Tech Science Press

A Three-Dimensional Real-Time Gait-Based Age Detection System Using Machine Learning

Muhammad Azhar[1,*], Sehat Ullah[1], Khalil Ullah[2], Habib Shah[3], Abdallah Namoun[4] and Khaliq Ur Rahman[5]

[1]Department of Computer Science & IT, University of Malakand, Chakdara, 18800, Pakistan
[2]Department of Software Engineering, University of Malakand, Chakdara, 18800, Pakistan
[3]College of Computer Science, King Khalid University, Abha, 62529, Saudi Arabia
[4]Faculty of Computer and Information Systems, Islamic University of Madinah, Madinah, 42351, Saudi Arabia
[5]Department of Statistics, Abdul Wali Khan University, Mardan, 23200, Pakistan
*Corresponding Author: Muhammad Azhar. Email: azharitteacher@gmail.com

Abstract: Human biometric analysis has gotten much attention due to its widespread use in different research areas, such as security, surveillance, health, human identification, and classification. Human gait is one of the key human traits that can identify and classify humans based on their age, gender, and ethnicity. Different approaches have been proposed for the estimation of human age based on gait so far. However, challenges are there, for which an efficient, low-cost technique or algorithm is needed. In this paper, we propose a three-dimensional real-time gait-based age detection system using a machine learning approach. The proposed system consists of training and testing phases. The proposed training phase consists of gait features extraction using the Microsoft Kinect (MS Kinect) controller, dataset generation based on joints' position, pre-processing of gait features, feature selection by calculating the Standard error and Standard deviation of the arithmetic mean and best model selection using R^2 and adjusted R^2 techniques. T-test and ANOVA techniques show that nine joints (right shoulder, right elbow, right hand, left knee, right knee, right ankle, left ankle, left, and right foot) are statistically significant at a 5% level of significance for age estimation. The proposed testing phase correctly predicts the age of a walking person using the results obtained from the training phase. The proposed approach is evaluated on the data that is experimentally recorded from the user in a real-time scenario. Fifty (50) volunteers of different ages participated in the experimental study. Using the limited features, the proposed method estimates the age with 98.0% accuracy on experimental images acquired in real-time via a classical general linear regression model.

Keywords: Age estimation; gait biometrics; classical linear regression model

1 Introduction

Age is a significant human characteristic that can be used to evaluate a person's identification, security, and health [1]. Because of its significance, age evaluation cannot be based solely on human perception [2]. Automatic age evaluation uses a person's physical characteristics to determine their appropriate age or range of ages [3]. A person's age can be classified into two categories: apparent age, which is based on physical characteristics and the person's real age, which is the person's actual age [4]. For age classification using biometric features, a lot of research has been carried out via face images [5–12] and gait [13–21]. Age Classification using face images has many applications in a variety of fields, like the prevention and age verification of cybercrime in the gaming industry. Face-based age estimation is divided into two categories, such as age prediction and face representation. Face representation uses shallow appearance, local binary patterns, and bionic features [22–25]. This is a classification or regression problem to obtain feature representations of each facial image for age estimation. As a result, age estimation using a facial image presents challenges for the traditional age estimation technique. The primary drawback of the current method is that face-based prediction performance depends on image quality and face exposure. Face-based age estimation has applications in security, entertainment, human-computer interface, and audiovisual. However, due to factors like a mask covering the face, face makeup, and plastic surgery, existing face-based age detection algorithms are not very accurate. Age estimation using face images is not feasible for live surveillance because most security cameras only produce limited texture information. On the other hand, human gait is unique and recognized as a behavioral biometric feature. Human gait is defined by two essential characteristics: walking style and posture [26]. Walking is a voluntary activity, although the overall gait is controlled by the nervous system [27]. A type of behavioral biometric that can be trained to predict human age is gait. Gait age is the age determined by a person's gait, as compared to chronological age, which reflects the person's actual age [27]. Gait has received a lot of attention recently due to the invasiveness of video monitoring. Comparing gait to other biometrics, there are a number of benefits. For instance, it can be recognized from a distance. Additionally, gait patterns discovered through videos and images is difficult to conceal. The gait-based features don't require subject cooperation or high-resolution images. However, using gait to extract gait features is a challenging task. For age estimation using gait, different systems have been proposed so far [28–32]. The research work carried out in the area has certain limitations, like specific age limits and image- or video-based classification. Some of the researchers have classified the age group into children, adults, and older people, which is obviously a restricted age-based classification [33]. Similarly, Davis [28] categorized the age group into children and adults, while Begg et al. [34] categorized them into younger and elder people. Due to increasing age variances, which have a negative effect on the estimation's accuracy, all of these works have produced significant estimation errors. The proposed efforts must overcome these constraints and produce an accurate estimation of the age group in the real environment in order to be effective. This is due to the limited scope of these research works. It ensures real-based estimation while overcoming the issues with image/video-based estimation and a limited age range.

The structure of this paper is as follows: In Section 2, the literature review is covered, Section 3 presents the proposed system, and Experimental work is described in Part 4. Section 5 describes the comparison to the state of the art, and finally, Section 6 described the conclusion.

2 Literature Review

Age Calculation using gait is a modern research, therefore, limited investigations have been carried out so far. The first study on this area was published by Lu et al. [35]. An effective encoding strategy

is used to transform individual age values into binary format. A multi-label guided (MLG) technique was developed using gait energy images (GEIs) to combine the age information for age estimation. In order to estimate age using face images, the authors reported a baseline algorithm [32,36]. Lu et al. [37] presented a manifold analysis technique to estimate age. Similarly, another study estimates human age by integrating gait and facial data [38]. These Studies all used a single-group independent estimating model, which increased estimation errors as the age variation increases. To achieve better accuracy and to handle the problems faced by a single group independent estimation model, the authors in [39] proposed a group dependent method for Estimating human age using gait. Similarly, Davis [28] estimated human age using different gait features, such as stride width, frequency, and leg length. Human ages have been classified by Begg et al. [34] into younger (28.4 mean age) and old (69.2 mean age) people. Through many features, such as height, leg length, and the relationship between the head and body, the authors in [40] categorized human ages into children and adults. Similarly, the authors in [40] divided human ages into three categories: young children (under 15), adults (15–65), and the elderly (after 65 years). Through the use of computer vision methods, gait features can be extracted from images or videos, including the walking patterns of people. Model-based or model-free features based on computer vision. Model-based features are achieved through testing Body parameters in the images or video. Different approaches have been proposed so far using a model-based approach. The authors in [40,41] used many biological studies and various features for age classification. Children's upper limbs are shorter and closer to the ground than those of adults, according to age classifications performed on children by Ince et al. [30]. For the first time, Davis [28] took the opportunity to categorize ages using just 15 participants. Begg et al. [34] used Support Vector Machines (SVM) to classify Ages based on minimum foot clearance. For the purpose of classifying a person as a kid or an adult, Lu et al. [35] retrieved various parameters, including stride length, speed, body length, leg length, and head-to-body ratio. Aderinola et al. [42] retrieved many parameters for age identification with 96% accuracy, including step length, upper limbs, gait speed, and length of lower limps. In contrast, model-free gait features are referred to as Appearance-based features since they stress a person's physical characteristics in videos or images. The two fundamental methods used in model-free feature extraction are background subtraction and silhouette generation. Different approaches for age Estimations have been proposed by the researchers so far using model-free approaches. Sakata et al. [15] used a large gait dataset, which contained more than 60,000 people for the age estimation. Makihara et al. [32] used a deep residual network for the multitasking classification of subjects depends on gender and age. Sakata et al. [15] proposed a method for age prediction using confidence score. Xu et al. [43] used age estimation to discover participants and count age groupings. Abirami et al. [44] provided a technique for estimating age using height data. The age regression task was presented by Zhu et al. [45] as a sequence of binary age classifiers. Xu et al. [46] used the gait cycle's silhouette for a small image to estimate age. The previous research mostly proposed facial/camera-based age estimation, and hence produce low accuracy due to limited texture information when face covered by mask. Because of the limited age range and high estimation errors in image-based estimation, the researchers recommended estimating age using gait.

The main contributions of the proposed research work as follows: (1) preparation of a new dataset for age estimation; (2) Extraction and selection of features using different statistical analyses such as T-test, ANOVA technique, R^2 and adjusted R^2 (adj-R^2) techniques; (3) Using a simple linear regression model for the complex problem of age estimation. The proposed model is computationally optimal with very low computational cost and highest accuracy; (4) the proposed method can be applied in a real-time scenario for the new user, with data extracted from MS Kinect; (5) the proposed system is

compared with the state-of-the-art system using different parameters such as accuracy, technique, and dataset used.

3 Proposed System

The proposed system consists of two main parts: training and testing. The proposed training phase consists of different components, i.e., extraction of Skeletal information through Microsoft Kinect (MS Kinect), dataset generation, Pre-processing, feature selection method, best model selection, and finally age Estimation is carried out using the best-fit model (see Fig. 1).
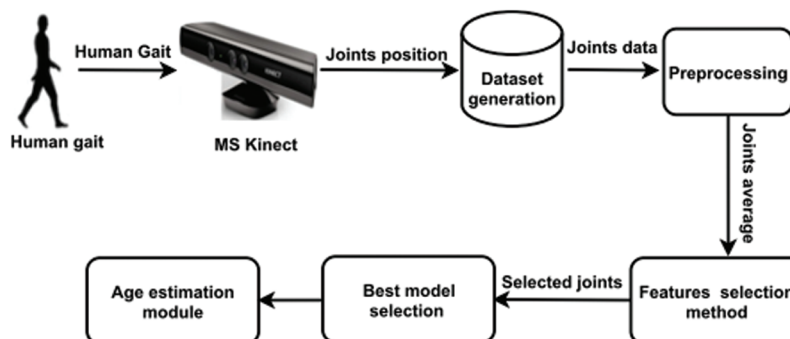

Figure 1: Detail system model of the proposed system

The proposed testing phase automatically estimates the age of a walking person in real-time using the results obtained from the training phase (See Fig. 2).
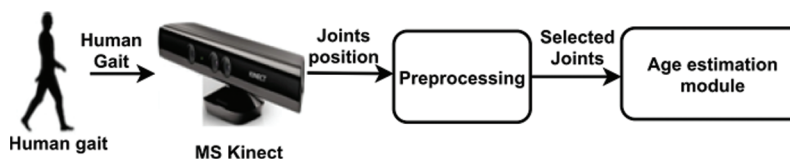

Figure 2: Schematic of our proposed system model

Algorithm: Algorithm for estimating the age of walking person

1: Collect coordinates of all joint points from the Kinect, i.e., $P_J = (x_i, y_i, z_i)$, $i = 1, 2 \ldots n$, and $j = 1, 2 \ldots 20$;

2: Calculate the arithmetic mean and combined arithmetic mean of each joint X, Y, and Z coordinates;

3: Calculate the standard error of the arithmetic mean and standard deviation for feature selection;

4: Apply R^2 to different subsets of joints arithmetic means for the best model selection;

5: Apply adj-R^2 to different subsets of joints arithmetic means for the best model selection;

6: Select the set of joints having the highest accuracy;

7: Apply the Classical Liner Regression Model (CLRM) to the set of joints;

8: Finally, the age estimation of the walker is carried out;

3.1 Dataset Generation

We created our own dataset because there were no other datasets that contained both skeleton joint position and were large enough gender information. In this research work, 273 individuals, all

7–70 years old, participated in the experiment. The authors asked each volunteer to walk in a free pose in different directions inside the Kinect recognition space (see Fig. 3).

Figure 3: Walking directions of subjects from different directions

To record the 3D joints position from volunteers, a low-cost Microsoft Kinect V1 camera is used. The specification of the Kinect camera used in terms of resolution is (640×480). The depth information between the objects and the camera is captured by this sensor in addition to the conventional RGB image of the depicted object. The MS Kinect consists of a 3D depth sensor, a RGB camera, a tilt motor, and a Microsoft array as shown in Fig. 4a. Microsoft Kinect provides the complete set with 20 useful joints from head to feet as shown in Fig. 4b.
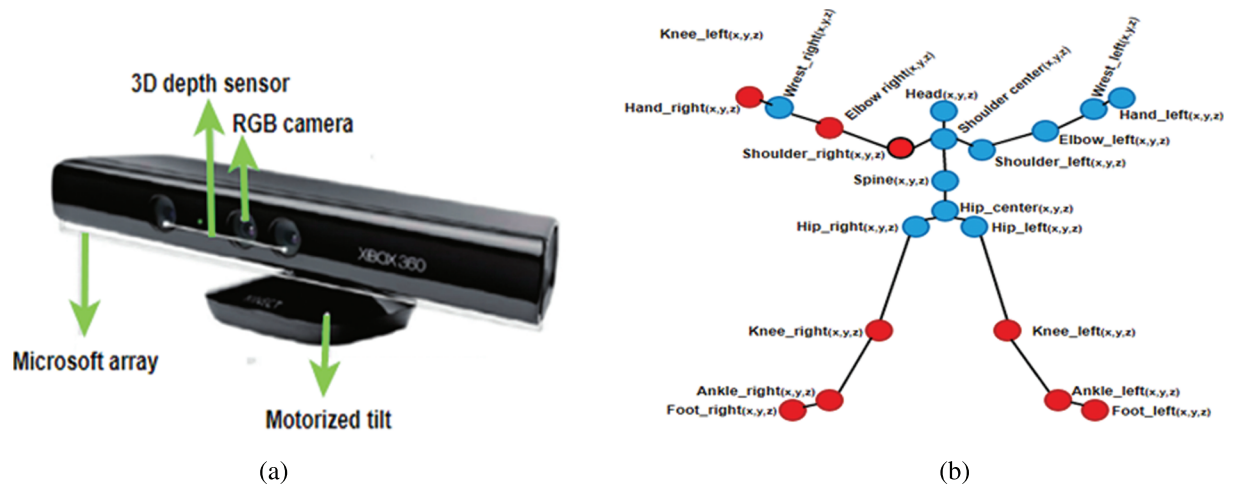

Figure 4: (a) Microsoft kinect sensor, (b) Different human joints

The accuracy of MS Kinect was tested by recording multiple records for each of the subjects. The measurement was determined from different distances and the optimal distance was determined to be 6 feet. The height and angle of the MS Kinect were 3.4 feet and 0 degrees at 30 frames per second (fps), respectively. All volunteers were free to take any action or position at any time. Because the average of all frames was used to extract the feature, there was no time limit.

3.2 Pre-Processing

The authors used 20 joints to capture the functionality in the classification phase. The position of the joint P_j is defined as: $P_j = x_i + yi + z_i$, where $P_j = 1, 2, 3 \ldots 20$ and $i = 1, 2, 3 \ldots n$. In this phase,

the extracted data is pre-processed before feeding the machine learning tools. Pre-processing includes calculating the arithmetic mean of joints for each axis, and then calculating the combined arithmetic mean for each joint.

3.2.1 Arithmetic Mean and Grand Arithmetic Mean of Joints

As the Kinect sensor provides 30 frames per second, approximately, and each joint position is represented in X, Y, and Z coordinates for each frame. Therefore, the arithmetic mean for joints is computed as

$$\overline{X}_{Joint(i)} = \frac{1}{n} \sum_{i=1}^{n} \left(X_{Joint(i)} \right), \text{ For } i = 1, 2, 3 \ldots n \tag{1}$$

where $\overline{X}_{Joint(i)}$ is the mean of joints for X coordinate. Using Eq. (1), the arithmetic mean is calculated for Y and Z coordinates. The grand mean of joint X, Y, and Z coordinates is calculated as

$$\overline{X}_C = \frac{1}{3} \left(\overline{X}_{Joint(i)} + \overline{Y}_{Joint(i)} + \overline{Y}_{Joint(i)} \right) \tag{2}$$

where, $\overline{X}_C$ is the combined arithmetic mean of joint $\overline{X}_{Joint(i)}$, $\overline{Y}_{Joint(i)}$ and $\overline{Z}_{Joint(i)}$ respectively.

3.3 Feature Selection Method

All body features were evaluated collectively and individually for each classification method throughout the classification phase. However, using all body features in the classification can result in a lower percentage of accuracy. As each joint moves in X, Y, and Z coordinates, therefore all the combinations of 60 features were tested. On the other hand, to improve classification accuracy, it is important to combine the features according to best model selection criteria R^2 and adjusted R^2. The best model was identified based on the percentage of accuracy for most contributing joints. We checked each percentage of accuracy in the classification based on standard error. If the accuracy rate exceeds 90%, the individually classified feature will be selected and combined with the other selected features. Otherwise, the features were not added to the selected set of features. The standard error measures accuracy. Higher standard errors cause less accuracy. The standard error of the arithmetic mean for shoulder right-joint can be calculated as

$$S.E \left(\overline{X}_{Sh\_r} \right) = \frac{\sigma_{sh\_r(x)}}{\sqrt{n}} \tag{3}$$

where n is the size of data and $S.E \left(\overline{X}_{Sh\_r} \right)$ is the standard errors for shoulder right-joint in X coordinates. Similarly, $\sigma_{sh\_r(x)}$ is the standard deviation of shoulder right-joint and can be defined as

$$\sigma_{xShr} = \sqrt{\frac{\sum_{i=1}^{N} \left(X_{i(Sh\_r)} - \overline{X}_{Sh\_r} \right)^2}{N}} \tag{4}$$

The standard error and standard deviation can be represented in the same way using Eqs. (3) and (4). The standard error shows the consistency of joints and *P*-value shows the significance of the joints. The lower the standard error, the higher will be the consistency. Similarly, the lower the *p*-value, the higher the significant level of joints. The standard errors and *P*-value of the joints: right shoulder, right elbow, left knee, right hand, left ankle, right knee, right ankle, right foot, and left foot are low, therefore, these joints are consistent and significant.

3.4 Best Model Selection

The coefficient of determination (R^2) and (Adj – R^2) techniques are used to select the best fitted model for age estimation. To determine the best fitted model for which R^2 is high i.e., if $R^2 = 90\%$, then 90% age is explained by joints and 10% due to other factors such as height, etc. Mathematically, R^2 can be written as

$$R^2 = \frac{\sum_{i=1}^{n} \left(\hat{y}_i - \bar{y}\right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2} \tag{5}$$

where $\hat{y}_i$ is the estimated age,

Where y_i is the value of a walking person age, $\hat{y}_i$ is the estimated age, and $\bar{y}$ is the mean age of a walking person. Also, the adjusted R^2 is used to select a best fitted model. Mathematically, the adjusted R^2 is defined as

$$Adj\ R^2 = 1 - \left(1 - R^2\right) \frac{\{n - 1\}}{\{n - (k + 1)\}} \tag{6}$$

where n is the size of persons and k is the number of parameters included in the model. The ranges of R^2 and Adj-R^2 lie between 0 and 1. When results of R^2 and Adj-R^2 are near to zero, tells us weak relationship and near to one, tells us strong relation between dependent (Joints) and independent variables (age).

3.5 Classification Method

The classification table for CLRM is used to find which human joints contribute the most to age detection. The most-contributed joints will be determined based on their accuracy. The most-contributed joints with an accuracy rate of more than 90% will be considered on the basis of standard error. Normally, the relationship among variables is direct, inverse and curving. To capture the relationship between variables, classical linear regression models (CLRM) are widely used. The linear relationship between one of the dependent variables, and one or more of the independent variables is known as regression. The CLRM is used when the dependent variable is continuous and follows normal distribution. In this study, the dependent variable is the age of a walking person and is continuous, which satisfies the important assumption of normality. Also, the Independent variables are the contributions or movements of 20 different human joints during gait. The results show that only nine joints out of twenty joints are the most heavily contributed joints in age estimation.

The CLRM is mathematically defined as

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \cdots + \beta_p X_{ip} + \epsilon_i \tag{7}$$

where Y_i is the dependent variable, β_0 is intercept form, β_i are the slop parameter, X_i s are independent variables, and ϵ_i is a random error.

3.5.1 Estimation of Model Procedures

Estimating the model parameters of the classical linear model (CLM) is one of the key requirements. The least square is used because the least square estimators are more accurate and effective for estimating a model's unknown parameters. We can write the CLRM in the form of matrices as

$$
\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \beta_0 & \beta_1 X_{11} & \beta_2 X_{12} & \beta_3 X_{13} & \cdots & \beta_p X_{1P} \\ \beta_0 & \beta_1 X_{21} & \beta_2 X_{22} & \beta_3 X_{23} & \cdots & \beta_p X_{2P} \\ \beta_0 & \beta_1 X_{31} & \beta_2 X_{32} & \beta_3 X_{33} & \cdots & \beta_p X_{3P} \\ & & & \vdots & \ddots & \vdots \\ \beta_0 & \beta_1 X_{N1} & \beta_2 X_{N2} & \beta_3 X_{N3} & \cdots & \beta_p X_{NP} \end{bmatrix} + \begin{bmatrix} \in_1 \\ \in_2 \\ \in_3 \\ \vdots \\ \in_N \end{bmatrix} \tag{8}
$$

Taking $\beta_0, \beta_1, \beta_2 \ldots \beta_p$ common

$$
\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{12} & X_{13} & \cdots & X_{1P} \\ 1 & X_{21} & X_{22} & X_{23} & \cdots & X_{2P} \\ 1 & X_{31} & X_{32} & X_{33} & \cdots & X_{3P} \\ & & \vdots & & \ddots & \vdots \\ 1 & X_{N1} & X_{N2} & X_{N3} & \cdots & X_{NP} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_P \end{bmatrix} + \begin{bmatrix} \in_1 \\ \in_2 \\ \in_3 \\ \vdots \\ \in_N \end{bmatrix} \tag{9}
$$

$$ \underline{Y} = X\underline{\beta} + \underline{\epsilon} \tag{10} $$

where $\underline{Y}$ is a vector of order N × 1 for age observations, and X is a data matrix of order N × (P + 1) for various human joints, β is a vector of order (P + 1) × 1 of unknown parameters of the general linear regression model and $\underline{\epsilon}$ is the vector of order N × 1 of the error term. Assumptions are required for general linear regression models such that the error term (difference between observed age and estimated age of walking person) is normally distributed with mean zero and constant variance, i.e., $\in_i \sim N(0, \sigma^2)$. Constant variance means that there is no hetroscedasticity, and the independent variables are not correlated (no multi-collenearity). The response variable (age) is normally distributed with mean $X\beta$ and variance σ^2 i.e., $Y \sim N(X\beta, \sigma^2)$. To estimate the ordinary least squares estimators $\widehat{\beta}$ will be obtained in the form of matrices as, $\widehat{\beta} = (X^t X)^{-1} X^t \underline{Y}$ which is the estimator for $\underline{\beta}$, provided that $(X^t X)^{-1}$ exists. The $(X^t X)^{-1}$ matrix will always exist if the predictors (joints) variables are linearly independent. Consider the three variables in this case (Y = age, X_1 = Foot left and X_2 = Foot right). Then

$$
X^t X = \begin{bmatrix} 1 & 1 & \ldots & 1 \\ X_{11} & X_{21} & \ldots & X_{N1} \\ X_{12} & X_{22} & \ldots & X_{N2} \end{bmatrix} \begin{bmatrix} 1 & X_{11} & X_{12} \\ 1 & X_{21} & X_{22} \\ \vdots & \vdots & \vdots \\ 1 & X_{N1} & X_{N2} \end{bmatrix} \tag{11}
$$

$$
X^t X = \begin{bmatrix} n & \sum X_{i1} & \sum X_{i2} \\ \sum_{i=1}^{N} X_{i1} & \sum X_{i1}^2 & \sum X_{i1} X_{i2} \\ \sum_{1}^{N} X_{i2} & \sum X_{i1} X_{i2} & \sum X_{i2}^2 \end{bmatrix} \tag{12}
$$

Also

$$
X^t \underline{Y} = \begin{bmatrix} 1 & 1 & \ldots & 1 \\ X_{11} & X_{21} & \ldots & X_{N1} \\ X_{12} & X_{22} & \ldots & X_{N2} \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_N \end{bmatrix} \tag{13}
$$

$$X^t \underline{Y} = \begin{bmatrix} \sum_{i=1}^{n} Y_i \\ \sum_{i=1}^{n} X_{i1} Y_i \\ \sum_{i=1}^{n} X_{i2} Y_i \end{bmatrix} \tag{14}$$

Now the least squares normal equations $(X^t X) \widehat{\underline{\beta}} = X^t \underline{Y}$ for two joints can be expressed as

$$\begin{bmatrix} n & \sum_{i=1}^{n} X_{i1} & \sum_{i=1}^{n} X_{i2} \\ \sum_{i=1}^{n} X_{i1} & \sum_{i=1}^{n} X_{i1}^2 & \sum_{i=1}^{n} X_{i1} X_{i2} \\ \sum_{i=1}^{n} X_{i2} & \sum_{i=1}^{n} X_{i1} X_{i2} & \sum_{i=1}^{n} X_{i2}^2 \end{bmatrix} \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} = \begin{bmatrix} \sum Y_i \\ \sum X_{i1} Y_i \\ \sum X_{i2} Y_i \end{bmatrix} \tag{15}$$

$$\sum_{i=1}^{n} Y_i = n\hat{\beta}_0 + \hat{\beta}_1 \sum_{i=1}^{n} X_{i1} + \hat{\beta}_2 \sum_{i=1}^{n} X_{i2} \tag{16}$$

$$\sum_{i=1}^{n} X_{i1} Y_i = \hat{\beta}_0 \sum_{i=1}^{n} X_{i1} + \hat{\beta}_1 \sum_{i=1}^{n} X_{i1}^2 + \hat{\beta}_2 \sum_{i=1}^{n} X_{i1} X_{i2} \tag{17}$$

$$\sum_{i=1}^{n} X_{i2} Y_i = \hat{\beta}_0 \sum_{i=1}^{n} X_{i2} + \hat{\beta}_1 \sum_{i=1}^{n} X_{i1} X_{i2} + \hat{\beta}_2 \sum_{i=1}^{n} X_{i2}^2 \tag{18}$$

By solving Eqs. (16)–(18), will give the OLS (ordinary least square) estimators.

3.5.2 Testing Hypothesis of Regression Coefficients

The hypothesis about regression coefficients is either significant or insignificant, i.e., H_0: $\underline{\beta} = 0$ vs. H_A : $\underline{\beta} \neq 0$. For such testing of hypothesis, F-test is used and is defined as $F = \frac{SSR/P}{SSE/n-k}$ or $F = \frac{MSR}{MSE}$ where SSR is the sum of squares of regression, P is the number of predictors (joints) included in the model, SSE is the sum of squares of error term, n is the number of observations (persons), and k is the number of parameters included in the model. Also, SSR and SSE can be computed in terms of matrices as $SSR = \widehat{\underline{\beta}}^t X^t \underline{Y} - \frac{(\sum Y_i)^2}{n}$ and $SSE = \underline{Y}^t \underline{Y} - \widehat{\underline{\beta}}^t X^t \underline{Y}$. To test the significance of any individual regression coefficients (joints) as β_i are H_0: $\beta_i = 0$ vs. H_A: $\beta_i \neq 0$. For individual joint testing, the t-test is used and is defined as $t = \frac{\hat{\beta}_i}{S.E(\hat{\beta}_i)}$, the null hypothesis. H0 is rejected if, $|t| > t_{\alpha/2}^v$ where $|t|$ is a calculated absolute value of the t-test, $t_{\alpha/2}^v$ is a tabulated value for the t-test, and $v = n - k$ is the degree of freedom.

To predict the age of a walking person on the basis of data obtained form 3D Kinect and regression, the CLRM is used. For calculating the age of a single subject, CLRM can be written as

$$Y_1 = \beta_0 + \beta_1 (X_{11}) + \beta_2 (X_{12}) + \beta_3 (X_{13}) + \beta_4 (X_{14}) + \beta_5 (X_{15}) + \beta_6 (X_{16}) + \beta_7 (X_{17}) + \beta_8 (X_{18}) + \beta_9 (X_{19}) + \epsilon_1 \tag{19}$$

$$Age = \beta_0 + \beta_1 \left(\overline{X}_c Sh_r \right) + \beta_2 \left(\overline{X}_c E_r \right) + \beta_3 \left(\overline{X}_c H_r \right) + \beta_4 \left(\overline{X}_c K_r \right) + \beta_5 \left(\overline{X}_c A_r \right) + \beta_6 \left(\overline{X}_c F_r \right)$$
$$+ \beta_7 \left(\overline{X}_c K_r \right) + \beta_8 \left(\overline{X}_c A_r \right) + \beta_9 \left(\overline{X}_c F_r \right) + \epsilon_1 \tag{20}$$

where $\beta_0, \beta_1 \dots \beta_9$ are the least square estimators and ϵ_1 is the random error. The random error is the difference of the estimated age and observed age.

4 Experimental Study

An experimental study is conducted on a self-created dataset that contains gait features of 273 subjects. As we are interested in age factors, this dataset has age ranges from 7 to 70 years. There are several advantages of this dataset. This dataset is larger in size than the other self created dataset, providing enough subject detail for almost all the tests. Beside, a wide range of ages also gives an ideal dataset for testing the result. Furthermore, the dataset is consisted of 3D joint positions, while other contains 2D joint data. Therefore, the proposed dataset is ideal and verify the reliability of the proposed system. We carried out experimental analyses to assess the accuracy of different joints set for the age classification.

4.1 Protocol and Task

To ensure that the proposed system is feasible, we carried out an experiment via MS Kinect. We placed Kinect on a table of 3.0 feet height. Fifty (50) volunteer subjects participated in the experimental study. The path and direction to be followed during the experiment were initially demonstrated to the subjects. The task consisted of casual walking of a subject in front of the MS Kinect in a horizontal direction while following a predetermined path in the Kinect recognition space (see Fig. 5).
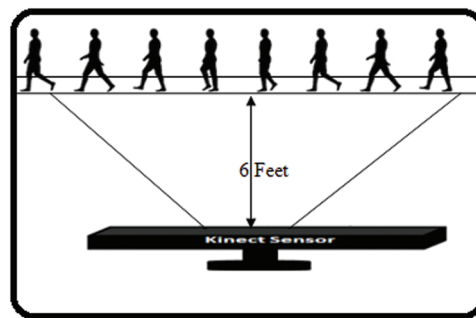

Figure 5: Walking directions of subject

As a classification method, we used CLRM because age is a continuous variable. For testing the validity of the CLRM, the ANOVA test is used, and all our data seem relevant and highly significant.

4.2 Experimental Result

The results are presented in this section from the experimental evaluation. To test the validity of the proposed system, we performed different experiments using 50 walking subjects in different directions inside the Kinect recognition space. Before starting the experiment, the actual ages of the subjects were recorded. All of the subjects were assigned to one of five groups: A, B, C, D, or E (See Table 1). Each group consisted of 10 subjects each with an age range of 7 to 70 years.

4.2.1 Analysis Based on T-Test

The T-test is used to determine the importance of a specific joints. In Table 2, $\overline{X}_c Sh_r$, $\overline{X}_C E_r$, $\overline{X}_C H_r$, $\overline{X}_C K_l$, $\overline{X}_C A_l$, $\overline{X}_C F_l$, $\overline{X}_C F_r$, $\overline{X}_C K_r$, $\overline{X}_C A_r$ are the combined averages of right shoulder, right elbow, right hand, left knee, left ankle, left foot, right foot, right knee, and right ankle, respectively. In Table 2, the p-value for all the joints is less than 0.05, which means that all the joints are significant at 5% level of significance.

Table 1: Mean accuracy of the proposed model

Group	Training	Testing	Age range	Subject calculated	Accuracy
A	55	10	07–20	09	90%
B	55	10	21–30	10	100%
C	55	10	31–40	10	100%
D	55	10	41–50	10	100%
E	53	10	51–70	10	100%
		Mean accuracy			**98%**

Table 2: Coefficients, standard error (SE), T-value and *P*-value of the predictors

Predictors	Coefficient	SE	T-value	*P*-value
Constant	−18.88	2.981	−6.33	0.000
$\overline{X}_c Sh_r$	47.610	21.51	2.210	0.031
$\overline{X}_C E_r$	−0.520	23.17	−0.020	0.024
$\overline{X}_C H_r$	7.050	10.84	0.650	0.018
$\overline{X}_C K_l$	−24.34	46.02	−0.530	0.043
$\overline{X}_C A_l$	71.81	54.37	1.320	0.032
$\overline{X}_C F_l$	−65.37	50.00	−1.310	0.047
$\overline{X}_C K_r$	44.93	30.75	1.460	0.032
$\overline{X}_C A_r$	−4.190	7.440	−0.070	0.044
$\overline{X}_C F_r$	−54.30	53.50	−1.010	0.041

4.2.2 Analysis of Variance (ANOVA) for the Best Fitted Model

To test the significance of more than two joints simultaneously, ANOVA technique is used. From Table 3, all joints included in the model are significant because the *P*-value for the over all model is 0.000. It suggests that these 9 joints play an important role in the age estimation.

Table 3: Analysis of variance (ANOVA) for the best fitted model

S.O.V	DF	SS	MS	F-value	*P*-value
Regression	9	1368.87	152.10	26.14	0.000
Errors	56	325.79	5.82	-	-
Total	65	1694.67	-	-	-

Where, DF is the degree of freedom and SS is the sum of square for regression, MS is the mean square, and F-value is the calculated value of F-statistic. In Table 4, the results of the models are compared by R^2 and Adj-R^2, which show higher accuracy of 88% and 91%, respectively. It means that only nine joints play significant role in the age estimation of a walking person.

Table 4: Coefficient of determination (R^2 and Adj-R^2)

Model	R^2	Adj-R^2
Sh_r, E_r, W_r, H_r, Hip_r, K_r, A_r, F_r	70%	62%
Sh_l, E_l, W_l, H_l, Hip_l, K_l, A_l, F_l	60%	54%
Hip_c, Spine, Sh_r, Head	58%	48%
Sh_r, E_r, H_r, K_l, A_l , F_l, K_r, A_r, F_r	91%	98%

The screen shorts of experiments 1, 2, 3 and 4 are shown in Fig. 6a, while experiment 5 is shown in Fig. 6b. In experiment 1, the subject walked in front of the MS Kinect from left to right. The program recorded the values of the most-contributed joints as 0.9910, 0.8631, 0.7292, 0.6613, 0.5884, 0.5515, 0.7116, 1.6217 and 0.5828 respectively; therefore, the age of the walking subject is recorded as 17 years. In experiment 2, the subject walked in front of the MS Kinect and the program recorded the age of a walking subject as 19 years. In experiment 3, the subject walked from right to left and the recorded age is 26 years. Similarly, in experiment 4, the recorded age is 34 years. In experiment 5, the walking subject in the real environment is shown and the recorded age is 40 years (Fig. 6b).

The difference between observed age y_i and estimated age $\hat{y}_i$ of a walking person is shown in Table 5. In each experiment, the proposed system correctly recorded the age of 49 walking subjects. Only the age of one subject is wrongly recorded (Table 5).

There are forty-nine observations for which the difference is zero between the observed value and the estimated age of a walking person. On the other hand, there is one observation for which the difference is 2. The results indicate the applicability of the model for age estimation of the walking persons.

The relationship between the estimated ages of a walking person with the most-contributed joints is shown in Fig. 7.

The model shows a linear relationship between estimated ages, $\hat{Y}_i$ of a walking person with the shoulder right joint. As the average value of a joint, shoulder right increases with the increase in age value. There is direct relationship between age and the shoulder right joint, and also, observations are made near to the straight line $(\hat{y}_i)$. There is also a linear relationship between estimated age and joint foot left while the observations are spread about the line and show slight variation between the age of a walking person and the foot left joint, the model shows a linear relationship between the estimated ages of a walking person with the elbow right joint. As the average value of a joint, elbow right increase with the increase in the age of a walking person. There is a direct relationship between the age and elbow-right-joint and also observations lie near the straight line $(\hat{y}_i)$. On the other hand, there is also a linear relationship between estimated age and knee left-joint, while the observations are spread about the line and show slight variation between age of a walking person and knee-left joint. On the other hand, the average value of joint ankle-left increases with the increase in age of a walking person. There is a direct relationship between age and the ankle-left joint and observations are spread about the straight line $(\hat{y}_i)$. There is linear relationship between estimated age and knee-right joint. While there is less variation between age and knee-right joint, as compared to the ankle-left joint.

(a)
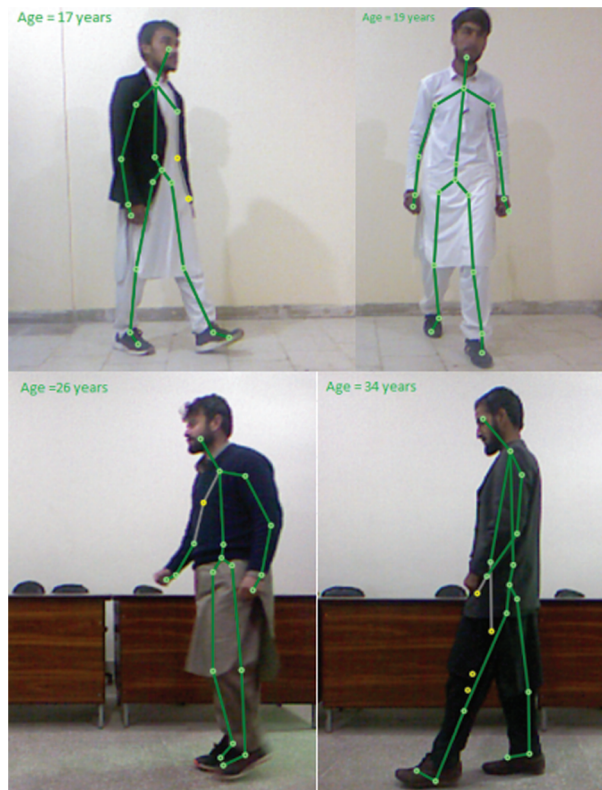
(b)

Figure 6: (a) Age calculation of walking subject, (b) Age calculation in real environment

Table 5: Histogram of errors between actual ages and estimated ages of walking person

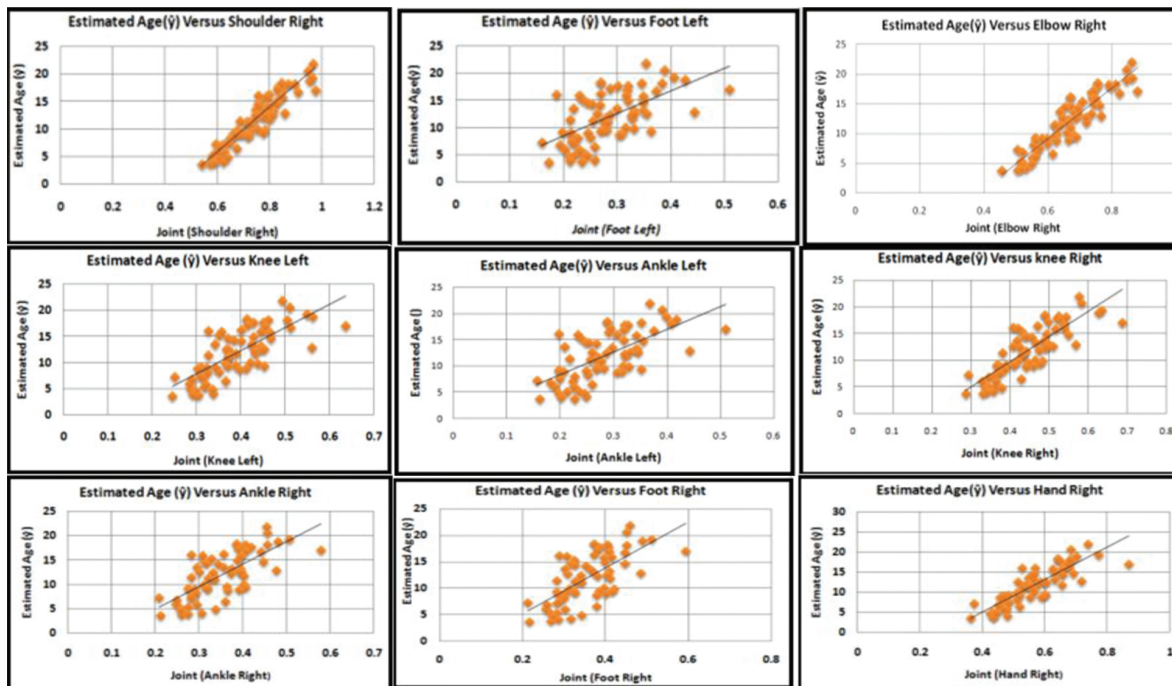| $y_i - \hat{y}_i = 0$	$y_i - \hat{y}_i = \pm 1$	$y_i - \hat{y}_i = \pm 2$	$y_i - \hat{y}_i = \pm 3$	Other value
49	00	01	00	00

Figure 7: Scatter plot against the most-contributed joints

From Fig. 7, the fitted general linear model shows a linear and positive relationship between the estimated ages of a walking person and the joint ankle-right, while the observations are spread about the line and show a slight variation between the age of a walking person and the joint ankle-right. On the other hand, age of a walking person increases with the increase in average value of joint foot. There is a direct relationship between age and joint foot right and also observations are spread about the straight line $(\hat{y}_i)$ and show variation between age and joint foot right and observations are not clustered about the fitted line. All the graphs show the same nature of relationship (See Fig. 7).

Similarly, there is a linear and direct relationship between estimated age and the right hand joint during walking. As the average value of the right hand joint, increases with the increase in age of a walking person. Also, the observations are clustered around the fitted line and show less variation as compared to other joints. There is a linear and direct relationship between the estimated age and all the joints under consideration. This means that the average value of joints increases with the increase in age of a walking person.

4.3 Discussion

This research work aims to calculate the age of a walking person on the basis of the 3D Kinect and general linear regression models. First, the authors have considered all the possible joints for the age prediction of walkers. With the help of the best model selection criteria R^2 and adjusted R^2, the authors then used the most significant or contributing joints of a walking person for the estimation of age. The highly contributed joints are shoulder right, hand right, elbow right, knee right, knee left, ankle right, ankle left, foot left and right, which predict the age of a walking person. Table 3 provides the individual joint results as coefficients of model, sum of squares, mean squares, and *P*-value. The coefficient of determination (R^2) for the proposed model is 91% and the adjusted R^2 is 88% (see Table 4). The model

shows higher accuracy for the age estimation of a walking person. The best model is one for which R^2 is high, which is decided on the basis of R^2. As the *P*-value for all joints is less than 0.05, this means that these joints are significant at a 5% level of significance. For the analysis, the authors consider only 50 walking persons. The method of ordinary least squares and the matrix approach were used to estimate the model parameters. A scatter diagram shows a linear relationship between estimated age and the most significant joints of a walking person.

5 Comparative Studies with the State-of-the-Art System

We compared the proposed system with the existing approaches of gait-based age classification according to dataset, technique, and accuracy. All the existing approaches generated their own dataset, but Zhang et al. [47], produced comparatively large dataset with a maximum of 205 subjects (see Table 6).

Table 6: System comparison between the proposed system and the current system

Author	Years	Data set	Technique	Accuracy
Davis [28]	2001	Self (15)	Linear perception	95.0%
Aderinola et al. [42]	2010	Self (14)	HMM	83.3%
Makihara et al. [33]	2011	Self (168)	KNN	80.0%
Abirami et al. [44]	2013	Self (178)	KNN	86.0%
Zhang et al. [47]	2015	Self (26)	Random forest	95.0%
Yoo et al. [48]	2017	Self (205)	SVM	85.6%
Zhu et al. [45]	2021	Self (154)	Random forest	96.0%
Proposed system	**2022**	**Self (273)**	**CLRM**	**98.0%**

The proposed method presented a large dataset with 273 subjects. The maximum accuracy in the existing approaches is 96%, while the proposed system shows 98.0% accuracy. Therefore, the proposed system is efficient in terms of accuracy and the dataset used.

6 Conclusions

This research paper proposes a novel method for age detection via gait-based 3D joint position. Our main contribution is that the age of walking subject is automatically detected in real-time via MS Kinect. The second contribution is the collection of a unique dataset of 3D skeleton joint position data, which is available on request. On the basis of a dataset generated from 273 people ranging in age from 7 to 70 years, the best age detection performance of 98.0% was achieved using CLRM, and 9 selected features (right shoulder, right elbow, right hand, left knee, right knee, right ankle, left ankle, left foot and right foot). The experimental result of the proposed approach proved that the proposed system was different from the existing approaches in terms of large datasets used, limited features, and high accuracy. Moreover, in future, the security measures can be further improved through intensive investigations of both gender and age of the walker with a single and limited set of joints. The study recommends the use of the same model for the exact identification of the person in future works apart from the recognition of age and gender only.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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