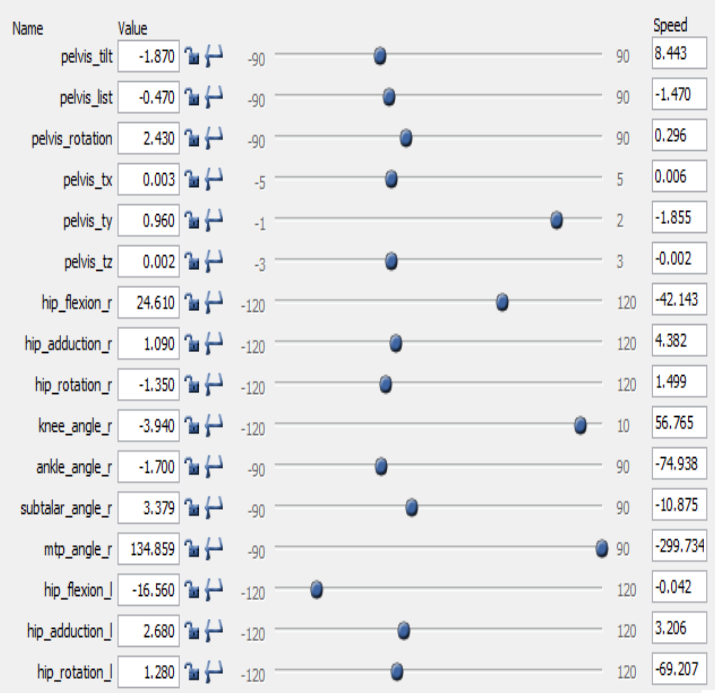
Name	Value			Speed
pelvis_tilt	-9.782	-90	90	8.443
pelvis_list	-9.352	-90	90	-1.470
pelvis_rotation	-2.317	-90	90	0.296
pelvis_tx	0.003	-5	5	0.006
pelvis_ty	0.966	-1	2	-1.855
pelvis_tz	0.002	-3	3	-0.002
hip_flexion_r	39.488	-120	120	-42.143
hip_adduction_r	12.679	-120	120	4.382
hip_rotation_r	18.380	-120	120	1.499
knee_angle_r	-26.256	-120	10	56.765
ankle_angle_r	-39.074	-90	90	-74.938
subtalar_angle_r	3.379	-90	90	-10.875
mtp_angle_r	134.859	-90	90	-299.734
hip_flexion_l	-1.829	-120	120	-0.042
hip_adduction_l	-4.520	-120	120	3.206
hip_rotation_l	-5.003	-120	120	-69.207

Fig. 7. **Coordinates of crouch3 dataset**



Name	Value			Speed
pelvis_tilt	-15.170	-90	90	8.443
pelvis_list	-22.390	-90	90	-1.470
pelvis_rotation	45.370	-90	90	0.296
pelvis_tx	0.003	-5	5	0.006
pelvis_ty	0.960	-1	2	-1.855
pelvis_tz	0.002	-3	3	-0.002
hip_flexion_r	52.770	-120	120	-42.143
hip_adduction_r	-19.760	-120	120	4.382
hip_rotation_r	10.120	-120	120	1.499
knee_angle_r	-48.760	-120	10	56.765
ankle_angle_r	20.450	-90	90	-74.938
subtalar_angle_r	3.379	-90	90	-10.875
mtp_angle_r	134.859	-90	90	-299.734
hip_flexion_l	33.770	-120	120	-0.042
hip_adduction_l	-9.120	-120	120	3.206
hip_rotation_l	23.150	-120	120	-69.207

Fig. 8. **Coordinates of crouch4 dataset**



Name	Value			Speed
pelvis_tilt	-1.870	-90	90	8.443
pelvis_list	-0.470	-90	90	-1.470
pelvis_rotation	2.430	-90	90	0.296
pelvis_tx	0.003	-5	5	0.006
pelvis_ty	0.960	-1	2	-1.855
pelvis_tz	0.002	-3	3	-0.002
hip_flexion_r	24.610	-120	120	-42.143
hip_adduction_r	1.090	-120	120	4.382
hip_rotation_r	-1.350	-120	120	1.499
knee_angle_r	-3.940	-120	10	56.765
ankle_angle_r	-1.700	-90	90	-74.938
subtalar_angle_r	3.379	-90	90	-10.875
mtp_angle_r	134.859	-90	90	-299.734
hip_flexion_l	-16.560	-120	120	-0.042
hip_adduction_l	2.680	-120	120	3.206
hip_rotation_l	1.280	-120	120	-69.207

Fig. 9. Coordinates of normal dataset

When the figure.5 is simulated, then the cordinates of the human GAIT data set is captured and shown in figure.6, 7, 8, 9 for crouch2, crouch3, crouch4, normal datasets respectively.

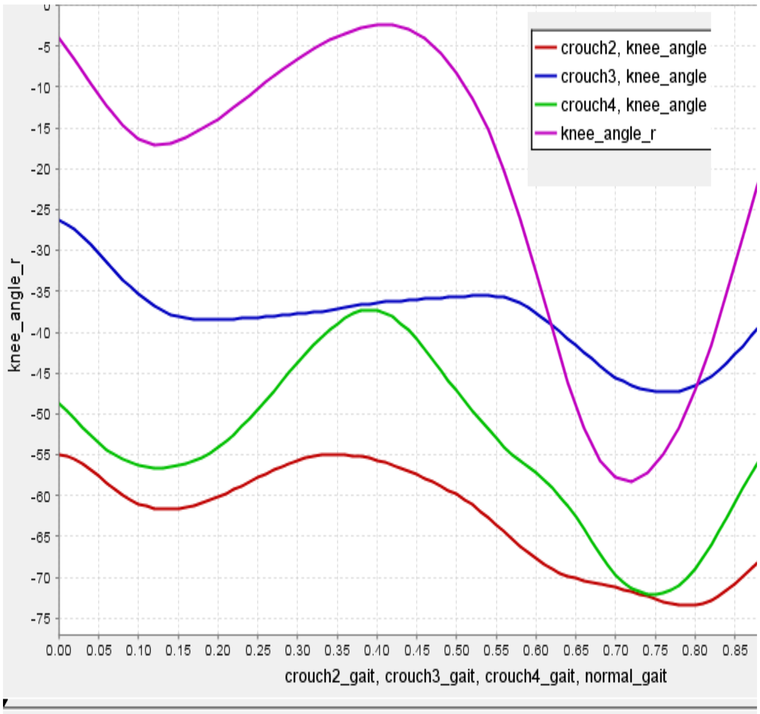


Fig. 10. Plot of crouch2, crouch3, crouch4, normal datasets respectively.

Figure 10 shows plot of knee angle curve of data set crouch2(red), crouch3(blue), crouch4(green), normal(purple) respectively.

3.2 Feature Selection

In this paper 16 features are extracted. The features are collected from different joints while locomotion [12-13]. In all the four datasets 16 features are extracted which is listed in table 1.

TABLE I. List of 16 features of gait dataset

Feature Category	Feature Name
F1	Pelvis_tilt
F2	Pelvis_list
F3	Pelvis_rotation
F4	Pelvis_tx
F5	Pelvis_ty
F6	Pelvis_tz
F7	hip_flexion_r
F8	hip_adduction_r
F9	hip_rotation_r
F10	knee_angle_r
F11	ankle_angle_r
F12	ankle_angle_l
F13	knee_angle_l
F14	hip_flexion_l
F15	hip_adduction_l
F16	hip_rotation_l

4. CLASSIFICATION

Classification of GAIT data is done through two following techniques:

4.1 Back Propogation

In this technique we train the system with 16 input neurons in the input layer and we get 4 neurons in the output layer. For adjusting the weights of the network, training is done by back-propagation algorithm. The Accurate classification (training and testing) of back propagation comes out to be 69.825%

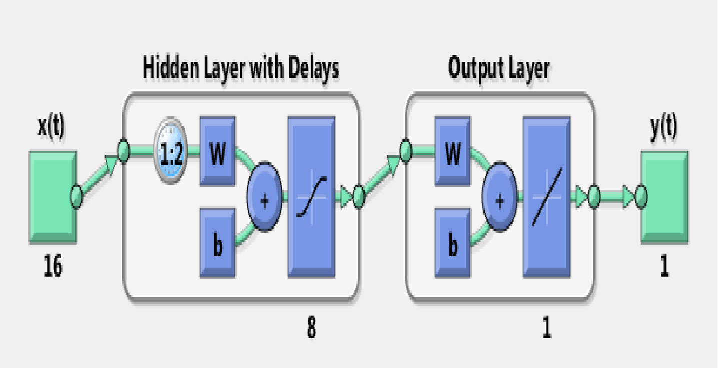


Fig. 11. Model of Back Propogation algorithm

Now the back propagation algorithm is used to train and test the system. Training of system shows 100% accuracy and testing of system shows 39.65% accuracy in figure 12.

Figure 12 shows accuracy percentage on y axis and number of training and testing iterations are performed on x axis.

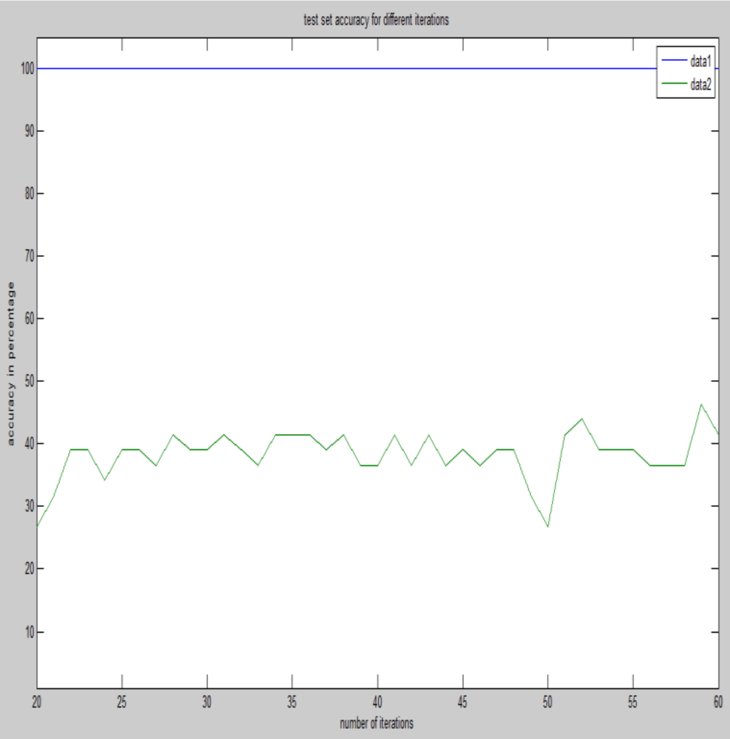


Fig. 12. **Training(blue line-100%) and testing(green line-39.65%) accuracy of back propogation**

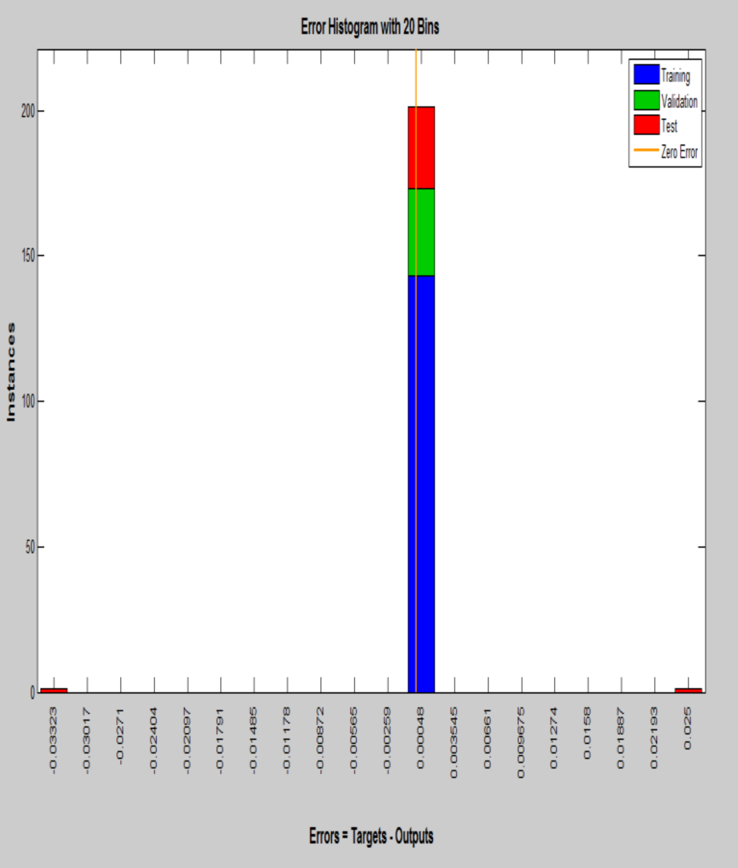


Fig. 13. **Error histogram**

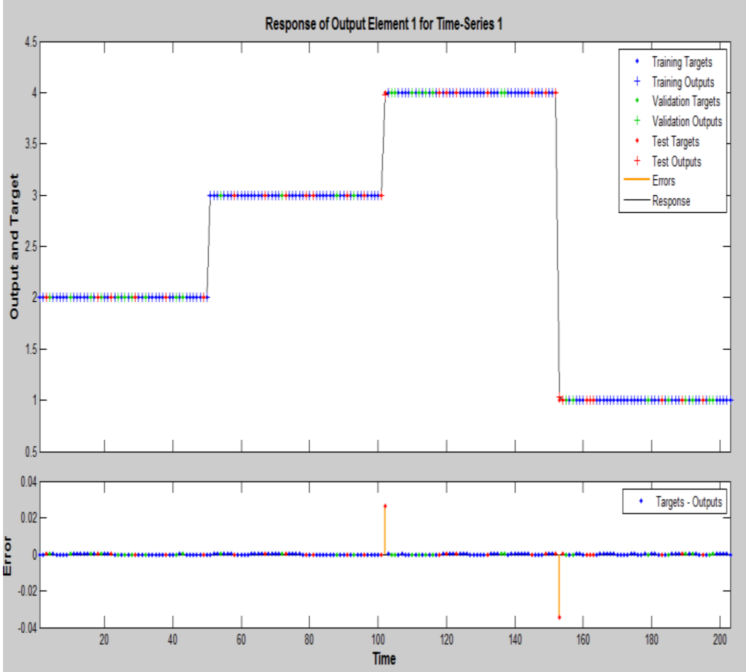


Fig. 14. **Plot response**

Figure 13 shows error histogram in which on y-axis there are instances and on x axis it shows error as output. Figure 14 shows the plot response where on y-axis there are outputs and targets and on x axis is plot against time. Figure 15 shows error autocorrelation diagram. Figure 16 shows performance of the back propagation system and the best validation performance is 6.1068e-011 and on y-axix mean square error count is taken. . Figure 17. Gives the training state gradient value=5.4746e-006, Mu=1e-008 and validation checks=0. Figure 18. Shows at training r=1, output=1*target+8.4e-008; validation r=1; output=1*target+-8.8e-007; test r=0.99998, output=1*target+0.0062; target r=1; output=1*target+0.00094 [15-23].

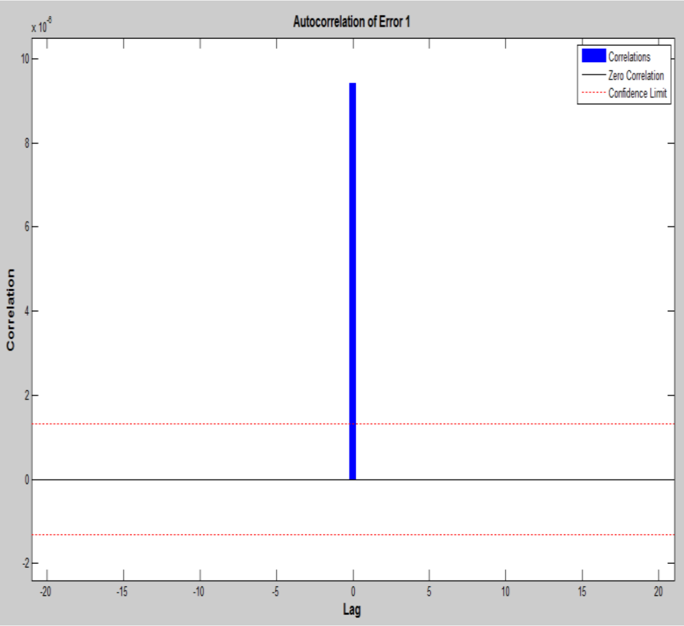


Fig. 15. **Error autocorrelation**

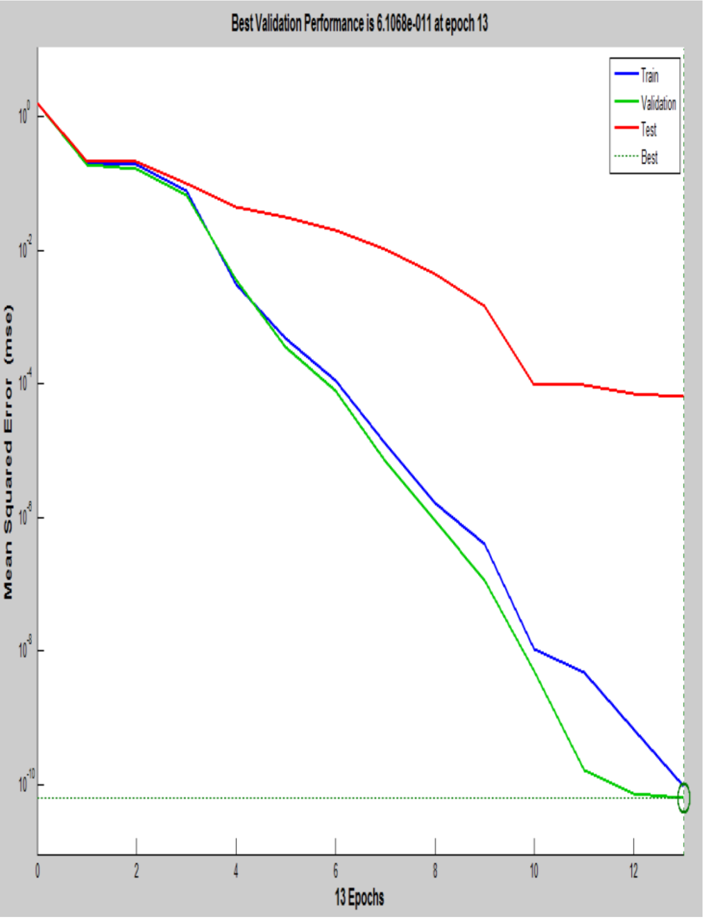


Fig. 16. **Model of Back Propogation algorithm**

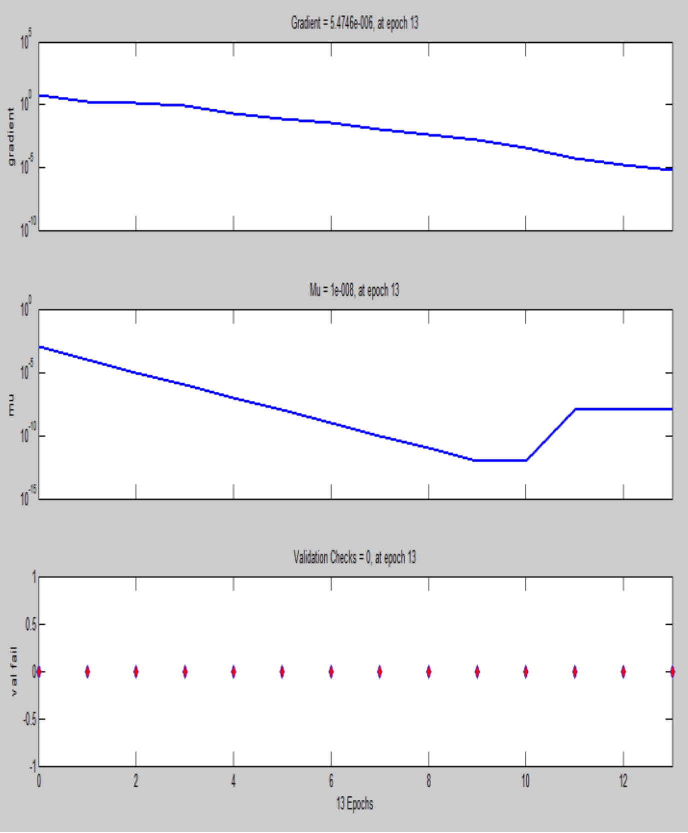


Fig. 17. **Training state**

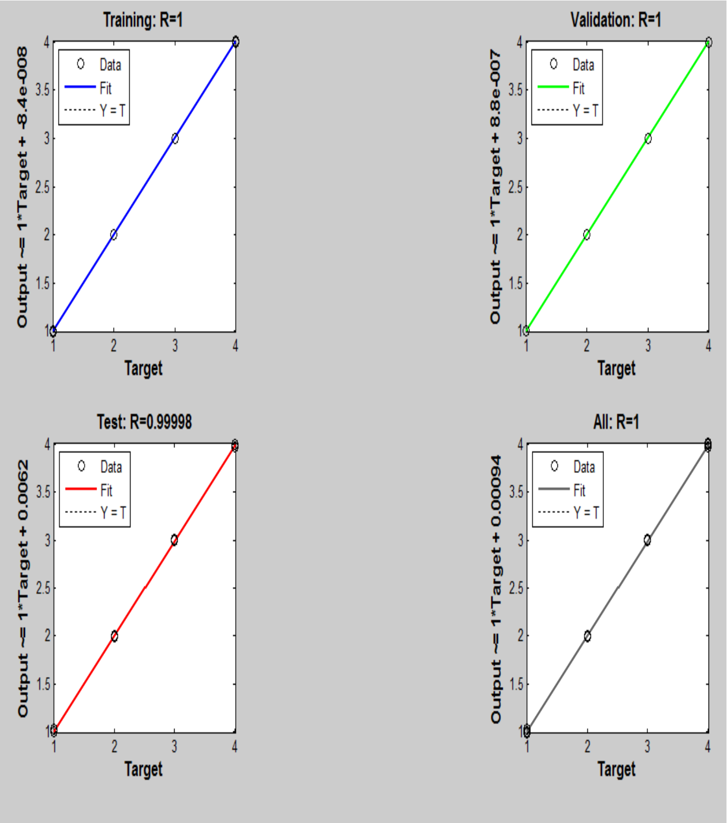


Fig. 18. **Regression**

4.2 KNN

In KNN classification the number of *k* values such as 3, 5, 7 and 9 were used in the training phase. The training and the testing was performed and the accurate classification of KNN (training and testing) comes out to be 61.25% [14].

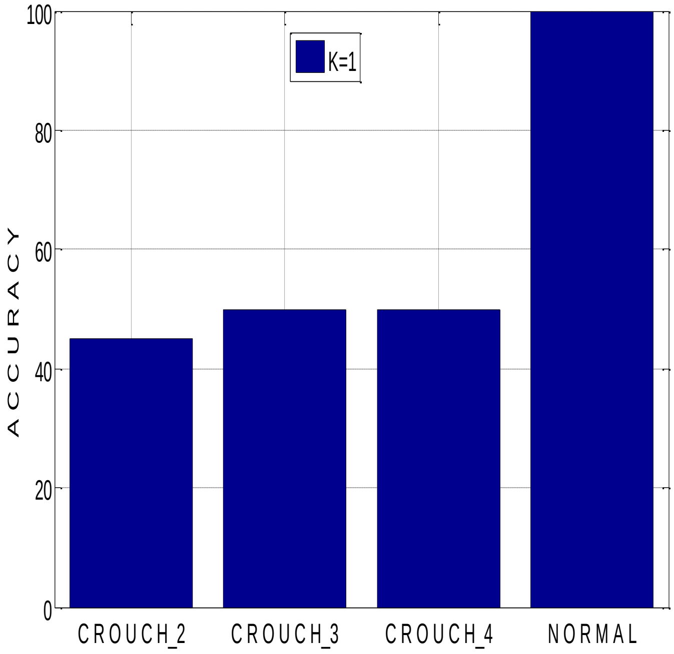


Fig. 19. **Accuracy for KNN when k=1**

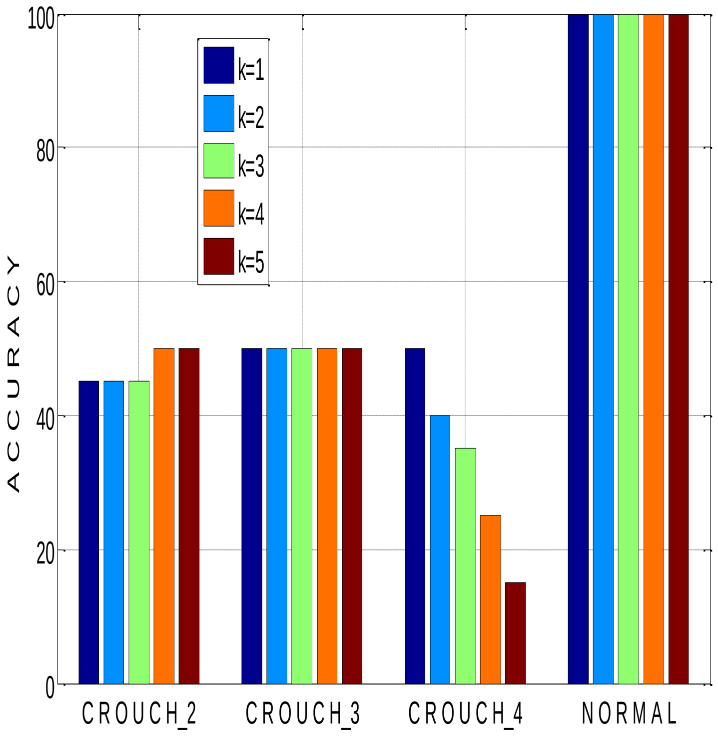


Fig. 20. **Accuracy of classification of KNN when k=1,2,3,4,5**

TABLE II. **Accuracy for KNN**

Category/Method	**KNN(k=1,2,3,4,5)**
Normal Gait	100,100,100,100,100
Crouch 2 Gait	50,50,50
Crouch 3 Gait	50,50,50
Crouch 4 Gait	45,40

5 DISCUSSIONS AND RESULTS

This paper shows two main approaches in gait classification i.e. back propagation and KNN. After comparing the testing and training results we get better results using back propagation learning technique. The whole work of paper is to describe the classification technique of different type of GAIT into following four categories: Normal, crouch2, crouch3, crouch4 using back propagation and KNN [39]. When the training of data is done then the output of will be either four options i.e. Normal, crouch2, crouch3, crouch4. If the testing data set is tested on the proposed system then the output must be normal GAIT if the classifier classifies it as normal data or the output will be abnormal GAIT data if the classifier classifies it as crouch2, crouch3, crouch4 in any of these three categories [17-18].

5.1 Performance

After comparing the overall accuracy of back propagation and KNN, the performance of back propagation is best for 16 features of human GAIT.

***Back* propagation**: The Accurate classification (training and testing) of neural network(back propagation) comes out to be 69.825%
KNN: The accurate classification of KNN (training and testing) comes out to be 61.25%.

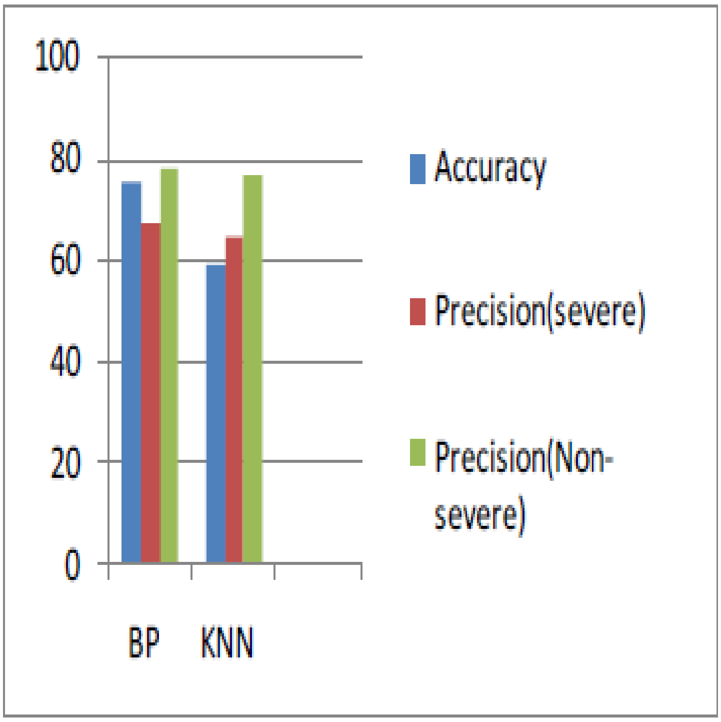


Fig. 21. **Comparision of back propagation and KNN**

The result shown in figure.21 describes that back propagation performs better than KNN if we increase the number of neighbors in KNN the classification accuracy decreases [40].

TABLE III. **Accuracy comparision of back propagation and KNN**

	Table Column Head		
	Back Propagation	***KNN***	***Better***
Accuraccy	69.825%	61.25%	Back Propagation

5.2 Conclusion

For 16 input features the overall accuracy we get from back propagation algorithm is 69.825%

Therefore the proposed system can be used to identify the human gait and to know which locomotion provides normal GAIT and abnormal GAIT.

5.3 Future Scope

The proposed system can be used in surveillance systems, to detect any upcoming disease related to GAIT human locomotion, recognisition system.

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