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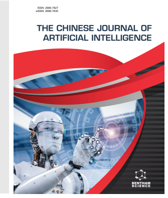
RESEARCH ARTICLE



Robust and Lightweight System for Gait-based Age Estimation towards Viewing Angle Variations

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Abstract: ***Background***: In computer vision applications, gait-based age estimation across several cameras is critical, especially when following the same person from various viewpoints.

Introduction: Gait-based age recognition is a very challenging task as it involves multiple hurdles, such as a change in the viewpoint of the person. The proposed system handles this problem by performing a sequence of tasks, such as GEI formation from silhouette, applying DCT on GEI and extracting the features and finally using MLP for age estimation. The proposed system proves its effectiveness by comparing the performance with state-of-the-art methods, conventional methods and deep learning-based methods. The performance of the system is estimated on OU-MVLP and OULP-Age datasets. The experimental results show the robustness of the system against viewing angle variations.

Objective: This study aimed to implement the system, which adopts a lightweight approach for gait-based age estimation.

Methods: The proposed system uses a combination of the discrete cosine transform (DCT) and multi-layer perceptron (MLP) on gait energy image (GEI) to perform age estimation.

Results: The performance of the system is extensively evaluated on the OU-MVLP and OULP-Age datasets.

Conclusion: The proposed system attains the best mean absolute error (MAE) of 5.05 (in years) for the OU-MVLP dataset and 5.65 for the OULP dataset.

Keywords: Gait, age estimation, GEI, OU-MVLP, OULP, DCT.

1. INTRODUCTION

Over the period of the last 20 years, gait has been reckoned to be a distinctive feature in behavioral biometrics where a person's cooperation is not needed, and the recognition can be done from a particular distance through a camera [1]. Due to this, there is an edge in gait-based person identification, and thus, it is used in numerous applications, like criminal inspection, vigilance systems, and selective restriction of access to a place or other resource using camera recordings. Along with recognition [2-5], gait can also be used for various purposes like age estimation [6-11], gender prediction [12, 13], and disease prediction [14]. Age determination using gait analysis has numerous inherent applications. For instance, when a customer's age is determined in the shopping mall, then an advertisement that is more relevant to the customer's age can be shown, resulting in an increase in the sale of the product. In the case of a criminal investigation, if a witness gives information, such as the age of the suspect, then all the persons of that particular age can be extracted through the camera recordings, which will ultimately help in the investigation. The gait-based age estimator can also be useful in searching for lost children in circuses, cinema halls, sports stadiums, railway stations, airports, shopping malls or any other public places.

Practically, the methods for age estimation using gait features can be divided into two groups: regression-based methods [7, 8, 15] and classification-based methods [9, 10, 16]. The classification-based methods generally consider every age as a single class, whereas the regression-based methods work out on a regression problem from a gait characteristic to perform age prediction. The aforementioned studies are based on a limited number of data for training the system. Hence, these studies utilize conventional machine learning methods like support vector regression and support vector machines for solving the gait-based age estimation problem. Lu *et al*. [7] have applied multiple linear regressions to expose the relationship between the projected gait features and the ground-truth age values. The study [8]

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generated a larger dataset of 1728 persons having ages varying from 2 to 94 years and then applied the Gaussian process regression method for age estimation. They [15] specified five optimal age groups to stabilize the exchange between age group classification and age group-dependent age regression. They used a combination of Gaussian kernel with SVR to train their model. The study [16] pioneers the research for age and gender classification by constructing a multi-view gait dataset. They included 88 males and 80 females with ages varying from 4 years to 75 years. They considered 25 views for gait observation and categorized the gait features into four classes: children (4 years to 15 years), male adults (15 years to 65 years), female adults (15 years to 65 years) and aged (65 years and above). However, the performance of their system for age and gender classification was view-dependent.

Due to the shortage of training data [5], most of the researchers have implemented traditional machine learning methods, like support vector regression [17] and support vector machines [18]. Nevertheless, recent studies focus on deep learning methods [19-21] for age estimation due to the availability of much larger datasets, such as the OU-ISIR gait database [22] containing more than sixty thousand persons' gaits. In a recent study, it is observed that the accuracy of gait-based age estimators is uncertain and varies as per the age groups [23]. The uncertainty in age prediction for children (less than two years) is very less in comparison with an adult age (approximately 20 years) group, where it is quite large [24]. Therefore, it is quite challenging to estimate the age from human gait. The uncertainty could be due to the following reasons:

- Variation in the body shape of subjects with similar age group.
- Similarity in body shape of subjects with different age groups.
- No texture-based cues present in gait images.

In some applications, uncertainty in gait-based age determination plays a significant role, for instance, searching for a person by his/her age as input. As indicated in a study [24], it would be significant for a group of people having age within a range of 5 ± 2 years. Contrarily, if the age of a person is in the range of 30 to 39, then the gait-based age estimator will show many persons having age within a huge range of 20 to 40 years.

Therefore, this study identifies the following research gaps in gait-based age estimation:

- The age group-dependent models do not predict the exact age of a person.
- To the best of our knowledge, only Xu *et al*. [25] have shown the performance of age estimation under the viewing angle variations.
- Most of the recent studies attempted to solve the gait-based age estimation problem by using a deep learning approach. However, the deep learning-based system demands high computation and uses GPU based system, increasing the implementation cost of a system.

This study attempts to handle the research gap identified in the above paragraph in the following manner:

- This study adopts a lightweight approach for gait-based age estimation under viewing angle variations of subjects.
- We initially take the input gait image, then extract the binary silhouette and construct GEI. Furthermore, we use discrete cosine transform (DCT) for retrieving the gait-based features and finally apply Multilayer perceptron (MLP) for age estimation.
- We have verified our experimental results using the two largest datasets, OULP-Age and OU-MVLP. The proposed system confirms the authenticity by comparing the results with the state-of-the-art.

The organization of the remaining sections of the paper is as follows: Section 2 highlights the related work in gait-based age prediction methods. Section 3 discusses the proposed system architecture for age estimation. Section 4 shows the experimental results of the proposed system and compares the result with other benchmarking works. Section 5 highlights the conclusion and shows the area for future works.

2. MATERIALS AND METHODS

2.1. Human Age Group Classification Based on Gait

The techniques of classifying human age using gait generally enlist features like static and dynamic gait behaviors. For instance, Davis [9] used the features like the length of legs, the width of stride, and the frequency of strides to categorize the gait into children and adult age groups. Begg *et al*. [10] have categorized people as younger and aged by applying the data of foot clearance. Chuen *et al*. [26] showed the usage of parameters like head-to-body ratio and length of legs for the classification of children's age and adult age. Nabila *et al*. [27] have highlighted the spatiotemporal features, such as arm swing, hunched posture, and length of stride, to show the difference between younger and elderly people. Xu *et al*. [24] have proposed a method for handling uncertainty problems in various age groups. Li *et al*. [15] have analyzed the human growth process and divided the age into 5-year intervals, resulting in nine age groups. They have proposed an age group-dependent framework to handle the large estimation errors (when variation in age is large). Mansouri *et al*. [28] used a fusion of gait contours and silhouette descriptors to categorize gait images into young and elderly.

Contrary to the above-mentioned research works, few studies show the use of appearance-based methods for the classification of various age groups. For instance, Mannami *et al*. [16] utilized the frequency-domain characteristics and categorized the person's age into 3 groups: children (below 15 years), adults (in the range of 15 to 65 years), and the aged (more than 65 years). Abirami *et al*. [29] have combined gender and age for age estimation. They used Hilbert-Schmidt Independence Criterion to maximize the correlation between gender and age. However, it can be observed that age group classification methods have some drawbacks related to age groups and insufficient experimental validation.

Aderinola *et al*. [30] have conducted an extensive survey of scientific literature on gait-based age estimation from 2001 to 2021. In this survey, they followed similar age groups as the study [16] for the discussion. They concentrated on vision-based and sensor-based approaches for gait-based feature extraction. They also showed the effect of different covariates on vision-based and sensor-based gait data. Furthermore, the findings of the study include the following: 1) Model-free gait descriptors, *i.e*., GEI, are more robust than model-based gait descriptors. 2) There is a research gap for age estimation under the viewing angle variations. Hence, this study adopts the GEI and considers multiple viewing angles for age estimation.

2.2. Human Age Estimation Based on Gait

Estimating an age based on gait behavior is the latest advancement in gait-related studies, and therefore, not much work is done in this field. Recently, some research work has begun on age classification based on gait. The earliest study on age estimation using gait behavior is done by Lu and Tan [8]. They encoded age as binary and applied multi-label k-nearest neighbors for classification. Thereafter, Makihara *et al*. [11] used Gaussian process regression (GPR) and estimated the age of persons. They combined the face recognition method with gait behavior. Lu and Tan [6] used analytical methods to discover a low-dimensional feature for age estimation. Marin-Jimenez *et al*. [19] proposed a multi-task CNN model, which takes input as a fixed-length optical flow sequence and gives output as various biometric traits for age estimation, person identification, and gender recognition. Zhang *et al*. [20] used a deep ConvNet to capture the gait characteristic from GEI. In order to achieve better accuracy in age estimation, they have applied a multi-task learning framework. Sakata *et al*. [23] used a deep learning framework (DenseNet) for gait-based age classification. They used the world's largest gait dataset having age variations up to ninety years. Their study shows superior results in the classification of age. Riaz *et al*. [31] have gathered the inertial data of gait from 86 different persons and performed the analysis for age estimation. During data gathering, they considered angular velocities and 6D accelerations of a person. They mounted inertial measurement units on the chest for recording the inertial data. Furthermore, they divided the recorded data (long sequences of inertial signals) into single steps and evaluated 50 spatio-spectral features from every step. Finally, they trained the features with MLP, SVM, and random forest classifiers. These trained data were used for both age estimation and person recognition.

After studying the above-mentioned research works, we have identified that convolution neural network (CNN) based methods are more used in recent works, and they have also given better results for gait-based human age estimation. After going through the experimental setup of the CNN-based study, it can be learned that the computation cost of the system becomes very high as it demands high processing power. The other limitation is that these methods are carried out by considering only one viewpoint for age estimation. Thus, to overcome these limitations, our study has considered implementing a lightweight system for gait-based age estimation under various viewpoints. This study also tries to authenticate the results by comparing them with other studies done for age estimation using gait behavior.

2.3. Proposed Method

Fig. (**1**) elucidates the proposed technique. The detailed functioning of the proposed system is explored in the forthcoming subsections.

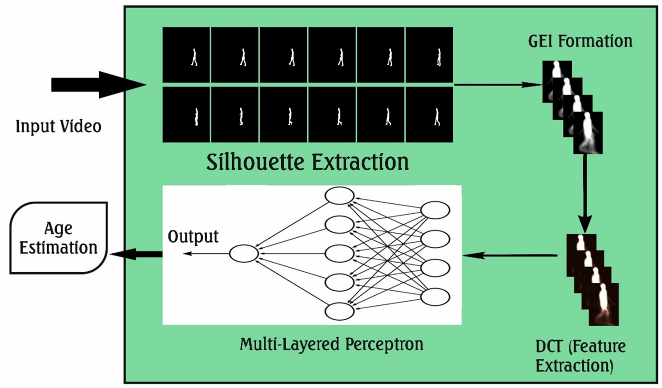

Fig. (1). Overview of proposed system. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

2.4. Formation of Gait Energy Image (GEI)

We have obtained silhouettes from a person's walking sequences. Silhouette is a black and white image having the outline of a person in the foreground. The appearance-based method includes processing silhouettes using gait. As a person's clothes, color and texture influence can be avoided using the appearance-based method; it is superior to the model-based method for a person's gait identification. Here, we have followed the most popular representation for silhouette-based gait, *i.e*., GEI [32, 33]. We have evaluated GEI from a sequence of silhouettes. In this experiment, we have fixed the GEI size as 88 x 128 pixels. GEI is very simple and, at the same time, yields highly effective gait features. GEI is estimated as follows:

$$GEI(x,y) = \frac{\sum_{t=1}^{N_{G.}} S_t(x,y)}{N_{G.}} \tag{1}$$

where $S_t(x,y)$ indicates the binary gait silhouette, t is the counting variable for the gait frame, x and y are coordinates of the 2D image, and $N_{G.}$ is the number of gait frames extracted from one cycle of the periodic walk.

Fig. (2). Gait energy image. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

Fig. (**2**) illustrates the formation of GEI from gait silhouettes. GEI comprises both physiological and spatiotemporal information about the human body during walking. It can be observed that GEI representation saves computation time and storage space for recognition. Let $S_t(x,y)$ is formed by adding distortions $e_t(x,y)$ to an actual gait picture frame $g_t(x,y)$. Thus, $S_t(x,y) = g_t(x,y) + e_t(x,y)$. Assuming that the distortions in the gait picture are evenly spread and not related to t, $e_t(x,y)$ can be computed from the following equation:

$$e_t(x,y) = \begin{cases} e_{1t}(x,y): P\{e_t(x,y) = -1\} = m \\ P\{e_t(x,y) = 0\} = 1 - m, \text{if } g_t(x,y) = 1 \\ e_{2t}(x,y): P\{e_t(x,y) = 1\} = m \\ P\{e_t(x,y) = 0\} = 1 - m \text{ if } g_t(x,y) = 0 \end{cases}$$

$$E\{e_t(x,y)\} = \begin{cases} -m, if\, g_t(x,y) = 1 \\ m, if\, g_t(x,y) = 0 \end{cases}$$

$$\sigma^2{}_{e_t(x,y)} = \sigma^2{}_{e_{1t}(x,y)} = \sigma^2{}_{e_{2t}(x,y)} = m(1-m)$$

In $N_{G.}$ frames, let R picture frames have $g_t(x,y) = 1$ for the position(x,y). Thus Eq. (1) will be specified as:

$$GEI(x,y) = \frac{\sum_{t=1}^{N_{G.}} S_t(x,y)}{N_{G.}}$$

$$= \frac{\sum_{t=1}^{N_{G.}} (g_t(x,y) + e_t(x,y))}{N_{G.}}$$

$$GEI(x,y) = \frac{R}{N_{G.}} + \frac{\sum_{t=1}^{N_{G.}} e_t(x,y)}{N_{G.}} = \frac{R}{N_{G.}} + \bar{e}(x,y) \qquad (2)$$

Therefore, GEI noise can be represented as:

$$\bar{e}(x,y) = \frac{\sum_{t=1}^{N_{G.}} e_t(x,y)}{N_{G.}}$$

$$= \frac{1}{N_{G.}}\left[\sum_{t=1}^{R} e_{1t}(x,y) + \sum_{t=R+1}^{N_{G.}} e_{2t}(x,y)\right] \qquad (3)$$

$$E\{\bar{e}(x,y)\} = \frac{1}{N_{G.}}\left[\sum_{t=1}^{R} E\{e_{1t}(x,y)\} + \sum_{t=R+1}^{N_{G.}} E\{e_{2t}(x,y)\}\right]$$

$$= \frac{1}{N_{G.}}[R(-m) + (N_{G.I.} - R)m]$$

$$E\{\bar{e}(x,y)\} = \frac{(N_{G.} - 2R)m}{N_{G.}} \qquad (4)$$

$$\sigma^2{}_{\bar{e}_t(x,y)} = E\{[e(x,y) - E\{\bar{e}(x,y)\}]^2\} \qquad (5)$$

$$= \frac{1}{N_{G.}{}^2} E\left\{\left[\sum_{t=1}^{R}[e_{1t}(x,y) - E\{e_{1t}(x,y)\}] + \sum_{t=R+1}^{N_{G.}}[e_{2t}(x,y) - E\{e_{2t}(x,y)\}]\right]^2\right\}$$

$$= \frac{1}{N_{G.}{}^2}\left[R\sigma^2{}_{e_{1t}(x,y)} + (N_{G.} - R)\sigma^2{}_{e_{2t}(x,y)}\right] \qquad (6)$$

$$\sigma^2{}_{\bar{e}_t(x,y)} = \frac{\sigma^2{}_{\square_t(x,y)}}{N_{G.}} = \frac{m(1-m)}{N_{G.}} \qquad (7)$$

Thus, the mean of the noise in GEI toggles between $-m$ and m with various values of R. If R toggles between 0 and $N_{G.}$ at position(x,y), $E\{\bar{e}(x,y)\}$ toggles between m and $-m$. Therefore, both $\sigma^2{}_{\bar{e}_t(x,y)}$ and $E\{\bar{e}(x,y)\}$ of the noise for GEI are suppressed in comparison with the solo silhouette image on the particular positions. This proves the significance of GEI over a solo silhouette for obtaining gait features.

2.5. Discrete Cosine Transform (DCT)

A detailed comparison has been shown in a study to find the best-suited transform method for feature extraction in pattern recognition applications [34]. The outcome of the study highlights that the performance of DCT is superior to the other transform methods (Karhunen-Loeve Transform, Discrete Fourier Transform, Walsh-Hadamard Transform, and Haar Transform). The study [35] summarizes that DCT is better than DWT (Discrete Wavelet Transform) in terms of energy compaction, computational complexity, and performance time over the image data. Therefore, after GEI formation, we have applied DCT to it for feature extraction. Earlier, DCT was used for image compression [36, 37]. However, over the years, it has been observed that the pattern recognition community has shown more interest in DCT [38-41]. Basically, the DCT method is used to convert image data into frequency components [42]. It accumulates higher coefficient value components into the top left corner in the 2D matrix representation, whereas the lower coefficient values are kept in the bottom right of the 2D matrix. The following equation gives DCT matrix elements:

$$DCT(x,y) = \frac{1}{\sqrt{2}} C(x)C(y) \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} g(m,n) \cos\left[\frac{(2m+1)x\pi}{2N}\right] \cos\left[\frac{(2n+1)y\pi}{2N}\right] \quad \textbf{(8)}$$

Where N denotes the block size, $C(u) = \begin{cases} \frac{1}{\sqrt{2}}\ if\ u = 0 \\ 1\ if\ u > 0 \end{cases}$

and $g(m,n)$ represents the image in matrix g showing m, n^{th} matrix element.

The DCT coefficient at the (x,y) point in the DCT domain is denoted by $DCT\,(x,y)$. The DC coefficient $DCT(0,0)$ and the AC coefficients make up the DCT coefficients. The AC coefficients are used to calculate the focus value. Here, the primary goal is to recognize the optimal feature and extract it using DCT by reducing the dimension of GEI data.

Extraction of features using DCT contains 2 phases. The initial phase uses DCT on the complete GEI picture frame to get coefficients of DCT. The latter phase selects the coefficient with a high frequency, which is utilized for generating feature vectors as input to MLP.

Fig. (**3**) illustrates a pictorial representation of DCT applied to the GEI image. Fig. (**3**) consists of 3 blocks where the leftmost one is the GEI image, the rightmost top block represents DCT transformed picture, and the right side bottom block shows the categorization of coefficients of DCT. Generally, the coefficients of DCT are categorized into 3 sections: lower frequency components, moderate frequency components and higher frequency components. The lower frequency components are dependent on the light intensity of the surrounding, whereas other components contain meaningful data and can rebuild the picture again; thus, these components are acceptable for feature vector generation and can be used in gait identification.

2.6. Multilayer Perceptron Training (MLP)

During model training, for removing the outliers, normalization of feature vectors is carried out. Thus, a feature vector is transformed to have a mean of 0 and a variance of 1 in a normalized feature vector. Fig. (**4**) shows the flowchart of the tasks involved in MLP. For training the model, feature vectors that are normalized are given as input to the hidden blocks. The number of neurons in the hidden blocks is 700, 500, 200, 100, and 50, forming a completely linked dense node, respectively.

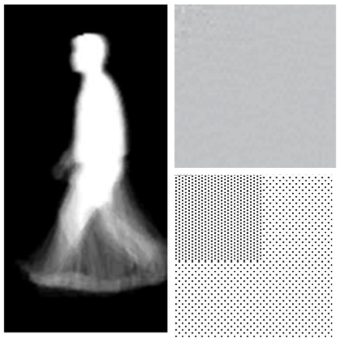

Fig. (3). Illustration of DCT on GEI with pictorial representation. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

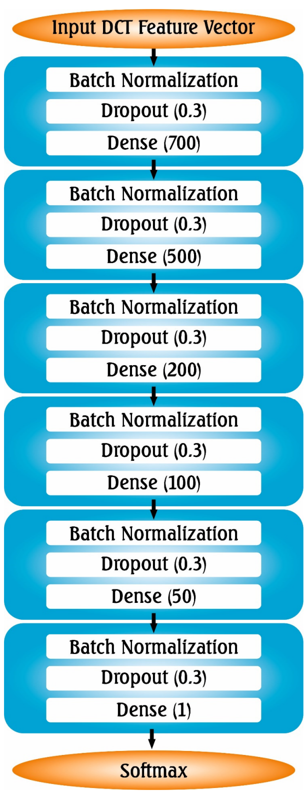

Fig. (4). Illustration of tasks involved in MLP. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

The proposed MLP model performs training by making smaller batch sizes and calculates the gradients of these batches. The purpose of adding a batch normalization layer is to increase the performance as well as consistency of each hidden layer's smaller version. The internal covariate shift can be reduced by eliminating gradient descent oscillation. Using the batch normalization approach, the output of each layer's mini-batch is modified, and it can be put into the following layer. During this training, we have run 1,000 epochs. Furthermore, to enhance the working of the MLP model, we have chosen an optimizer as RMSprop having a learning rate of 0.002 to tune the hyper-parameters.

3. RESULTS AND DISCUSSION

3.1. Datasets and Experimental Settings

3.1.1. A_1: OU-MVLP Dataset

The study is carried out on the OU-ISIR Gait Database, Multi-View Large Population Dataset (OU-MVLP) [43] to evaluate the performance of the proposed system. OU-MVLP is a well-known large dataset of gait images. This dataset is comprised of more than ten thousand individual gait images. Specifically, there are 10,307 gait images, out of which 5,114 are males, and 5,193 are females. The range of ages varies from 2 to 87 years old from 14 different viewing angles (0°-90°, 180°-270°). Fig. (**5**) illustrates the gait recording from various viewpoints. In this experiment, the dataset is partitioned into the same sizes of training and testing.

3.1.2. A_2: OULP-Age Dataset

The OULP-Age data set is considered one of the largest gait datasets [22]. It contains gait recordings of 63,846 persons. The camera records the walking sequences of persons at 30 fps, 640 by 480 pixels. The ages vary from 2 to 90 years old. Furthermore, the gait image of each person is normalized (*i.e.*, 88x128). The training and testing sets are formed by randomly dividing the dataset into two disjoint and equal parts. Thus, training and testing sets contain gait images of 31,923 persons.

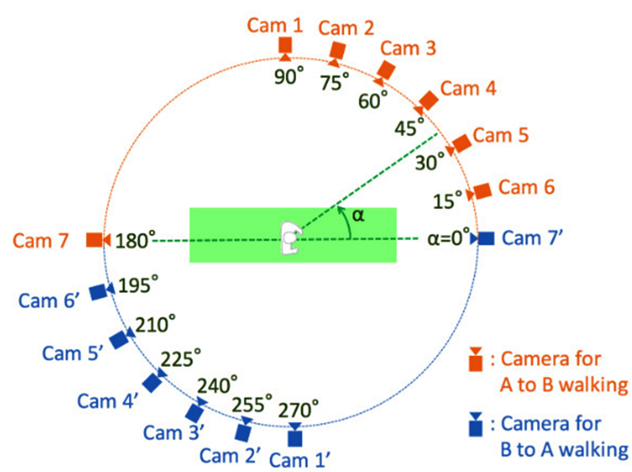

Fig. (5). The OU-ISIR gait database, Multi-View Large Population Dataset (OU-MVLP) [43]. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

3.2. Performance Evaluation Criteria

We have assessed the performance of age estimation using the gait feature. In this assessment, we have calculated a mean absolute error (MAE) between the actual input age (ground truth age) and system estimated age. The ground-truth label can be explained with the help of a probability distribution (discrete).

Let $\widehat{x_t} = [\widehat{x_\iota}, 0, \ldots., \widehat{x_t}, k-1]^T \in R^K$ be the estimated discrete probability distribution for the $t-th$ training ta $(1,2 \ldots\ldots, N_g)$, where N_g is total training data, k as age and $\widehat{x_t}, k$ as the likelihood for $k-th$ age label.

We evaluate the mean age from the distribution and measure the mean absolute error (MAE) as per the following equation:

$$Loss_{MAE} = \frac{1}{N_g}\sum_{t=1}^{N_g} |\widehat{y_\iota} - y_t| \quad (9)$$

$$y_t = \sum_{k=0}^{k-1} k\widehat{x_\iota}, k \quad (10)$$

Where, $\widehat{y_t}$ is expected age and y_t is actual age for t$-th$ training data.

3.3. Performance Evaluation on OULP-Age

We have tried to show the authenticity of the proposed system by matching its execution with state-of-the-art methods. Here, MAE (in years) is used as the metric for comparison. We have compared the gait-based age estimation results with both the conventional methods and deep learning-based methods. The conventional methods used for comparison are SVR (Gaussian), SVR (linear), AGDMLR [15], OPMFA [6], OPLDA [6], and GPR with k nearest neighbors and results with k = 10; 100; 1000 [11]. Fig. (**6**) illustrates that the proposed system outperforms the other conventional methods for gait-based age estimation. The deep learning-based methods used for comparison are DenseNet [23], Multi-task [20], Multi-stage [44], GEINet [45], GEINet [24], GaitSet [24]. Fig. (**7**) shows that the performance of the proposed system is comparable with all the deep learning methods mentioned here. The experimental results signify that DCT can effectively decide different frequency components. DCT is inconsiderate of the variations in human appearances. Furthermore, the tuned MLP increases the performance of age estimation.

3.4. Performance Evaluation on OU-MVLP

After tuning the MLP, MAE for age estimation under every viewing angle is evaluated. To the best of our knowledge, only Xu *et al*. [25] have shown angle-wise performance analysis of age estimation. Therefore, this study compares its result to their findings. Table **1** shows the comparative analysis of the performance of age estimation under viewing angle variations. It is observed that the proposed system attains the best MAE of 5.05 for age estimation under a viewing angle of 90°. It is obvious that in the side view of a person, the majority of the gait features are observed, which helps in age estimation. At 0° viewing angle, comparatively fewer features are observed; hence the MAE rises to 7.47. It can be observed from Table **1** that the results of the proposed system are superior to their study's findings [25]. The study [25] used a deep learning approach to estimate the age of a person, whereas we used a lightweight approach. The results shown in Table **1** indicate that the model-free gait descriptors (GEI) have huge potential in gait recognition.

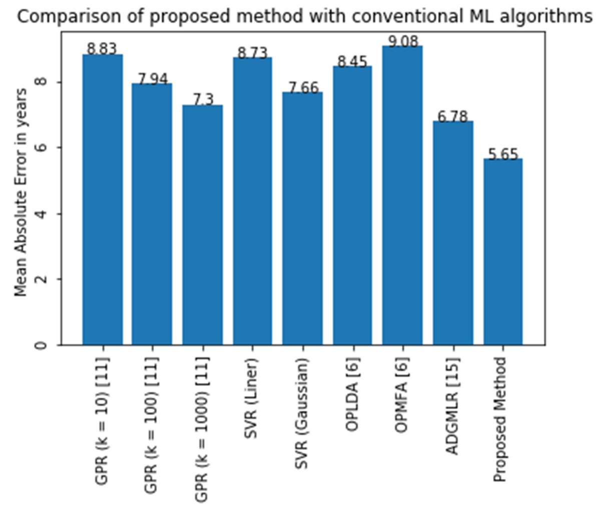

Fig. (6). Comparative analysis of performances of conventional ML methods with the proposed method. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

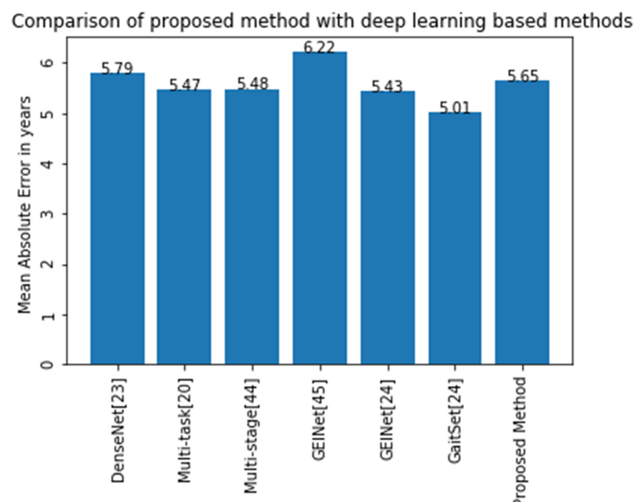

Fig. (7). Comparative analysis of performances of deep learning methods with the proposed method. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

It can also be seen that the proposed system shows outstanding performance for every viewpoint, especially at 90°, 270°, 255°, 75°, 30°, 45°, 60°, 240°, 225°, and 210°. Thus, the proposed system shows robustness to viewing angle variations.

To prove the authenticity of the proposed system, we have performed a statistical analysis of recent works done in the gait-based age estimation field. The outcomes of statistical analysis are represented in the tabular form in Table **2**. We have considered the benchmarking work for both classification and regression-based age estimation. It was observed that conventional machine learning algorithms could

Table 1. Comparative analysis of age estimation under viewing angle variations.

Angle	Xu *et al*. [25] (MAE for Age Estimation)	Proposed Method (MAE for Age Estimation)
0°	8.91	7.47
15°	8.83	6.56
30°	8.27	5.58
45°	8.48	5.72
60°	8.35	5.76
75°	8.08	5.44
90°	7.83	5.05
180°	9.24	7.41
195°	8.86	6.27
210°	8.61	5.67
225°	8.48	5.80
240°	8.11	5.95
255°	7.88	5.43
270°	7.74	5.26

Table 2. Statistical analysis of recent works done in the gait-based age estimation field.

Authors	Year	Dataset (No. of subjects)	Technique	Feature	Task	Performance
Yoo & Kwon [46]	2017	Handcrafted (205)	SVM	Hybrid	Classification	CCR 85.6%
Punyani *et al*. [47]	2018	USF (122)	ML-KNN	Hybrid	Regression	MAE 6.57 years
Hema & Pitta [48]	2019	OULP (4007)	SVM	Hybrid	Classification	CCR 91.8%
Aderinola *et al*. [49]	2021	Handcrafted (154)	Random Forest	Hybrid	Classification	CCR 96%
Xu *et al*. [24]	2021	OULP-Age (63846)	Deep Learning	Kinematic	Regression	MAE 5.01 years
Xu *et al*. [25]	2021	OU-MVLP(10307)	Deep Learning	Kinematic	Regression	Mean MAE 8.41
Proposed Method	2022	OULP-Age (63846)	DCT+MLP	Kinematic	Regression	MAE 5.65
Proposed Method	2022	OU-MVLP(10307)	DCT+MLP	Kinematic	Regression	Mean MAE 5.95

perform better in smaller datasets. Most of the studies using conventional machine learning follow hybrid feature extraction methods. The hybrid features are a fusion of kinematic and biological features of a gait. Generally, the hybrid feature extraction techniques work on a handcrafted dataset, where the setup for recording the biological gait features is maintained. However, the size of the dataset is small. To verify the functioning of the system, a larger dataset is needed. The recent deep learning approaches have used vision-based inputs; hence, they used kinematic features to perform the age estimation. These methods have verified their results on larger datasets like OULP-Age, OULP, and OU-MVLP. It is observed that these methods have used a regression-based approach and attained a noteworthy performance. However, the proposed system has adopted a lightweight approach and attained a comparable performance to deep learning methods.

CONCLUSION

Gait-based age recognition is a very challenging task as it involves multiple hurdles, such as a change in the viewpoint of the person. The proposed system handles this problem by performing a sequence of tasks, such as GEI formation from silhouette, applying DCT on GEI and extracting the features and finally using MLP for age estimation. The proposed system proves its effectiveness by comparing the performance with state-of-the-art methods, conventional methods and deep learning-based methods. The performance of the system is estimated on OU-MVLP and OULP-Age datasets. The experimental results show the robustness of the system against viewing angle variations.

This study focuses on viewing angle variations and solves the problem of age estimation under various viewing angles. However, this study does not consider the other variations, which creates problems in age estimation, thus showing a research direction for future work to be carried out against variations like carrying conditions and walking speed for gait-based age estimation.

The MLP method used for machine learning in this study has the advantage of easy implementation. However, it can run into over-fitting problems, losing its capacity to generalize. Moreover, the choice of biases, the number of hidden layers and units in each layer, and the number of training epochs are rather arbitrary, often not yielding optimum results.

A new class of nature-inspired computational intelligence algorithms like monarch butterfly optimization (MBO), earthworm optimization algorithm (EWA), elephant herding optimization (EHO), moth search (MS) algorithm, Slime mould algorithm (SMA), hunger games search (HGS), colony predation algorithm (CPA), Harris hawks optimization (HHO), *etc*., has emerged which can bridge the gap between machine learning and optimization. Based on the metaphor of the instincts, hunting skills and social behavior of animals, these metaheuristic algorithms poise a delicate balance between exploration and exploitation in searching for the optimal global solution. The elevated performance and increased convergence speed of some of these computational intelligence algorithms can be incorporated into the MLP training algorithm to address the issue of optimization of the algorithm training weights and hyperparameters.

LIST OF ABBREVIATIONS

CNN	=	Convolution Neural Network
CPA	=	Colony Predation Algorithm
DCT	=	Discrete Cosine Transform
EHO	=	Elephant Herding Optimization
EWA	=	Earthworm Optimization Algorithm
GEI	=	Gait Energy Image
HGS	=	Hunger Games Search
HHO	=	Harris Hawks Optimization
MAE	=	Mean Absolute Error
MLP	=	Multilayer Perceptron
MS	=	Moth Search
SMA	=	Algorithm, Slime Mould Algorithm

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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