iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 Issue: III Month of publication: March 2022

DOI: https://doi.org/10.22214/ijraset.2022.40979

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

Gait Movement Analysis Using Polynomial Regression

Suraj Agrawal[1], Rahul Yadala[2], Piyush Goyal[3], Dr. Jyoti Bharti[4]
[1, 2, 3] Department of Computer Science & Engineering, Maulana Azad National Institute of Technology, Bhopal, India
[4]Assistant Professor, Department of Computer Science & Engineering, Maulana Azad National Institute of Technology, Bhopal, India

Abstract: Human gait recognition is a 2nd Generation Biometrics which focuses on distance and is unobtrusive. Human gait recognition is identification of a person based on their walking style. It is a Human Cooperation free biometric system. Many studies related to gait include subjects walking well below or above comfortable (free) speed. For this reason, a descriptive study examining the effect of walking speed on gait was conducted. The purpose of the study was to create a single-source, readily accessible repository of comprehensive gait data for a large group of children walking at a wide variety of speeds. Regression analysis is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome variable') and one or more independent variables (often called 'predictors', 'covariates', or 'features'). A Complete gait cycle is obtained when all the values are present from 0 to 100% completely. If there are any missing values in the gait cycle it is referred to as incomplete gait cycle. The prediction of the person speed or recognizing the person based on incomplete values becomes a complex task .So in order to predict or estimate the missing speed value we use the Polynomial regression technique. To predict the missing value we created Polynomial regression models. Thus, we try to compare these models with the Linear Regression models.
Keywords: Gait, Biometrics, Regression Analysis, Gait Cycle, Polynomial Regression

I. INTRODUCTION

The headway accomplished through the development of human appendages is called Human Gait. We can characterize Human Gait as bipedal and biphasic forward drive of focal point of gravity of the human body. Also, crooked developments of various sections of the body are in interchange style with least consumption of vitality. We can describe the diverse walk designs by contrasts in components, for example, appendage development designs, generally speaking speed, powers, motor and potential vitality cycles, and changes in the contact with the surface (ground, floor, and so on.). The different manners by which a human can move, either normally or because of specific preparing is the thing that human walk depicts. [1]

Gait analysis is the systematic study of animal locomotion, to be more specific, it is the study of human motion where we use the human eye and the brain of observers, in addition to using instrumentation for measuring movements of the body and its mechanics. A (bipedal) gait cycle is defined as the timely ordered sequence of movements of body during locomotion in between the event when one foot contacts the ground and when that same foot again contacts the ground, and also involves propulsion of the center of gravity in the direction of motion. A single gait cycle is also known as a stride.

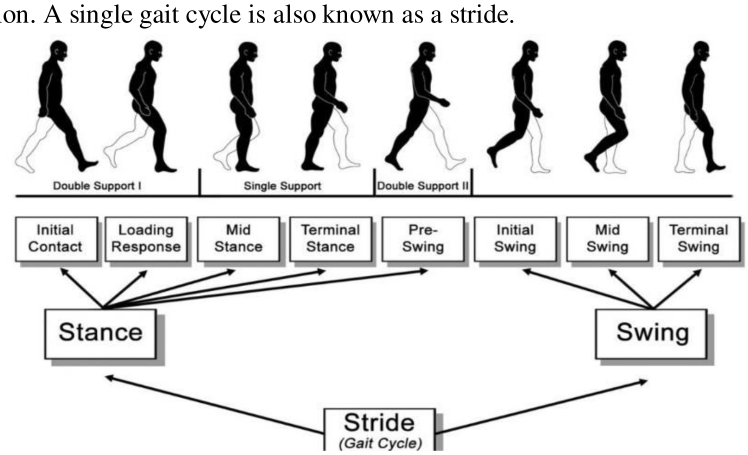

Fig 1. Gait Cycle of a person

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

II. METHODOLOGY

A. Application Overview

We are using Polynomial Regression in gait analysis for value prediction and predicting the missing value in given data set using polynomial regression. It gives better accuracy then the linear model and helps in predicting the correct values. Firstly, the dataset is unorganized so we have done pre-processing to convert the dataset in which we can easily apply the polynomial regression model for predicting the missing values.

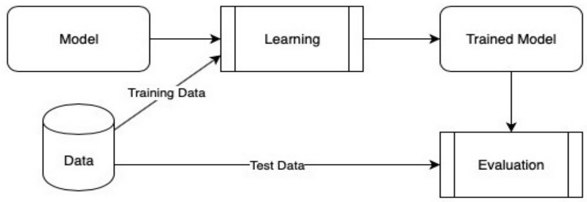

Fig 2. Application Architecture

We have used Python for developing a polynomial regression model to predict missing values. We have used many packages like Numpy, pandas, scikit learn, etc. For training the model we have used 70% of data of dataset and rest 30% of data is for testing the model and for checking the accuracy which how accurate the values are predicted from the above model.

We have to predict the values of the slow, medium, fast walk based on age (Young or Adult) and different kind of Angle, GRF, Moment, Power and Muscles. We have created 12 regression model for each tables of dataset which are Young and Slow Walk Regression, Young and Medium Walk Regression, Young and Fast Walk Regression, Adult and Slow Walk Regression, Adult and Medium Walk Regression, Adult and Fast Walk Regression, Young and Slow Walk using Medium and Fast Walk values Regression, Young and Medium Walk using Slow and Fast Walk values Regression, Young and Fast Walk using Medium and Slow Walk values Regression, Adult and Slow Walk using Medium and Fast Walk values Regression, Adult and Medium Walk using Slow and Fast Walk values Regression, Adult and Fast Walk using Medium and Slow Walk values.

B. Database Design

1) *Database Source:* The database is extracted from, A multiple-task gait analysis approach: kinematic, kinetic and EMG reference data for healthy young and adult subjects. The database contains data from different tasks presented in the article: walking at natural speed-(N), walking very slow-(XS), walking slow-(S), walking medium-(M), walking fast-(L), walking on toes-(T), walking on heels-(H), stair ascending-(U) and stair descending-(D).
2) *Data Structure:* Each Angle Contains 101 corresponding values for Gait Cycle ranging from (0-100%)The given database is in CSV format and is given as follows- Variable name with sense of positive/negative appropriate, Gait Cycle Percentage, subtract (mean, 1sd), mean, Add (mean, 1sd) for young and adult speeds.

III.IMPLEMENTATION

Complete gait cycle is formed only when the values are present from 0 to 100% gait cycle completely. If at any point of time or at any part of gait cycle values are missing then incomplete gait cycle is formed. Predicting the person speed or recognizing a person based on the missing speed values becomes complex. So in order to predict or estimate the missing speed value we use the polynomial regression technique. To predict the missing value we created polynomial regression models.

A. Single Walk

This method determines or predict the missing speed value at given gait cycle using only any one of the remaining walks. So we have created 6 polynomial regression models for each tables of dataset which are:

1) Young and Slow Walk Regression
2) Young and Medium Walk Regression
3) Young and Fast Walk Regression
4) Adult and Slow Walk Regression
5) Adult and Medium Walk Regression
6) Adult and Fast Walk Regression.

For each regression model independent variable vector is taken from the pre-processed dataset. So the equation for these models can be represented as:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_m x_i^m + \varepsilon_i \ (i = 1, 2, \ldots, n)$$

Where, $[\beta_1, \beta_2 \ldots \beta_n]$ is the coefficient vector
m is the number of parameters respective part has taken into consideration
y is the required missing speed value
And β_0 is the gait cycle (%) of the missing speed value.

B. Multiple Walk

This method determines or predict the missing speed value at given gait cycle using both of the remaining walks. So we have created another 6 polynomial regression models which are:

1) Young and Slow Walk using Medium and Fast Walk values Regression
2) Young and Medium Walk using Slow and Fast Walk values Regression
3) Young and Fast Walk using Medium and Slow Walk values Regression
4) Adult and Slow Walk using Medium and Fast Walk values Regression
5) Adult and Medium Walk using Slow and Fast Walk values Regression
6) Adult and Fast Walk using Medium and Slow Walk values Regression

But in order to use both of remaining walks coefficient vector is modified by combining it with the vectors of both of the remaining speeds independent variable vectors. Concatenated vector will be used as final coefficient vector. However, independent variable vector of required speed is taken from the pre-processed dataset.

So the equation for these models can be represented as:

$$\mathbf{Y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_{50} \end{pmatrix}, \mathbf{X} = \begin{pmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ \vdots & \vdots & \vdots \\ 1 & x_{50} & x_{50}^2 \end{pmatrix},$$

$$\beta = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{pmatrix}, \epsilon = \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_{50} \end{pmatrix}$$

It can be can be expressed in the form of a design matrix **X**, a response vector **Y**, a parameter vector $\vec{\beta}$, and a vector of $\vec{\varepsilon}$ of random errors. The i row of X and Y will provide the x and y value for the ith data sample. Then the model can be rewritten as a form of linear equations:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \ldots & x_1^m \\ 1 & x_2 & x_2^2 & \ldots & x_2^m \\ 1 & x_3 & x_3^2 & \ldots & x_3^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \ldots & x_n^m \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

Which when using the notation of a pure matrix, it is given by:

$$\mathbf{Y} = \mathbf{X}\vec{\beta} + \vec{\varepsilon}.$$

The estimated polynomial regression coefficients in form of vectors (using the least squares estimation) is given as:

$$\widehat{\vec{\beta}} = (\mathbf{X}^{\mathsf{T}}\mathbf{X})^{-1}\ \mathbf{X}^{\mathsf{T}}\mathbf{Y},$$

Assuming m < n is the required condition for the matrix to be invertible; then since X is a Vandermonde matrix, the invertible condition holds true if all the xi values are unique. This is the process of unique least-squares solution.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

We try solving a 2nd Degree Polynomial to get the results using regression.

$$y=c_0+c_1x+c_2x^2$$

There are 3 partial derivatives as there are 3 coefficients. Given by,

$$\frac{\partial r}{\partial c_0} = 2\sum_{i=0}^{n}(c_0+c_1x_i+c_2x_i^2-y_i)$$
$$\frac{\partial r}{\partial c_1} = 2\sum_{i=0}^{n}(c_0x+c_1x^2+c_2x^3-x_iy_i)$$
$$\frac{\partial r}{\partial c_2} = 2\sum_{i=0}^{n}(c_0x^2+c_1x^3+c_2x^4-x^2y_i)$$

Setting the partial Derivatives equal to 0,

$$2\sum_{i=0}^{n}(c_0+c_1x_i+c_2x_i^2-y_i)=0$$
$$2\sum_{i=0}^{n}(c_0x+c_1x^2+c_2x^3-x_iy_i)=0$$
$$2\sum_{i=0}^{n}(c_0x^2+c_1x^3+c_2x^4-x_i^2y_i)=0$$

Solving the above equation,

$$\begin{aligned} c_0n &+ c_1\sum_{i=0}^{n}x_i &+ c_2\sum_{i=0}^{n}x_i^2 &= \sum_{i=0}^{n}y_i \\ c_0\sum_{i=0}^{n}x_i &+ c_1\sum_{i=0}^{n}x_i^2 &+ c_2\sum_{i=0}^{n}x_i^3 &= \sum_{i=0}^{n}x_iy_i \\ c_0\sum_{i=0}^{n}x_i^2 &+ c_1\sum_{i=0}^{n}x_i^3 &+ c_2\sum_{i=0}^{n}x_i^4 &= \sum_{i=0}^{n}x_i^2y_i \end{aligned}$$

Converting into matrix form,

$$\begin{bmatrix} n & \sum_{i=0}^{n}x_i & \sum_{i=0}^{n}x_i^2 \\ \sum_{i=0}^{n}x_i & \sum_{i=0}^{n}x_i^2 & \sum_{i=0}^{n}x_i^3 \\ \sum_{i=0}^{n}x_i^2 & \sum_{i=0}^{n}x_i^3 & \sum_{i=0}^{n}x_i^4 \end{bmatrix}\begin{bmatrix} c_0 \\ c_1 \\ c_2 \end{bmatrix}=\begin{bmatrix} \sum_{i=0}^{n}y_i \\ \sum_{i=0}^{n}x_iy_i \\ \sum_{i=0}^{n}x_i^2y_i \end{bmatrix}$$

Generalizing the equation,

$$\frac{\partial}{\partial c_m}\sum_{i=0}^{n}(c_0+c_1x_i+c_2x^2\cdots c_mx^m-y_i)^2=2\sum_{i=0}^{n}(c_0x^m+c_1x^{(m+1)}+c_2x^{(m+2)}\cdots c_mx^{(2m)}-x^my_i)$$

Where m is the degree of the polynomial, and n is the number of known data points. This, if you follow the math, leads to a generalized matrix:

$$\begin{bmatrix} n & \sum_{i=0}^{n}x_i & \sum_{i=0}^{n}x_i^2 & \cdots & \sum_{i=0}^{n}x_i^m \\ \sum_{i=0}^{n}x_i & \sum_{i=0}^{n}x_i^2 & \sum_{i=0}^{n}x_i^3 & \cdots & \sum_{i=0}^{n}x_i^{(m-1)} \\ \sum_{i=0}^{n}x_i^2 & \sum_{i=0}^{n}x_i^3 & \sum_{i=0}^{n}x_i^4 & \cdots & \sum_{i=0}^{n}x_i^{(m-2)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sum_{i=0}^{n}x_i^m & \sum_{i=0}^{n}x_i^{(m+1)} & \sum_{i=0}^{n}x_i^{(m+2)} & \cdots & \sum_{i=0}^{n}x_i^{2m} \end{bmatrix}\begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ \vdots \\ c_m \end{bmatrix}=\begin{bmatrix} \sum_{i=0}^{n}y_i \\ \sum_{i=0}^{n}x_iy_i \\ \sum_{i=0}^{n}x_i^2y_i \\ \vdots \\ \sum_{i=0}^{n}x_i^my_i \end{bmatrix}$$

This is the matrix representation of polynomial regression for any degree polynomial. And that's it. An overdetermined system is solved by creating a residual function, summing the square of the residual which forms a parabola/paraboloid, and finding the coefficients by finding the minimum of the parabola/paraboloid.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

IV. RESULT ANALYSIS

A. Evaluation Methods of Regression

The overview of statistical methods which are used to evaluate the performance of a regression model and also have performed analysis on experimental results obtained from this study. Prediction errors are also known as residuals. They show how far data points are from the regression line or how best the data is fit around the line. Four methods have been used to evaluate the performance of all regression models created here.

Following are the methods which are used to estimate the prediction performance:

1) *MAE (Mean of Absolute Value of Errors):* Mean of Absolute value of Errors. It performs comparison and measures deviation between actual and observed value. It deals with the problem of differentiability. Lower the value, better is the result.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$$

2) *MSE (Mean of Squared Errors):* Mean of Squared Errors. It is the difference between actual value and the predicted value. It is used to overcome the problem of differentiability in MAE. Lower the value, better is the result. A value of zero (0) indicates perfect fit.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$$

3) *RMSE (Square Root of Squared Errors):* Lower the value, better is the result.

$$RMSE = \sqrt{MSE} \quad (or) \quad RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

4) *R^2 Score (Coefficient of Determination):* It indicates the proportion of Variance explained by the model between mean of actual values and predicted values. It also indicates how much good are the predicted values fitted to the actual values. Its values always ranges from 0 to 1 indicating no-fit and fit respectively. Higher the value, the better is the result which means closer is the R2 value to 1, better is the model fitted. There are cases where R2 value result in negative indicating that the model fitted is worse than an average fitted model. R^2 is a comparison of Residual Sum of Squares (RSS) with Total Sum of Squares (TSS).

$$R^2 = 1 - \frac{RSS}{TSS}$$

B. Evaluations and Results

To evaluate the created regression models, we have made use of the above mentioned methods and also represented the results using tables and graphs. We have gait data speed values on EMG, kinetics and kinematics. EMG signals have captured speed values at various major muscles such as Gluteus maximus, Biceps femoris, Vastus medialis, Foot flex and Soleus. Kinematic data has joint rotations considering rotations at foot flex/extension, Hip ad/abduction, pelvic up/down obliquity and ankle dorsi/plantar flexion. Kinetics includes joint power, joint moment and ground reaction forces. Joint power is the total power absorbed or generated at knee, ankle and hip. Joint moment is total moment acting at a joint such as hip ad/abduction, knee ext. /flexion and ankle dorsi/plantar flexion at that specific instant during the gait cycle. Among all of the available EMG, kinetic and kinematic data, instead of taking all -of the parameters or joints, we have taken one parameter for each type of data i.e., at different angle (o), GRF (% body weight), Moment (N*m/kg), Power (W/kg) and Muscles (% max). To compare all the results we took gait cycle (%) in regular intervals. Tables 1, 2, 3 and 4 the evaluation results (MAE, MSE, RMSE and Accuracy) of the both single and multiple walk regression models at each degree of polynomial n = 2, 3, 4, 5. These values are calculated by using actual and predicted speed values.

Calculations for Polynomial Degree =2,

TABLE I
PREDICTION VALUES AT POLYNOMIAL DEGREE N = 2

Degree n =2	MAE		MSE		RMSE		R^2 Score	
	Single	Multiple	Single	Multiple	Single	Multiple	Single	Multiple
Young Slow	7.0136	0.3107	120.3014	0.1805	10.9682	0.4248	0.5834	0.9995
Young Medium	7.2727	0.2113	113.6538	0.0947	10.6609	0.3078	0.6818	0.9997
Young Fast	7.9677	0.3458	143.2979	0.2434	11.9707	0.4933	0.6250	0.9995
Adult Slow	7.1675	0.4675	116.0881	0.4441	10.7744	0.6664	0.6645	0.9986
Adult Medium	7.9025	0.4106	149.4125	0.3948	12.2234	0.6283	0.6524	0.9991
Adult Fast	8.6038	0.3208	156.4638	0.2136	12.5086	0.4622	0.6354	0.9994
Overall Value	7.6546	0.3445	133.2029	0.2618	11.5177	0.4971	0.6404	0.9993

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

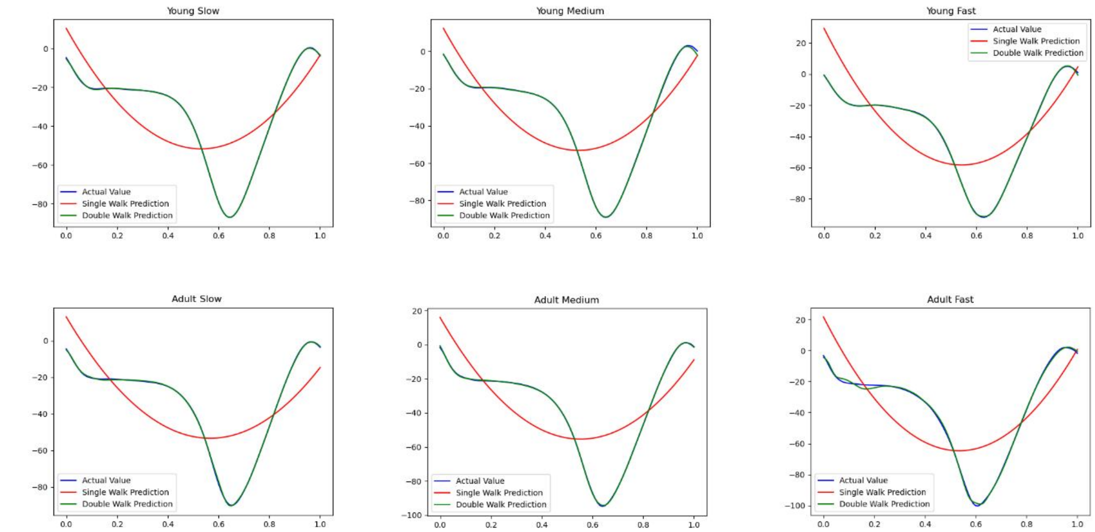

Fig 3. Prediction Values at Polynomial Degree n = 2

Calculations for Polynomial Degree =3,

TABLE III
PREDICTION VALUES AT POLYNOMIAL DEGREE N = 3

Degree n = 3	MAE		MSE		RMSE		R^2 Score	
	Single	Multiple	Single	Multiple	Single	Multiple	Single	Multiple
Young Slow	4.7374	0.0999	60.4887	0.0217	7.7775	0.1473	0.8290	0.9999
Young Medium	5.1453	0.0926	76.5715	0.0256	8.7505	0.1599	0.8020	0.9999
Young Fast	5.5836	0.1244	89.1176	0.0362	9.4402	0.1903	0.7780	0.9999
Adult Slow	5.1759	0.1622	65.7266	0.0841	8.1072	0.2900	0.8096	0.9998
Adult Medium	5.5819	0.1823	81.3018	0.0875	9.0168	0.2959	0.8061	0.9998
Adult Fast	6.0535	0.0996	90.2550	0.0211	9.5003	0.1452	0.8073	0.9999
Overall Value	5.3796	0.1268	77.2436	0.0460	8.7654	0.2047	0.8053	0.9999

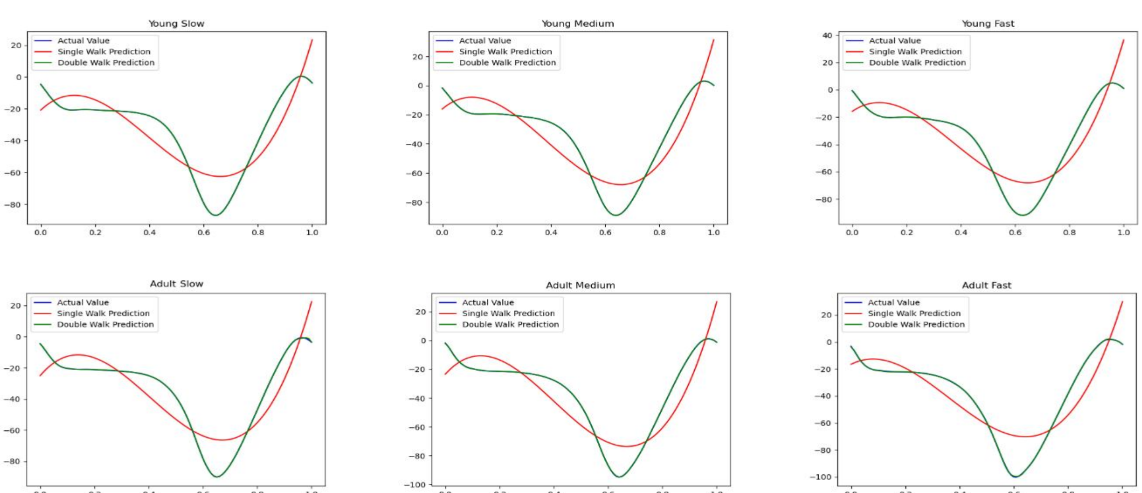

Fig 4. Prediction Values at Polynomial Degree n = 3

Calculations for Polynomial Degree =4,

TABLE IIIII
PREDICTION VALUES AT POLYNOMIAL DEGREE N = 4

Degree n = 4	MAE		MSE		RMSE		R^2 Score	
	Single	Multiple	Single	Multiple	Single	Multiple	Single	Multiple
Young Slow	4.9421	0.0911	48.7256	0.0217	6.9285	0.1473	0.8373	0.9999
Young Medium	4.9416	0.1296	54.3441	0.0256	7.2088	0.1599	0.8100	0.9999
Young Fast	4.9269	0.0774	57.8073	0.0217	7.2939	0.1377	0.7858	0.9999
Adult Slow	5.3132	0.1439	53.8170	0.0836	7.2903	0.2850	0.8177	0.9999
Adult Medium	5.3391	0.1061	60.4898	0.0489	7.6579	0.1989	0.8141	0.9999
Adult Fast	5.4189	0.0914	61.4231	0.0659	7.6045	0.2389	0.8154	0.9999
Overall Value	5.1470	0.1066	56.1012	0.0446	7.3307	0.1946	0.8134	0.9999

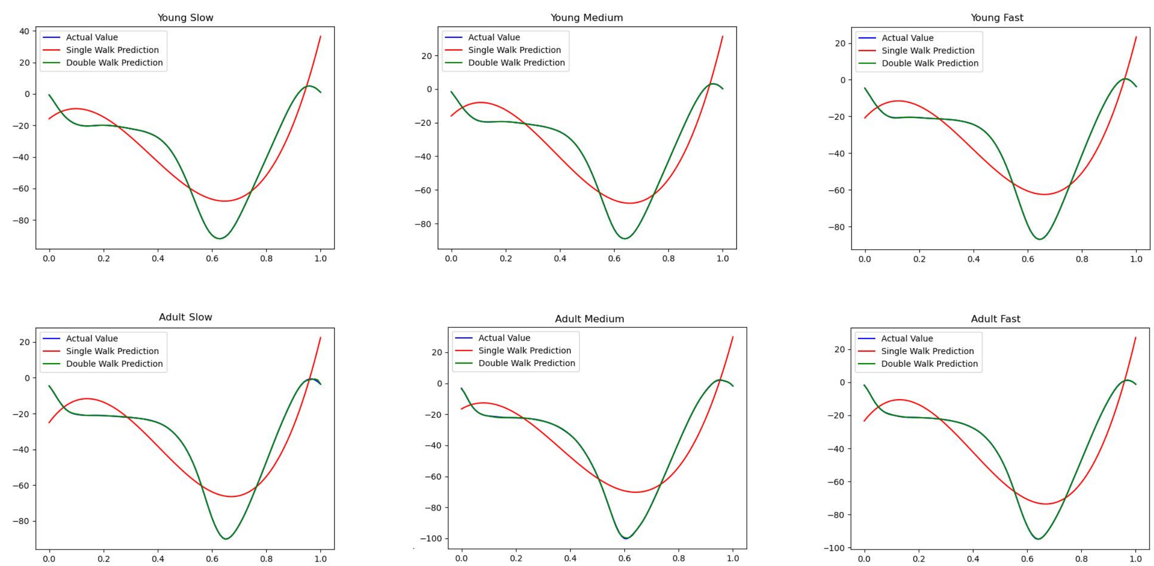

Fig 5. Prediction Values at Polynomial Degree n = 4

Calculations for Polynomial Degree =5,

TABLE IVV
PREDICTION VALUES AT POLYNOMIAL DEGREE N = 5

Degree n = 5	MAE		MSE		RMSE		R^2 Score	
	Single	Multiple	Single	Multiple	Single	Multiple	Single	Multiple
Young Slow	5.1467	0.0823	36.9625	0.0217	6.0796	0.1473	0.9400	0.9999
Young Medium	4.7379	0.1666	32.1166	0.0256	5.6671	0.1599	0.9546	0.9999
Young Fast	4.2702	0.0304	26.4970	0.0072	5.1475	0.0851	0.9671	0.9999
Adult Slow	5.4505	0.1256	41.9074	0.0831	6.4735	0.2800	0.9356	0.9999
Adult Medium	5.0964	0.0299	39.6777	0.0103	6.2990	0.1019	0.9479	0.9999
Adult Fast	4.7843	0.0833	32.5913	0.1107	5.7088	0.3327	0.9629	0.9999
Overall Value	4.9143	0.0864	34.9588	0.0431	5.8959	0.1845	0.9514	0.9999

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

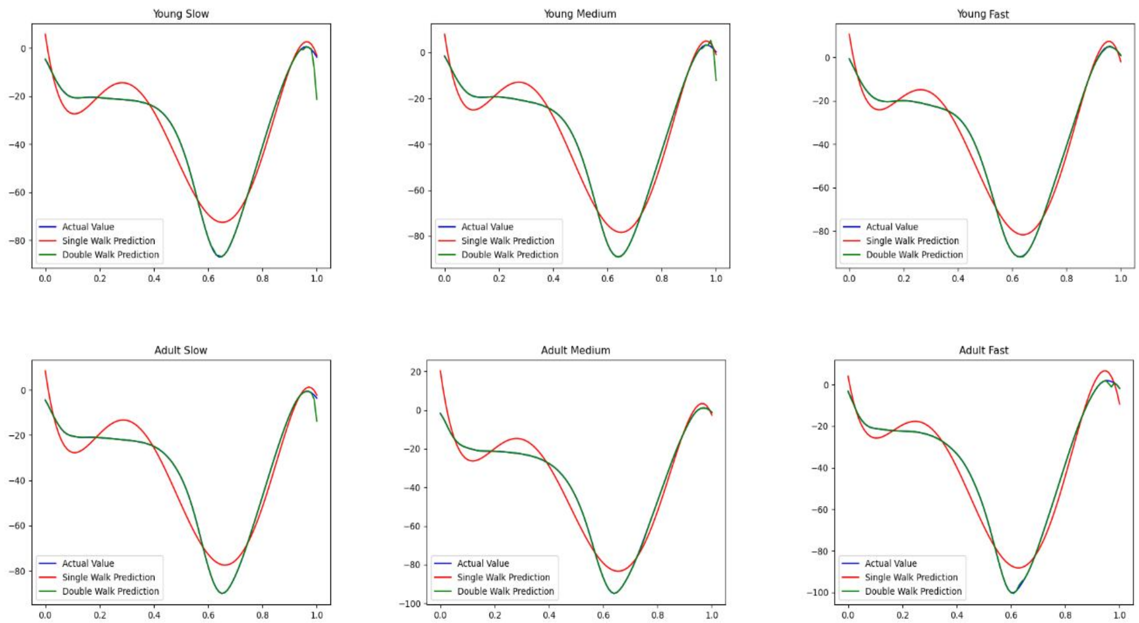

Fig 6. Prediction Values at Polynomial Degree n = 5

C. Comparison Between Linear & Polynomial Regression

The table gives us a comparison between the Linear & Polynomial Regression Model.

TABLE V
COMPARISON BETWEEN LINEAR AND POLYNOMIAL REGRESSION

Parameters	Linear Model		Polynomial (n=2)		Polynomial (n=3)		Polynomial (n=4)		Polynomial (n=5)	
	Single	Multiple	Single	Multiple	Single	Multiple	Single	Multiple	Single	Multiple
MAE	7.7851	0.5903	7.6546	0.3445	5.3796	0.1268	5.1470	0.1066	4.9143	0.0864
MSE	165.1293	0.7866	133.2029	0.2618	77.2436	0.046	56.1012	0.0446	34.9588	0.0431
RMSE	12.8309	0.8348	11.5177	0.4971	8.7654	0.2047	7.3307	0.1946	5.8959	0.1845
R2	0.5492	0.9979	0.6404	0.9993	0.8053	0.9999	0.8134	0.9999	0.9514	0.9999

The polynomial model method proves out to be better than the linear model according to our study. The accuracy improves as we increase the degree of the polynomial.

V. CONCLUSION

The use of the Polynomial regression model has proved out to be a good match for the Gait movement analysis as it improves the accuracy as well as other parameters for the prediction model. While comparing it with Linear Regression model, our model stands out and provides R2 score of 95.14% for single walk and 99.99% for multiple walk. As we increase the degree of polynomial it provides us improved result.

REFERENCES

[1] K. Bashir, T. Xiang, and S. Gong. Cross-view gait recognition using correlation strength. In BMVC, 2010.

[2] X. Ben, W. Meng, R. Yan, and K. Wang. An improved biometrics technique based on metric learning approach. Neurocomputing, 97:44 – 51, 2012

[3] I. J. Goodfellow, J. Pougetabadie, M. Mirza, B. Xu, D. Wardefarley, S. Ozair, A. Courville, Y. Bengio, Z. Ghahramani, and M. Welling. Generative adversarial nets. Advances in Neural Information Processing Systems, 3:2672–2680, 2014.

[4] Y. Guan, C. T. Li, and Y. Hu. Robust clothing-invariant gait recognition. In 2012 Eighth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, pages 321–324, July 2012.

[5] Michael H. Schwartz, Adam Rozumalski, Joyce P. Trost. The effect of walking speed on the gait of typically developing children

[6] M. A. Hossain, Y. Makihara, J. Wang, and Y. Yagi. Clothinginvariant gait identification using part-based clothing categorization and adaptive weight control. Pattern Recognition, 43(6):2281 – 2291, 2010.

[7] Gabriele Bovi, Marco Rabuffetti, Paolo Mazzoleni, Maurizio Ferrarin A multiple-task gait analysis approach: Kinematic, kinetic and EMG referencedata for healthy young and adult subjects

[8] A. Y. Johnson and A. F. Bobick. A multi-view method for gait recognition using static body parameters. In Proc. of 3rd International Conference on Audio and Video Based Biometric Person Authentication, pages 301–311, Jun. 2001.