International Journal on Advanced Science Engineering Information Technology

Vol.13 (2023) No. 6
ISSN: 2088-5334

Human Age Group Estimation Using Gait Features

Qian Fu Soo [a], Tee Connie [a,*], Michael Kah Ong Goh [a]

[a] Faculty of Information Science and Technology, Multimedia University, Jalan Ayer Keroh Lama, 75450, Melaka, Malaysia
Corresponding author: *tee.connie@mmu.edu.my

Abstract— **In many practical applications, identifying the target age group is essential for marketing products and services. For instance, gaming and entertainment companies need to understand which age groups are most likely to purchase their services. This knowledge allows them to optimize their products and services to better cater to their target audience. This study proposes an age group prediction system using gait features. Gait, in this context, pertains to an individual's unique walking style. A diverse dataset containing subjects from 3 to 70 years old is collected. The age group is classified into three categories: child, adult, and senior. The critical aspect of this research lies in the preprocessing techniques applied to the gait patterns. The gait patterns are extracted from landmark human joint positions' key point values and preprocessed using smoothening techniques. Additionally, dimension reduction techniques enhance computational efficiency and accuracy before feeding the features into a deep learning-based classifier. These preprocessing steps play a pivotal role in the success of the deep learning-based classifier. A promising accuracy of up to 95% is reported for correctly recognizing the human age groups. The outcomes of this investigation underscore the tremendous potential of leveraging machine learning techniques to refine marketing strategies and boost customer satisfaction. The proposed approach can aid companies in aligning their products and services with the preferences and needs of distinct age groups, thereby enhancing their market presence and resonance with their target audience.**

Keywords—**Age group estimation; LSTM; gait features; computer vision; machine learning.**

Manuscript received 15 Jan. 2023; revised 8 Jul. 2023; accepted 22 Sep. 2023. Date of publication 31 Dec. 2023.

I. INTRODUCTION

Human Gait is a collection of movements, including walking and sprinting, resulting from specialized patterns[1]–[3]. The characteristics of human movement include overall velocity, potential energy, pattern of limb movement, and force. It imparts a distinctive gait to humans for various categorizing purposes [4]–[6]. As a result of the diversity of human gaits, it is difficult to determine which characteristics are least correlated with age. To improve the system's accuracy, it is necessary to identify these movement characteristics among participants of various ages [7]–[10].

This study aims to develop a robust approach capable of identifying human age based on gait movement. Distinct locomotion patterns are observed among different age groups due to the physiological changes that occur as individuals age, leading to alterations in their movement patterns [11]–[13]. Data is captured through a camera in video format. However, preprocessing steps are necessary to enable the system to detect and analyze the video and its associated movement information.

Since the captured videos contain various confounding factors, the gait signals are prone to noise. Consequently, preprocessing is crucial in eliminating noise and smoothing out the gait signals. Several filtering techniques have been employed towards this objective. The experimental results highlight the significance of identifying an appropriate filtering technique for accurate age-group estimation.

A. Conventional Methods

In 2010, Zhang et al. [14] proposed a gait-based Hidden Markov Model (HMM) for age classification. The researchers created the database and included older and younger groups of 7 participants each. Participants were asked to walk in a straight line 3 times, and the camera recorded all movements. In the results, the HMM method performed better than the classifier of the naive Bayesian method. When using the HMM method, a correct rate of 83.33% could be achieved, and the silhouette features of the older and younger groups reflected different walking patterns.

Next, a team from Northeast Normal University, China [15] combined Gait and age range recognition with lower limb joint angles to identify human motion, successfully limiting the computational load and obtaining a higher age range recognition rate. The dataset was divided into training and testing parts, and the team used a K-nearest neighbor classifier to identify age based on participants' gait patterns. The classifier had a success rate of more than 90% in all cases, such as walking fast, walking diagonally, and walking slowly.

Nabila et al. [16] conducted an age recognition system for Gait based on the OU-ISIR database and the Silhouette model. The database includes data from 4007 people, a large population dataset. For the classification, SVM (Support Vector Machine) was used to solve the age recognition between two classes. According to the results, the SVM classification method achieved an accuracy of 74.47% with good recall and prediction of age groups.

In 2019, Hema et.al. [17] conducted two based models, face and gait models, to perform age classification. After the study, the Gait based model is more suitable than the face-based model because it is difficult for the face to get information if the subject is away from the camera. SVM was selected as the classifier and OU ISIR dataset was used for this age classification. It applied gait energy image (GEI), feature-to-example distance (FED), and gait energy image longitudinal projection (GLP) and gait energy image lateral projection (GTP) as gait energy image projection model (GPM). The results showed that GPM and GEI obtained better performance among other individual descriptors.

In the same year, Riaz et al. [18] studied age estimation based on human walking. They used 6D acceleration and angular velocity of 86 subjects as a dataset. This study used two types of sensors and the reason for this is to use two different sensors, i.e., smartphone sensor and APDM Opal IMU, and use the same proposed algorithm to show the performance. The collected data underwent processes like feature extraction, such as mean, median, kurtosis, etc. Various models such as Random Forest Regressor (RFR), Support Vector Regressor (SVR) and Multi-Layer Perceptron Regressor (MLP-NN) are applied in this study. In the results, random forest regression. A summary of the conventional machine learning methods is presented in Table I.

TABLE I
A SUMMARY OF CONVENTIONAL METHODS

Author	Method	Database	Recognition Rate	Pros	Cons
Zhang et al. (2010)	Hidden Markov Model (HMM)	-	83.33%	Build a new way contour feature extraction of Gait	Limited to small size of database
Yang & Wang (2016)	K-nearest neighbor (KNN)	-	97.06%	Giving possibility for detecting long distance cases	Can only solve the transient occlusion
Nabila et al. (2018)	Descriptor Silhouette Model, SVM	OU-ISIR	74.47%	On road elder security issue	A lower accuracy rate compared to other article
Hema et.al. (2019)	Support Vector Machine(SVM)	OU-ISIR	89.1%	Create a new efficiency descriptor	Age-related parameter be too important
Riaz et al. (2019)	Random Forest Regressor, Support Vector Regressor, Multi-layer Perceptron Regressor	-	8.22 RMSE	Clearly compare performance of each sensor	The privacy concern will occur when using smartphone sensor
Khabir et al. (2019)	K-nearest neighbor (KNN), Support Vector Machine (SVM),Random Forest	OU-IRIS	KNN-81.18% SVM-84.76% Random Forest-73.67%	Good to compare three model accuracy to Gait based age recognition system.	Still have feature that can be extracted in the dataset

B. Deep Learning Methods

Xu et al. [19] developed a gait-based age and gender estimation system. The OULP-age database was used in this system. The input was in GEI and the survey was performed with a deep convolutional neural network (ConvNet) for feature extraction. Multitask learning was used to estimate the age. In the results, the pre-trained data is more efficient compared to the data without pre-training. It achieved lower MAE and Huber results in all the tests, trained data achieved 5.69 MSE and 5.65 Huber in the tests.

In 2021, Saho et al. [20] proposed a gait comparing age and fall risk. Micro Doppler radar was used for data collection and participants were required to walk in a straight line within 10 meters. After that, the results will be divided into two groups, i.e., fallers/non-fallers and 50/70 years old group. Then, the model used in this paper with deep learning method is CNN. fallers/non-fallers and 50 years old (middle age group)/70 years old (old age group) groups achieved good results with accuracy of 78.9% and 81.6 respectively.

In the same year, Costilla-Reyes et al. [21] proposed a system to investigate the basis of healthy Gait in different age groups. The type of data collected was based on walking force and gait data while walking on the ground. The model was divided into 70% for training and 30% for testing. This study was conducted with deep learning and non-deep learning models to compare the different performance between each other. The deep learning results have a large range based on classification. It can achieve a maximum f-score of 97% and a minimum f-score of 58%.

Next, Chen et al. [22] conducted a wireless signal project to predict gait-based age estimation. The system detected Gait through wireless sensing and predicted age from the detected gait information. The environment was set up in a 20 m long and 1.5 m wide corridor in order to receive the gait data from the participants clearly. The model used in this study was Bagging Ensemble Learning. the overall accuracy based on this WIAGE system was 96.21%, which indicates a strong association and relationship between Gait and age.

Besides, Liu et al. [23] developed a system to focus on health using gait characteristics. The study investigated the gait patterns of participants in healthy and frail states and the gait changes in these states. After collecting data, they performed feature extraction using Alphapose and gait feature extraction, such as LGaitset, Gaitset, and DGaitset. The team then used VGG16 and AlexNet to perform the classification. 85.1% was achieved for AlexNet and 85.5% for VGG16.

In addition, Lv et al. [24] conducted a gait characterization based on alphapose human pose estimation. This study focused on pose estimation algorithms and the estimation of arthritis. TensorRT technique was used to detect video and process pose estimation, which can help improve performance and reduce latency. The results show that when TensorRT is used, latency will be reduced, and throughput can be increased by 97.19 compared to the results without the TensorRT technique. A summary of the deep learning methods is provided in Table II.

TABLE II
A SUMMARY OF DEEP LEARNING METHODS

Author	Method	Database	Recognition Rate	Pros	Cons
Zhang et al. (2019)	Multi-task learning	OU-ISIR	5.69 MSE	Given new types vision of age recognition	Did not have the accuracy score of age.
Saho et al. (2021)	Convolutional neural network	-	81.6%	Micro-Doppler radar can record data information in far distance	Data type is not video based.
Costilla-Reyes et al. (2021)	spatio-temporal deep learning model	uOM-Gait-69	96.99%	Provide many situation when the participant participate the study	The gap of result is big
Chen et al. (2021)	Bagging ensemble learning	-	96.21%	Wireless Signals to detect Gait and estimate the age is feasible	Need a very reliable environment to detect wifi signals
Liu et al. (2021)	AlexNet and VGG16	-	85.1% AlexNet 85.5% VGG16	Giving an experience on the unhealthy person gait change even in same age	Have a limitation when the participant in re-hospital status because it cannot record the status in that situation
Lv et al. (2022)	TensorRT	-	71.14%	More understanding about Alphapose and help to increase performance feature extraction	It cannot detect the target participant if there have a lot of people appear in camera.

II. MATERIAL AND METHOD

The proposed age group estimation method contains three important processes: body keypoint estimation, preprocessing, and age group classification. Body keypoint estimation aims to identify and locate specific body parts from the input video or image, such as joints, limbs, and other anatomical landmarks. These keypoints are essential reference points for analyzing the subject's gait pattern. After obtaining the body keypoints, the next step is preprocessing the data. Preprocessing is essential for enhancing the quality and suitability of the data for subsequent analysis. Once the preprocessed data is ready, it is used as input for the age group classification model. Age group classification involves training a deep learning model using a labeled dataset containing gait patterns and corresponding age group information. The model learns to identify patterns and relationships between gait features and age groups. During the classification phase, the model takes the preprocessed data as input and predicts the most likely age group for the individual based on their gait pattern. The overall process flow is depicted in Fig. 1.

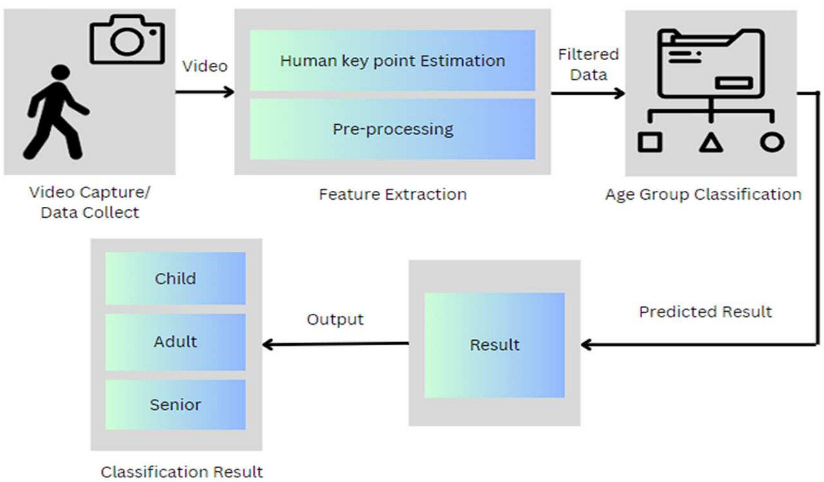

Fig. 1 Block diagram of the proposed system

A. Body Keypoints Estimation

Given an input video of a walking subject, AlphaPose [25] tracks the keypoints on the subject's body. AlphaPose involves two main stages: body part detection and pose estimation. In the first stage, AlphaPose detects and localizes various body parts. The second stage involves estimating the complete human pose by connecting the detected keypoints. AlphaPose effectively detects and localizes body parts in the input video by dividing the process into these two parts. It then predicts the positions of the body within bounding boxes and connects the keypoints to generate a comprehensive representation of the subject's pose. Some sample outputs of applying AlphaPose on the human age estimation dataset are depicted in Fig. 2.

Fig. 2 Example of an unacceptable low-resolution image

B. Preprocessing

The gait signals represented by the estimated keypoints can exhibit fluctuations or inconsistencies due to factors like irregular movement, variations in walking speed, or jerky camera movements. Towards this end, several smoothing techniques are applied to create a more continuous and smooth representation of the gait pattern. The preprocessing step helps to remove sudden variations and outliers, enabling better analysis and modeling.

1) Exponential Moving Average: The exponential moving average filter [26] is a type of moving average that gives more significance and weight to the nearest data points. It can also be used for time series datasets. The exponentially weighted moving average process reduces the weights exponentially, while the weighted moving average method continuously reduces the weights.

$$v_t = \frac{1}{\sum_{k=0}^{n-1}(1-a)^j} \sum_{j=0}^{n-1}(1-a)^{n-j-1} x_{j+1} \quad (1)$$

The time series will be used as input, where t equals k, k+1 up to n. The smoothing factor is defined as $a = \frac{2}{k+1}$. However, the value of k can only reach 3 because when the value of k exceeds 3, the result will be closer to 1. When k equals n, the number of observations will be reduced to one value.

2) Hampel Filter: The Hempel filter [27] is a smoothing filter method that approaches the median filter. The Hempel filter aims to identify and replace outliers in a given series. It utilizes a configurable rolling window to traverse the data. It calculates the median and median absolute deviation (MAD).

$$y_k = \{ {}^{x_k \; |x_k - m_k| \le tS_k}_{m_k \; |x_k - m_k| > tS_k} \quad (2)$$

The value of m_k in the equation represents the median, and the value of S_k in the equation represents the MAD estimate. An interesting finding of this filter is that it reverts to a standard median filter when the value of t is set to zero. Implementing the Hempel filter can be seen as reducing the aggressiveness by controlling the threshold value.

3) Savitzky-Golay Filter: The Savitzky-Golay filter [28] is one of the filter methods that can be applied to a set of data points. It is suitable for smoothed data sets without destroying the propensity of the data. This is achieved by fitting a continuous subset of adjacent data points using linear least squares, which is known as the convolution method. When the data points are equally spaced, it is possible to find an analytical solution to the least squares equation in the form of a set of singular "convolution coefficients" that can be applied to all subsets of data to estimate the smoothed signal.

$$Y_j = \sum_{i=-(m-1)/2}^{i=(m-1)/2} C_i y_{j+i} \frac{m+1}{2} \le j \le n - \frac{m-1}{2} \quad (3)$$

C. Age Group Classification

Once the gait signals have undergone preprocessing, the smoothed signals are ready to be utilized for age group classification. In this study, a deep learning model is employed, specifically a bidirectional Long Short-Term Memory (LSTM) model [29], [30].

The bidirectional LSTM model extends the capabilities of the traditional LSTM neural network. It consists of two independent LSTM networks that process the input sequence in both forward and backward directions. This bidirectional nature allows the model to capture information from the past and future steps, incorporating temporal dependencies and contextual information.

The bidirectional LSTM model is connected to an output layer, which performs the age group classification based on the learned representations from the gait signals. By leveraging the bidirectional LSTM architecture, the model can effectively capture the complex patterns and dynamics present in gait data, enabling accurate age-group estimation.

The utilization of bidirectional LSTM in gait analysis has proven beneficial, as it can effectively handle sequential data, such as time series of joint angles or accelerations recorded during walking or running. This approach allows the model to consider the dependencies and contextual information across multiple steps, improving the understanding and prediction of age groups based on gait patterns.

III. Result and Discussion

A. Dataset

1) Gait in the Wild Dataset: The Gait in the wild dataset is a dataset that was collected from various sources, including videos obtained from the Internet and real-world data. The aim was to create a diverse and representative dataset of gait patterns, referred to as the "gait in the wild" dataset. Participants in the videos were instructed to walk and display their entire body to ensure accurate gait pattern capture. The videos encompassed four different views: front, back, left, and right. This multi-angle approach enabled the system to capture different perspectives and angles of the participants, enhancing the system's ability to analyze gait changes and make accurate predictions.

The dataset comprises a total of 199,538 data points, with each data point representing a frame in a video. The data points contain several columns, including image ID, category ID, key points, box coordinates, score, and IDX (refer Fig. 3).

	image_id	category_id	score	box	idx	label	keypoints_1	keypoints_2	keypoints_3	keypoints_4	...	keypoints_399	keypoints_
0	0.jpg	1	2.410882	[1151.033203125, 226.5185089111328, 305.650024...	[0.0]	adult	1175.949219	319.655640	0.007255	1179.670654	...	0.000067	1236.296
1	0.jpg	1	1.300730	[1608.1002197265625, 200.97206115722656, 113.2...	[0.0]	adult	1663.320923	235.801575	0.000243	1668.168701	...	0.000931	1487.296
2	0.jpg	1	1.064944	[1764.0379638671875, 236.65277099609375, 93.77...	[0.0]	adult	1811.385620	267.313446	0.003024	1815.074585	...	0.000338	1753.208
3	0.jpg	1	0.685577	[1862.5074462890625, 191.62173461914062, 57.49...	[[0.0], [0.0]]	adult	1916.450684	187.226227	0.013181	1917.272461	...	0.001316	1727.984
4	1.jpg	1	2.410197	[1160.616943359375, 232.98043823242188, 253.94...	[0.0]	adult	1161.131592	320.480896	0.016825	1164.825684	...	0.000297	1204.380

Fig. 3 Gait in the wild dataset

One crucial feature of this dataset is the storage of keypoints, representing the human body patterns identified by the AlphaPose process. These keypoints play a significant role in gait analysis and age group estimation. The dataset has 76,576 data points labeled as senior, 54,666 labeled as adults, and 68,296 labeled as children. The senior age group has the most extensive representation in the dataset.

2) *Self-Collected Dataset*: The self-collected dataset is identical to the Gait in the Wild dataset. It is a combination of video-based data, but with a different representation. In this self-collected dataset, each row represents a video consisting of 25 frames of human keypoint data. The keypoint data is extracted from the AlphaPose JSON files. However, it should be noted that the extracted keypoints do not include head and hand keypoints. This exclusion is due to the fact that head and hand keypoints are often obscured when individuals are facing different directions during walking. For example, when people walk to the right, the left hand may be obscured.

The dataset contains a total of 3,100 columns representing the keypoints of the 25 frames. In terms of data collection, 3,837 videos were collected. The filenames of the videos provide brief information about the participants, including gender, age, and the number and direction of walking (refer Fig. 4). The "label" field in the dataset records the age-related labels of the participants and serves as the classification groups for the model to predict the age groups.

	image_id	category_id	score	box	idx	label	keypoints_1	keypoints_2	keypoints_3	keypoints_4	...	keypoints_399	keypoints_
0	0.jpg	1	2.410882	[1151.033203125, 226.5185089111328, 305.650024...	[0.0]	adult	1175.949219	319.655640	0.007255	1179.670654	...	0.000067	1236.296
1	0.jpg	1	1.300730	[1608.1002197265625, 200.97206115722656, 113.2...	[0.0]	adult	1663.320923	235.801575	0.000243	1668.168701	...	0.000931	1487.296
2	0.jpg	1	1.064944	[1764.0379638671875, 236.65277099609375, 93.77...	[0.0]	adult	1811.385620	267.313446	0.003024	1815.074585	...	0.000338	1753.208
3	0.jpg	1	0.685577	[1862.5074462890625, 191.62173461914062, 57.49...	[[0.0], [0.0]]	adult	1916.450684	187.226227	0.013181	1917.272461	...	0.001316	1727.984
4	1.jpg	1	2.410197	[1160.616943359375, 232.98043823242188, 253.94...	[0.0]	adult	1161.131592	320.480896	0.016825	1164.825684	...	0.000297	1204.380

Fig. 4 Self-collected dataset

Among the collected videos, there are 1,943 videos labeled as adults, making them the most numerous age group in the dataset. The child and senior groups follow, with 1,018 and 876 videos, respectively. This self-collected dataset serves as an important resource for training and evaluating the age group classification model. It captures variations in gait patterns across different age groups and provides valuable insights for accurate age group estimation based on gait analysis.

B. Evaluation of Baseline Performance

1) *Gait in the Wild Dataset*: During the training process, the proposed model achieved an accuracy score of 0.55 in the Gait in the Wild dataset. The results obtained from the confusion matrix in Fig. 5 indicate that the model performs exceptionally well in predicting the seniors' and children's age groups. However, the model's accuracy was comparatively lower for the adult group. This lower accuracy can be attributed to misclassifying some adults as either children or seniors.

One contributing factor to this result could be the presence of individuals with similar gait patterns in age groups that are close in age, such as children and seniors. The similarity in gait patterns may have led to misclassifications, resulting in a lower accuracy for the adult group. Another observation is that the validation loss increases after five iterations, indicating a potential overfitting problem in the model. This suggests the model may need further improvements to prevent overfitting and enhance its generalization capabilities.

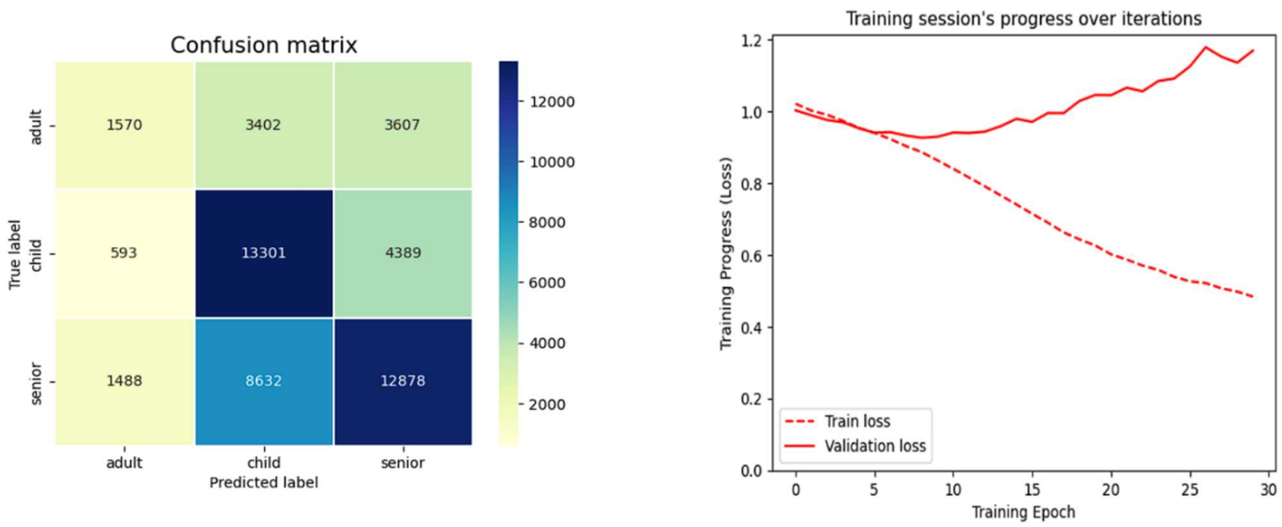

Fig. 5 Confusion matrix and loss curve of Gait in the wild dataset

2) Self-Collected Dataset: The self-collected dataset achieved an accuracy that was 3% lower than the field gait dataset (refer to Fig. 6). However, it exhibited a lower loss value of 0.15 compared to the field gait dataset, indicating a lower error rate in the self-collected dataset. The confusion matrix in Fig. 6 reveals that the model encountered difficulties in correctly identifying the senior and adult age groups. The gait patterns within these two groups may be highly similar, leading to challenges in distinguishing between them. Only a small number of cases from the senior group were accurately identified, while the model performed relatively well in predicting the adult group. The loss curve for the self-collected dataset demonstrates that the model performed correctly without any signs of overfitting. Although the training loss appears to be high, there are no indications of overfitting or underfitting issues. Overall, the loss curves of the self-collected dataset show promising performance compared to the Gait in the wild dataset.

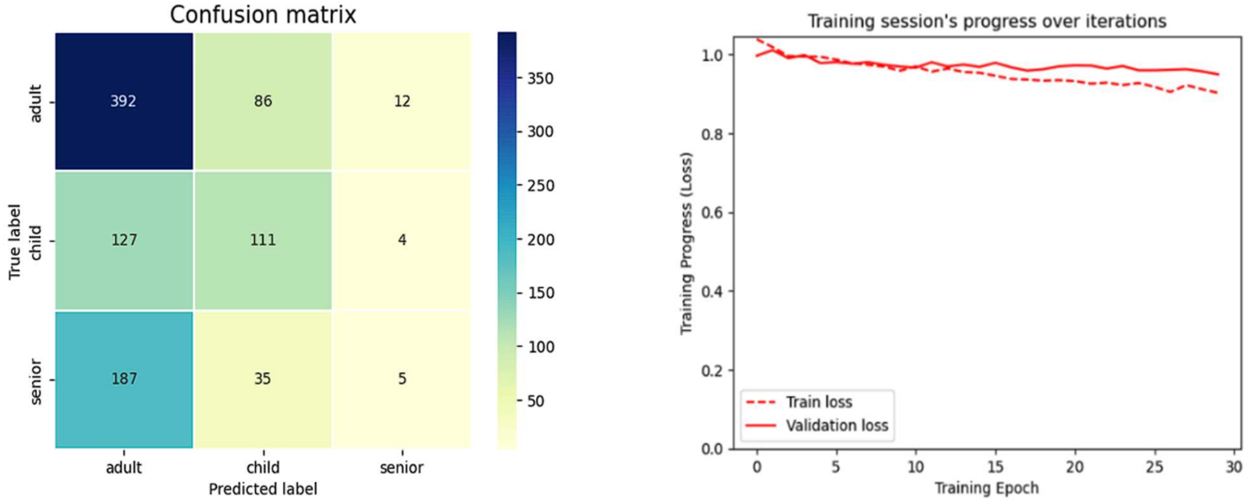

Fig. 6 Confusion matrix and loss curve of self-collection dataset

Table III provides a summary of the accuracy scores for the two datasets. The Gait in the wild dataset achieves a higher accuracy score, indicating better overall performance in age group classification. However, it is important to note that the training loss for this dataset is relatively high compared to the self-collected dataset.

TABLE III
BASELINE RESULTS OF GAIT IN THE WILD AND SELF-COLLECTED DATASETS

Dataset	Accuracy
Gait in the wild	55.0%
Self-Collected	52.9%

The high train loss in the Gait in the wild dataset suggests that the model may encounter challenges and make significant errors during the classification process. These errors can affect the accuracy of age group predictions. In contrast, the self-collected dataset exhibits a lower train loss, indicating a more accurate and reliable model. Although the accuracy score is slightly lower compared to the Gait in the wild dataset, the lower train loss suggests better generalization and improved performance in age group classification. Considering these findings, it is essential to carefully evaluate the trade-off between accuracy and train loss when choosing a dataset for age group estimation based on gait analysis. While the Gait in the wild dataset may have a higher accuracy score, the high train loss implies a higher likelihood of classification errors. On the other hand, the self-collected dataset offers lower train loss and a more reliable model for age group classification.

C. Analysis of Adult and Senior Classes

There is a common observation found in the two datasets. Due to their similar gait patterns, the system struggles to recognize the adult and senior groups accurately. To explore the impact of combining these two similar groups on the system's performance, an experiment is conducted by merging the age groups of seniors and adults into a single category named the "adult" group.

1) Gait in the Wild Dataset: The confusion matrix in Fig. 7 shows that the performance on the Gait in the wild dataset can be improved by combining the adult and senior groups. Examining the loss curve, we observe that the model exhibits overfitting after 15 training epochs, while it experiences underfitting before reaching 15 epochs. This may require further improvements to enhance its performance.

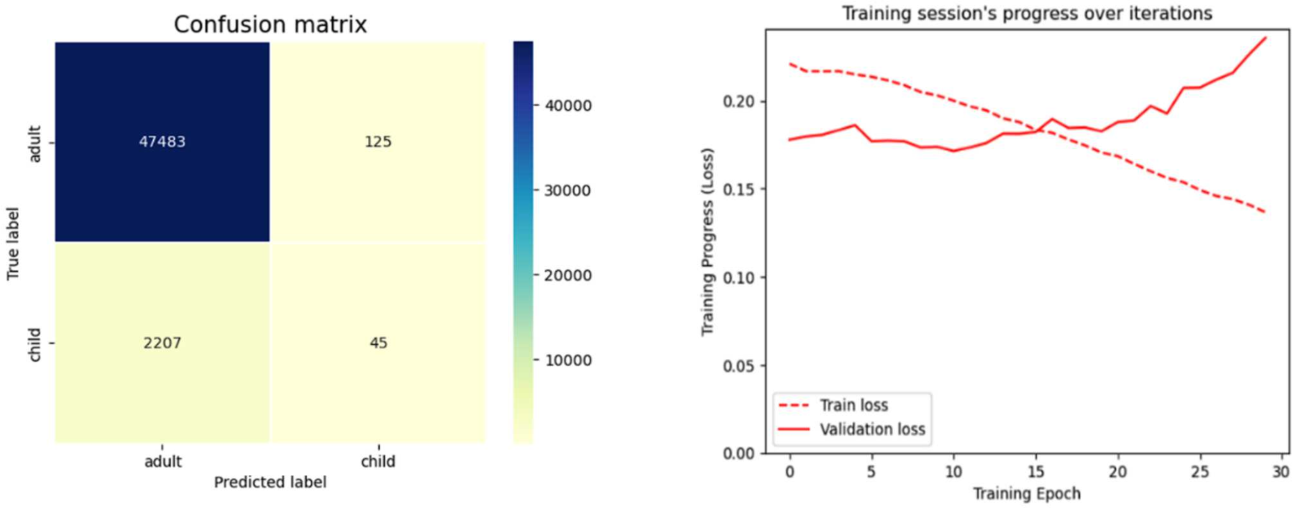

Fig. 7 Confusion matrix and loss curve of Gait in the wild dataset after group the adult and senior grouping

2) Self-Collected Dataset: The self-collected dataset demonstrates superior performance in combining the adult and senior groups as compared to the Gait in the wild dataset. The child group exhibits a higher prediction accuracy compared to the adult group. When considering the total number of samples, this model successfully predicts 85 instances from the child group. Analyzing the loss curve of the self-collected dataset in Fig. 8, we observe that the model comprehends the dataset well and makes accurate predictions. Furthermore, the model does not encounter any underfitting or overfitting problems, indicating a robust learning process.

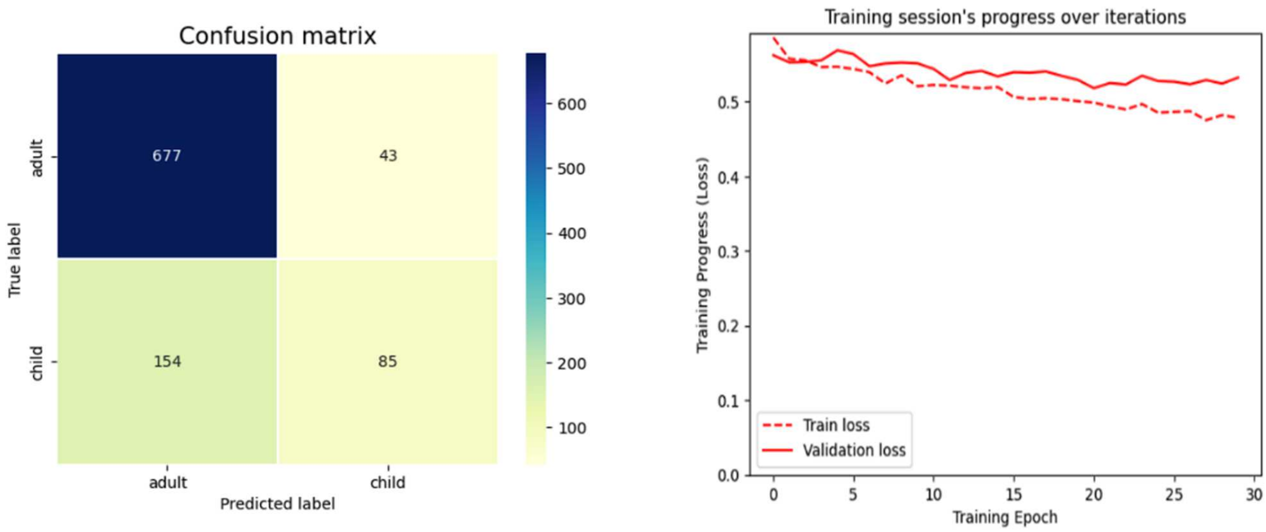

Fig. 8 Confusion matrix and loss curve of self-collected dataset after group the adult and senior grouping

Table IV presents the overall performance before and after combining the adult and senior groups. We observe that up to 40% improvement can be achieved in the Gait in the wild dataset, and a 26% improvement is achieved in the self-collected dataset. By merging these two groups into a single category called the "adult" group, the system no longer needs to distinguish between them based on gait characteristics. This reduces the complexity of the classification task, making it easier for the model to differentiate between the combined adult group and other age groups, such as children.

TABLE IV
RESULT AFTER GROUPING THE CLASSIFICATION GROUP

Dataset	Before Class Grouping	After Class Grouping
Gait in the wild	55.0%	95.0%
Self-Collected	52.9%	79.0%

D. Analysis of Filtering Techniques

The gait signal sets in the model lack stability, which prompted the utilization of filtering techniques to address this issue. Different filtering techniques are applied to both datasets to smoothen the gait signals, including the Savitzky-Golay filter, Hampel filter, and exponential moving average filter. The performance of applying the filtering techniques are provided in the subsequent sections.

1) Gait in the Wild Dataset:

- Exponential Moving Average (EMA) Filter

Fig. 9 shows the effectiveness of the EMA filter in preserving data information. The EMA filter successfully retains a significant portion of the data, as the "x" data remains largely unchanged. However, in the case of the "y" data, the filter removes numerous values that are considered too small. As a result, the "y" data undergoes more filtering, reducing the number of values. The "x" and "y" data components contain 25 information frames. It is important to note that after applying the EMA filter, the data exhibits increased complexity compared to the Gait in the wild dataset. This complexity arises due to the filtering process and the removal of certain values that do not meet the specified criteria.

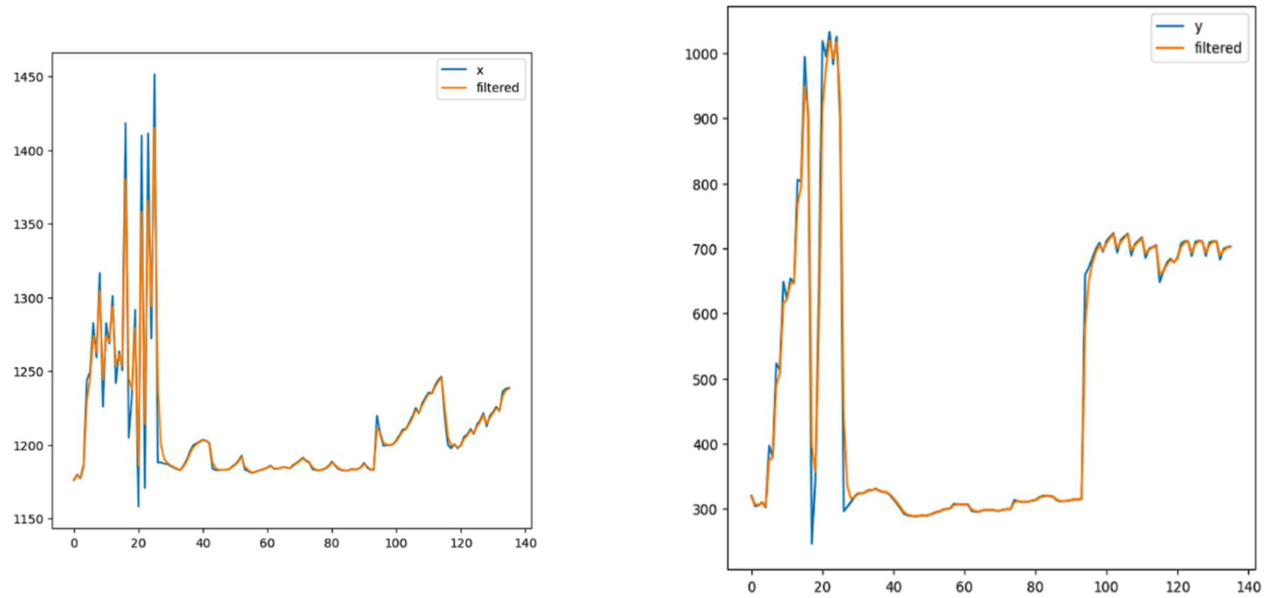

Fig. 9 A Comparison of applying exponential moving average filter in Gait in the wild dataset

Fig. 10 demonstrates that the utilization of the EMA filter has demonstrated improvements in the model's performance. It exhibits the ability to recognize certain instances from the child age group despite the relatively lower number of true labels assigned to this group. In comparison to other filters, the EMA filter provides a promising signal. Analyzing the loss curve, it is evident that the model achieves optimal performance when training is halted at epoch 25. Continuing training beyond this point may increase the likelihood of overfitting.

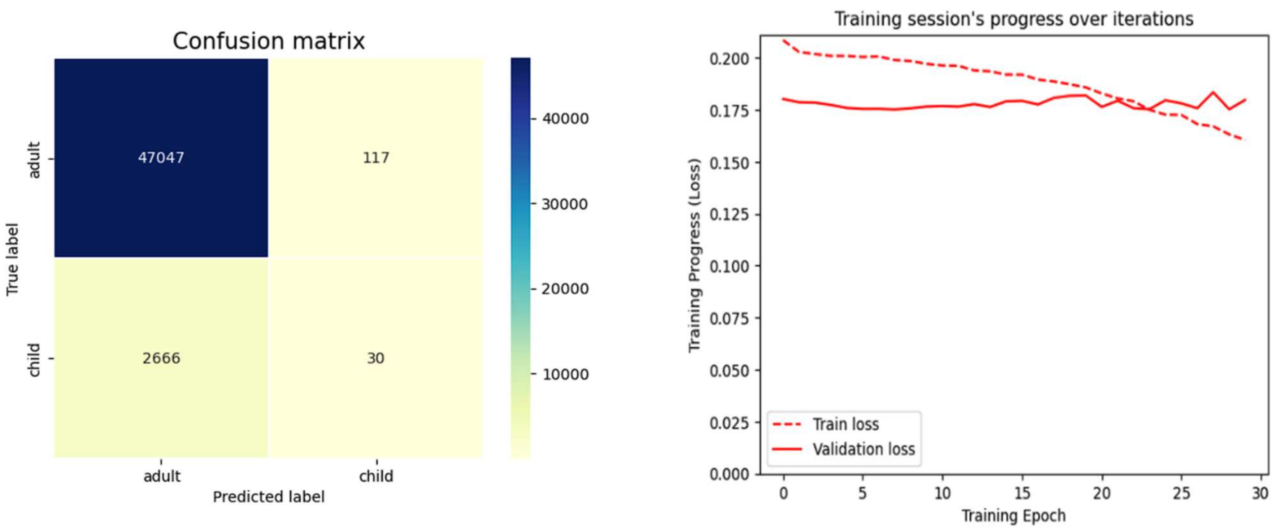

Fig. 10 Confusion matrix and loss curve of Gait in the wild dataset after applying Exponential Moving Average Filter

- Hampel Filter

When applied to both the x and y coordinates, the Hampel Filter exclusively filters the values at the front of the dataset (Fig. 11). Consequently, a lot of information is removed from the dataset, resulting in substantial differences compared to the original data. Regrettably, the Hampel Filter struggles to identify the child class accurately and instead predicts all classes as adult groups. This poor performance is evident in the results, as the model consistently predicts all answers as belonging to the adult group.

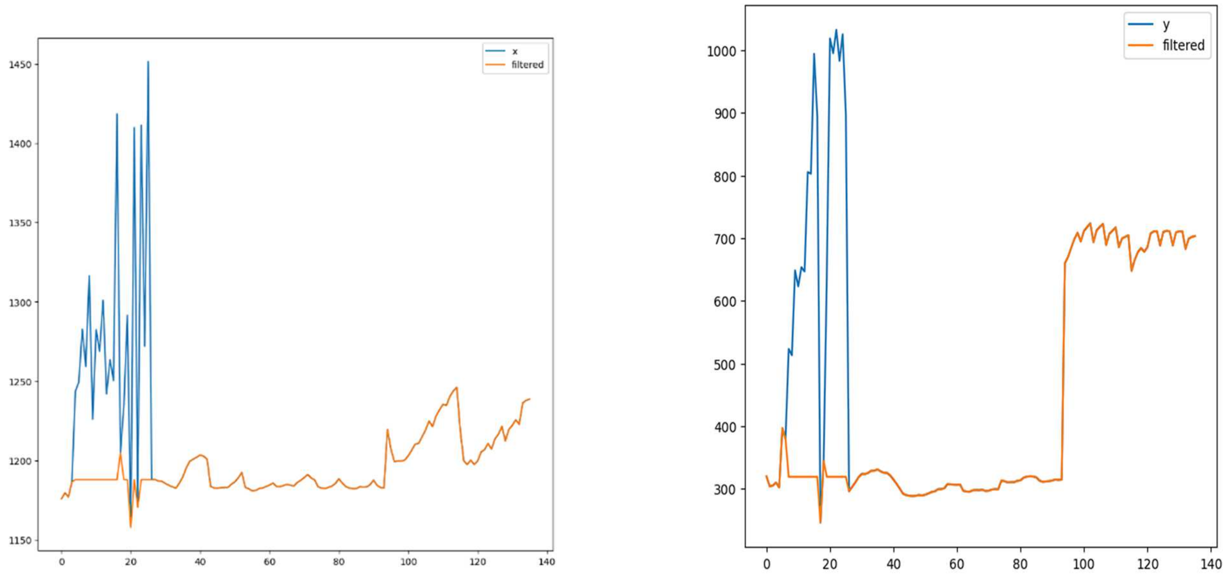

Fig. 11 A comparison after applying Hampel Filter in Gait in the wild dataset

Analyzing the loss curve in Fig. 12, it becomes apparent that the Hampel Filter encounters the problem of overfitting. This indicates that the model becomes excessively tuned to the training data, failing to generalize well to unseen examples. Consequently, the combination of the Hampel Filter and the associated results is unsatisfactory, requiring further investigation and potentially alternative approaches to address the shortcomings in accuracy and overfitting.

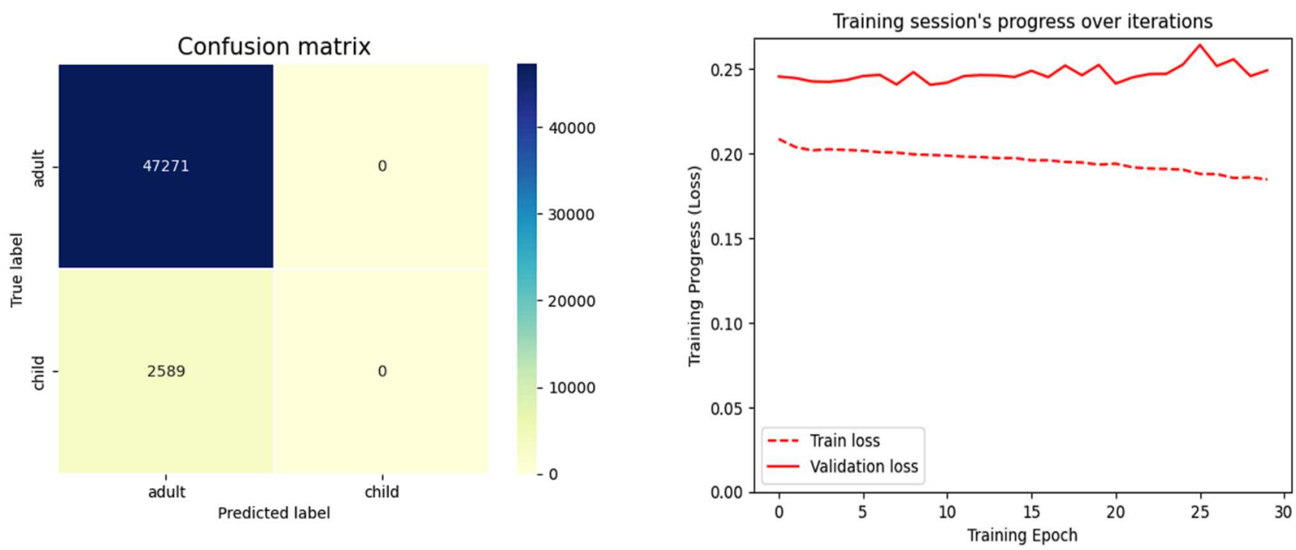

Fig. 12 Confusion matrix and loss curve of Gait in the wild dataset after applying Hampel Filter

- Savitzky-Golay Filter

Fig. 13 presents a comparison between the data before and after the application of the filtering technique. Specifically, the Savitzky-Golay filter is utilized to smooth the data, particularly in the "y" label. This filter modifies the data that lacks sufficient smoothness. Notably, if the data experiences sudden fluctuations with smaller and larger values, the filter eliminates the smaller values and increases them to achieve a smoother pattern.

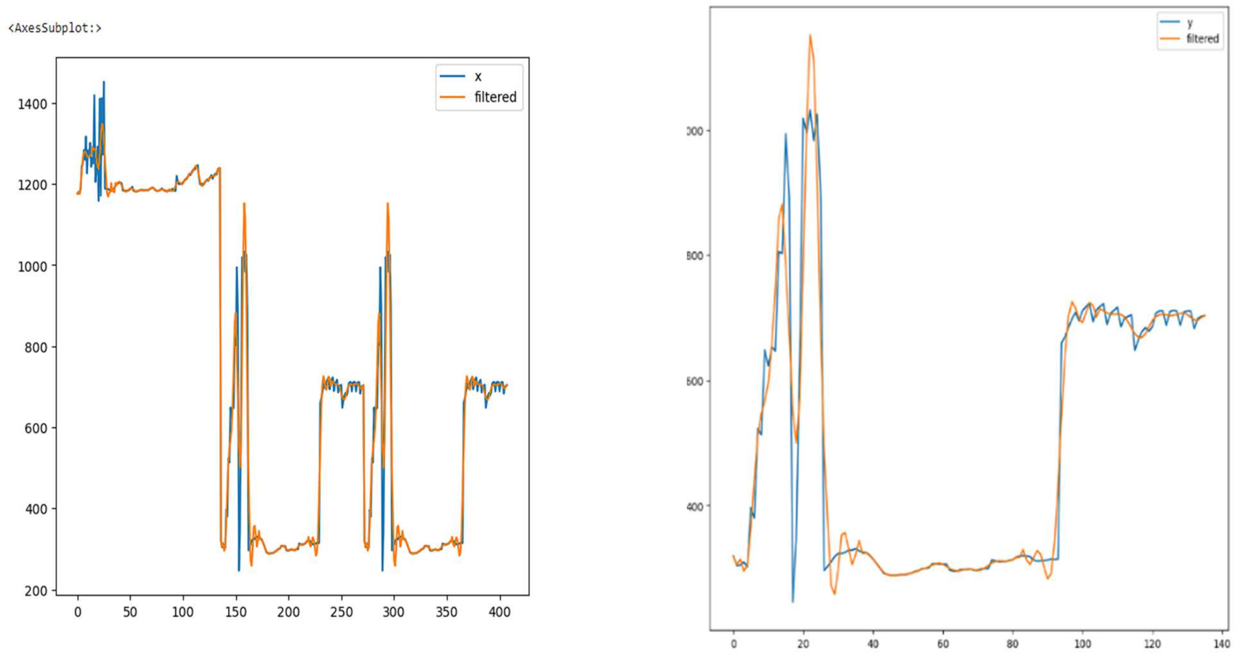

Fig. 13 A comparison after applying Savitzky-Golay Filter in Gait in the wild dataset

However, it is important to note that even after the Savitzky-Golay filtering, the model still struggles to correctly predict instances from the child class (refer to Fig. 14). This suggests that the model fails to comprehend the distinguishing characteristics between the adult and child age groups, even after the filtering process. Additional steps or adjustments may be necessary to enhance the model's understanding and classification of these distinct age groups.

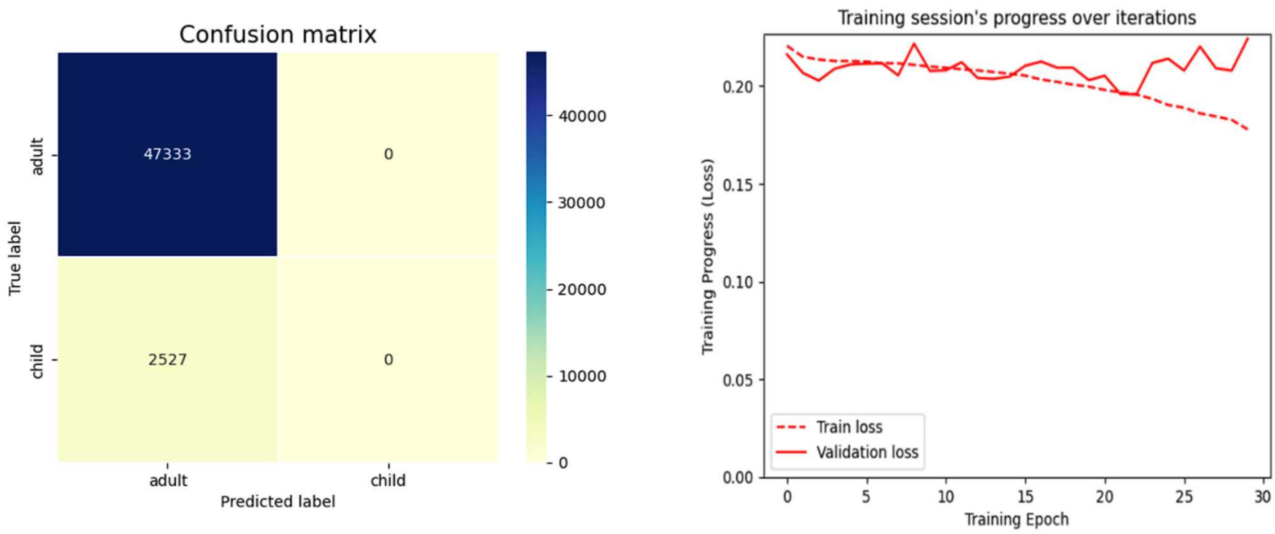

Fig. 14 Confusion matrix and loss curve of Gait in the wild dataset after applying Savitzky-Golay Filter

Table V summarizes after applying the filtering techniques on the Gait in the wild dataset.

TABLE V
RESULT OF GAIT IN THE WILD DATASET AFTER APPLYING THE FILTERING TECHNIQUES

Filter Technique	Accuracy	Training Loss
Exponential Moving Average	94.4%	0.213
Hampel	94.8%	0.202
Savitzky-Golay	94.9%	0.234

The performance improvement, although not drastically different across filters, signifies that the filters enhance the model's ability to understand and interpret the data. This, in turn, leads to improved recognition and classification accuracy.

2) *Self-Collected Dataset*

- Exponential Moving Average (EMA) Filter

The EMA filter is highly effective in preserving most of the data within the dataset. It selectively smooths the data when sudden high or low values are encountered, while retaining the majority of the dataset's information (refer Fig. 15). This filter enables the model to gain a clear understanding of the filtered data, facilitating accurate interpretation and classification.

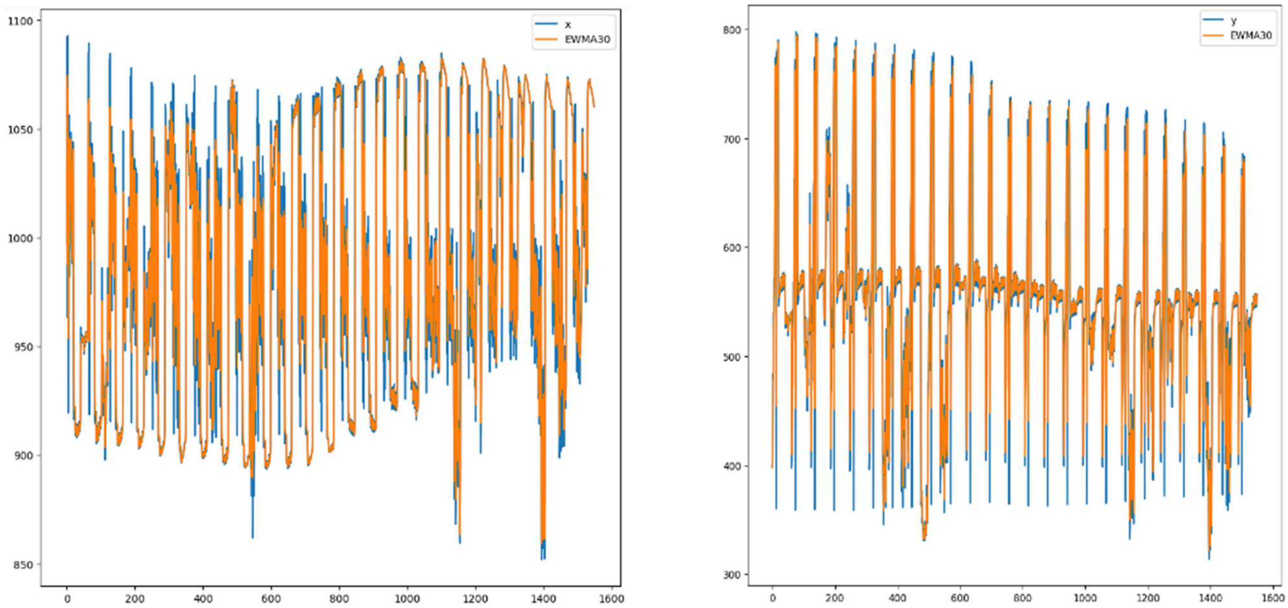

Fig. 15 Before and after view comparison after applying Exponential Moving Average Filter in Self-Collected dataset

While the results obtained from the EMA filter may not exhibit significant differences compared to other filters, they still contribute to improving the model's stability (refer to Fig. 16). However, it is worth noting that the accuracy of the EMA filter is slightly lower, with a decrease of 5% compared to the original dataset. Nonetheless, the loss curve of the EMA filter remains within acceptable parameters, demonstrating a normal and desirable progression. Both the training loss and the validation loss exhibit overall reduction.

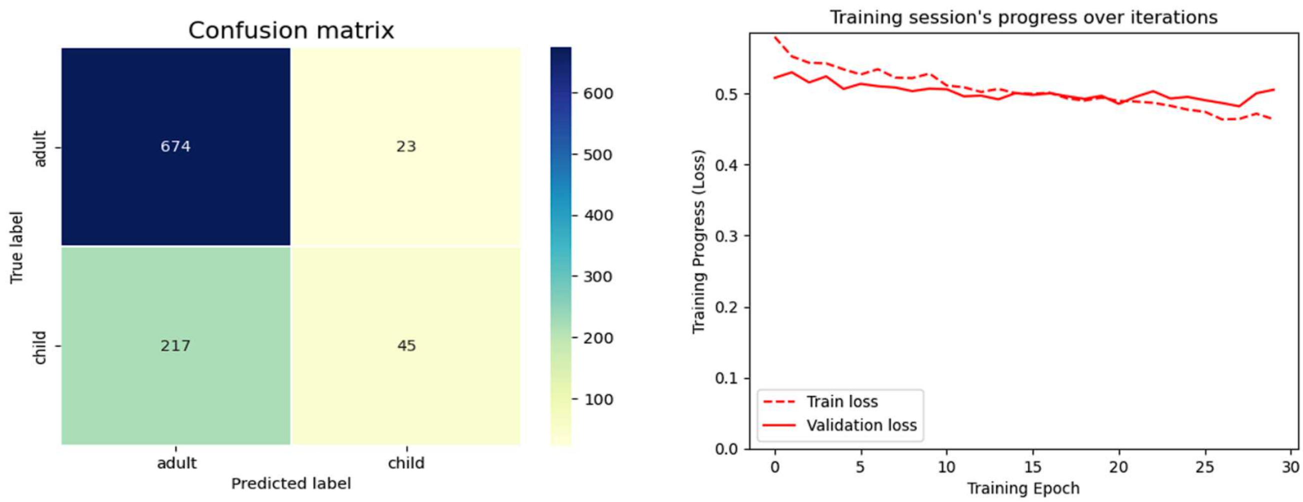

Fig. 16 Confusion matrix and loss curve of self-collected dataset after applying Exponential Moving Average Filter

- Hampel Filter

The Hampel filter primarily filters the data located towards the back side of the "x" tag, while the data in front of the "x" tag remains unchanged. The filtering effect on the "y" tag is partial, with only some of the data being filtered. In terms of performance, the Hampel filter exhibits similar results to the EMA filter. However, the accuracy of the Hampel filter is reduced by approximately 5% compared to the original dataset (refer to Fig. 17).

Unfortunately, the loss curve of the Hampel filter in Fig. 18 indicates that the model tends to overfit when the epoch length is longer. This suggests that prolonged training with the Hampel filter may lead to the model becoming too specialized for the training data, resulting in reduced generalization capabilities.

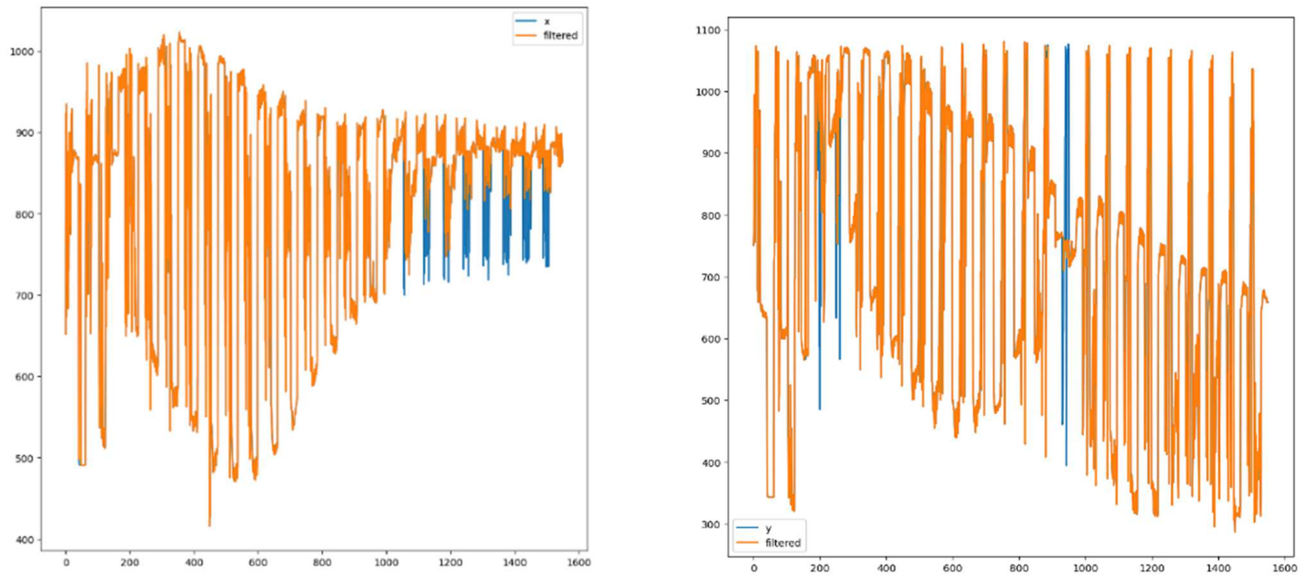

Fig. 17 Before and after view comparison after applying Hampel Filter in Self-Collected dataset

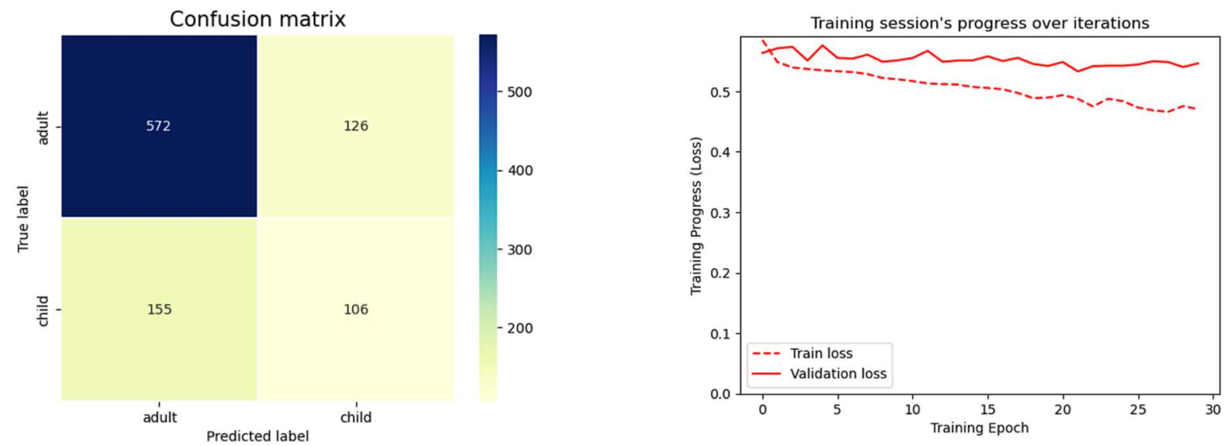

Fig. 18 Confusion matrix and loss curve of self-collected dataset after applying Hampel Filter

- Savitzky-Golay Filter

The Savitzky-Golay filtering technique tends to remove a considerable amount of information compared to other filtering techniques (refer to Fig. 19). Specifically, in the "x" label, smaller values are retained, while in the "y" label, smaller data points are eliminated, and larger values are introduced. This filtering process results in a reduction in dataset accuracy compared to the results obtained without any filters.

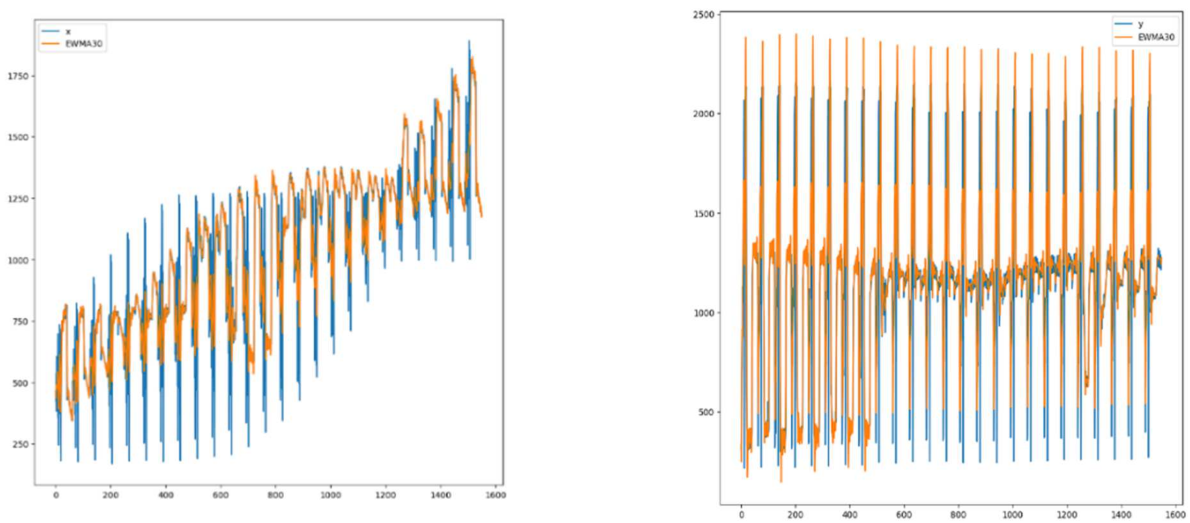

Fig. 19 Before and after view comparison after applying Savitzky-Golay Filter in Self-Collected dataset

Analyzing the loss curve, it is observed that the training loss of the model is relatively lower compared to the original dataset. This suggests that during the training process, the model may encounter fewer errors and exhibit improved performance in terms of minimizing the discrepancy between predicted and actual values.

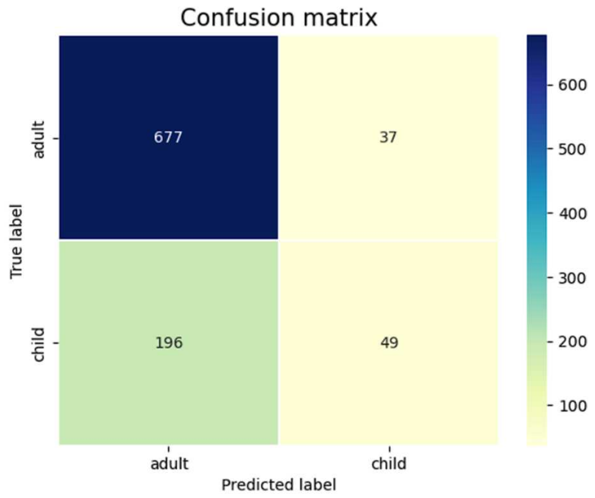

Fig. 20 Before and after view comparison after applying Savitzky-Golay Filter in Self-Collected dataset

Table VI presents the accuracy results after applying each filter. The Savitzky-Golay filter achieves the highest accuracy score of 75.7%. However, when comparing the performance of the filters across both datasets, it is observed that the EMA filter consistently delivers stable results. The EMA filter exhibits a slightly lower accuracy of 0.8% compared to the Savitzky-Golay filter. Although the Savitzky-Golay filter yields a higher accuracy score, the EMA filter's stability across the datasets makes it a reliable choice. The marginal difference in accuracy between the two filters suggests that the EMA filter can provide a satisfactory balance between performance and stability.

TABLE VI
RESULT OF SELF-COLLECTED DATASET AFTER APPLYING THE FILTERING TECHNIQUES

Filter Technique	Accuracy	Training Loss
Exponential Moving Average	74.9%	0.519
Hampel	70.7%	0.563
Savitzky-Golay	75.7%	0.506

E. Discussions

There are several interesting observations and findings from this study as follows:

- Both datasets encountered challenges in accurately identifying the adult and senior groups. However, the gait patterns in the wild dataset posed difficulties in classifying the adult group, while the self-collected data struggled with identifying the senior group.
- Combining the adult and senior groups proved beneficial in improving the overall performance. This approach allows for a more effective analysis of the gait similarities between the two groups, aiding in better classification accuracy.
- The wild dataset exhibited superior results when compared to the self-collected dataset, even without undergoing the filtering process. This suggests that the inherent characteristics of the wild data enabled better recognition and classification of the gait patterns.

IV. CONCLUSION

In this study, an age group classification system using gait analysis is developed and evaluated using the Gait in the wild dataset and a self-collected dataset. Recognizing the challenge in accurately distinguishing between the adult and senior groups due to their similar gait patterns, the attempt was made to combine these two groups. This combination resulted in substantial improvements, with an improvement of over 26% in the respective datasets. The system does have several limitations that should be considered. Clear visibility of the full body in the video input is necessary, and other individuals in the video can disrupt the system's performance. Additionally, the Gait in the wild dataset posed challenges in predicting the child group due to the limited number of "child" labels available. Future efforts will focus on self-improvement, continued study in related fields, and rigorous exploration of techniques to further enhance the system's accuracy and performance.

ACKNOWLEDGMENT

This research is supported by Fundamental Research Grant Scheme (FRGS/1/2020/ICT02/MMU/02/5) and MMU IR Fund (MMUI/220026).

REFERENCES

[1] Y. F. Ti, T. Connie, and M. K. O. Goh, “GenReGait: Gender Recognition using Gait Features,” *Journal of Informatics and Web Engineering*, vol. 2, no. 2, pp. 129–140, Sep. 2023, doi:10.33093/jiwe.2023.2.2.10.

[2] T. B. Aderinola, T. Connie, T. S. Ong, W.-C. Yau, and A. B. J. Teoh, “Learning Age From Gait: A Survey,” *IEEE Access*, vol. 9, pp. 100352–100368, 2021, doi: 10.1109/ACCESS.2021.3095477.

[3] N. Li and X. Zhao, “A Strong and Robust Skeleton-Based Gait Recognition Method with Gait Periodicity Priors,” *IEEE Trans Multimedia*, vol. 25, pp. 3046–3058, 2023, doi:10.1109/TMM.2022.3154609.

[4] H. Chao, K. Wang, Y. He, J. Zhang, and J. Feng, “GaitSet: Cross-view Gait Recognition through Utilizing Gait as a Deep Set,” *IEEE Trans*

Pattern Anal Mach Intell, pp. 1–1, 2021, doi:10.1109/TPAMI.2021.3057879.

[5] C. Song, Y. Huang, W. Wang, and L. Wang, “CASIA-E: A Large Comprehensive Dataset for Gait Recognition,” *IEEE Trans Pattern Anal Mach Intell*, pp. 1–16, 2022, doi: 10.1109/TPAMI.2022.3183288.

[6] Z. Zhang, L. Tran, F. Liu, and X. Liu, “On Learning Disentangled Representations for Gait Recognition,” *IEEE Trans Pattern Anal Mach Intell*, vol. 44, no. 1, pp. 345–360, Jan. 2022, doi:10.1109/TPAMI.2020.2998790.

[7] I. Hagoort, N. Vuillerme, T. Hortobágyi, and C. J. C. Lamoth, “Age and walking conditions differently affect domains of gait,” *Hum Mov Sci*, vol. 89, p. 103075, Jun. 2023, doi: 10.1016/j.humov.2023.103075.

[8] A. Macie, T. Matson, and A. Schinkel-Ivy, “Age affects the relationships between kinematics and postural stability during gait,” *Gait Posture*, vol. 102, pp. 86–92, May 2023, doi:10.1016/j.gaitpost.2023.03.004.

[9] K. A. Boyer *et al.*, “Age-related changes in gait biomechanics and their impact on the metabolic cost of walking: Report from a National Institute on Aging workshop,” *Exp Gerontol*, vol. 173, p. 112102, Mar. 2023, doi: 10.1016/j.exger.2023.112102.

[10] O. Jayakody *et al.*, “Age-related changes in gait domains: Results from the LonGenity study,” *Gait Posture*, vol. 100, pp. 8–13, Feb. 2023, doi:10.1016/j.gaitpost.2022.11.009.

[11] O. Jayakody *et al.*, “Age-related changes in gait domains: Results from the LonGenity study,” *Gait Posture*, vol. 100, pp. 8–13, Feb. 2023, doi:10.1016/j.gaitpost.2022.11.009.

[12] D. da S. F. de Campos, S. Shokur, A. C. de Lima-Pardini, M. Runfeng, M. Bouri, and D. B. Coelho, “Kinematics predictors of spatiotemporal parameters during gait differ by age in healthy individuals,” *Gait Posture*, vol. 96, pp. 216–220, Jul. 2022, doi:10.1016/j.gaitpost.2022.05.034.

[13] I. Hagoort, N. Vuillerme, T. Hortobágyi, and C. J. Lamoth, “Outcome-dependent effects of walking speed and age on quantitative and qualitative gait measures,” *Gait Posture*, vol. 93, pp. 39–46, Mar. 2022, doi: 10.1016/j.gaitpost.2022.01.001.

[14] D. Zhang, Y. Wang, and B. Bhanu, “Age Classification Base on Gait Using HMM,” in *2010 20th International Conference on Pattern Recognition*, IEEE, Aug. 2010, pp. 3834–3837. doi:10.1109/ICPR.2010.934.

[15] Chang Yang and Wenyong Wang, “A novel age interval identification method based on Gait monitoring,” in *2015 4th International Conference on Computer Science and Network Technology (ICCSNT)*, IEEE, Dec. 2015, pp. 266–269. doi: 10.1109/ICCSNT.2015.7490749.

[16] M. Nabila, A. I. Mohammed, and B. J. Yousra, “Gait-based human age classification using a silhouette model,” *IET Biom*, vol. 7, no. 2, pp. 116–124, Mar. 2018, doi: 10.1049/iet-bmt.2016.0176.

[17] M. Hema, K. Babulu, and N. Balaji, “Recognition of Gender using Gait Energy Image Projections Based on Random Forest Classifier,” *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 12, pp. 1518–1523, Oct. 2019, doi:10.35940/ijitee.L3104.1081219.

[18] Q. Riaz, M. Z. U. H. Hashmi, M. A. Hashmi, M. Shahzad, H. Errami, and A. Weber, “Move Your Body: Age Estimation Based on Chest Movement During Normal Walk,” *IEEE Access*, vol. 7, pp. 28510–28524, 2019, doi: 10.1109/access.2019.2901959.

[19] C. Xu *et al.*, “Real-Time Gait-Based Age Estimation and Gender Classification from a Single Image,” in *2021 IEEE Winter Conference on Applications of Computer Vision (WACV)*, IEEE, Jan. 2021, pp. 3459–3469. doi: 10.1109/WACV48630.2021.00350.

[20] K. Saho, K. Shioiri, M. Fujimoto, and Y. Kobayashi, “Micro-Doppler Radar Gait Measurement to Detect Age- and Fall Risk-Related Differences in Gait: A Simulation Study on Comparison of Deep Learning and Gait Parameter-Based Approaches,” *IEEE Access*, vol. 9, pp. 18518–18526, 2021, doi: 10.1109/ACCESS.2021.3053298.

[21] O. Costilla-Reyes, P. Scully, I. Leroi, and K. B. Ozanyan, “Age-Related Differences in Healthy Adults Walking Patterns Under a Cognitive Task With Deep Neural Networks,” *IEEE Sens J*, vol. 21, no. 2, pp. 2353–2363, Jan. 2021, doi: 10.1109/JSEN.2020.3021349.

[22] Y. Chen, R. Ou, Y. Deng, and X. Yin, “WIAGE: A Gait-based Age Estimation System Using Wireless Signals,” in *2021 IEEE Global Communications Conference (GLOBECOM)*, IEEE, Dec. 2021, pp. 01–06. doi: 10.1109/GLOBECOM46510.2021.9685336.

[23] Y. Liu *et al.*, “Application of Machine Vision in Classifying Gait Frailty Among Older Adults,” *Front Aging Neurosci*, vol. 13, Nov. 2021, doi: 10.3389/fnagi.2021.757823.

[24] X. Lv, N. Ta, T. Chen, J. Zhao, and H. Wei, “Analysis of Gait Characteristics of Patients with Knee Arthritis Based on Human Posture Estimation,” *Biomed Res Int*, vol. 2022, pp. 1–8, Apr. 2022, doi: 10.1155/2022/7020804.

[25] H.-S. Fang *et al.*, “AlphaPose: Whole-Body Regional Multi-Person Pose Estimation and Tracking in Real-Time,” Nov. 2022.

[26] H. Ahmed and A. Ullah, “Exponential Moving Average Extended Kalman Filter for Robust Battery State-of-Charge Estimation,” in *2022 International Conference on Innovations in Science, Engineering and Technology (ICISET)*, IEEE, Feb. 2022, pp. 555–560. doi: 10.1109/ICISET54810.2022.9775853.

[27] N. D. Nagahawatte, L. K. Cheng, R. Avci, L. R. Bear, and N. Paskaranandavadivel, “A generalized framework for pacing artifact removal using a Hampel filter,” in *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, IEEE, Jul. 2022, pp. 2009–2012. doi:10.1109/EMBC48229.2022.9871096.

[28] K. Hasan, M. M. Othman, S. T. Meraj, S. Mekhilef, and A. F. Bin Abidin, “Shunt Active Power Filter Based on Savitzky-Golay Filter: Pragmatic Modelling and Performance Validation,” *IEEE Trans Power Electron*, vol. 38, no. 7, pp. 8838–8850, Jul. 2023, doi: 10.1109/TPEL.2023.3258457.

[29] S. Prakash, A. S. Jalal, and P. Pathak, “Forecasting COVID-19 Pandemic using Prophet, LSTM, hybrid GRU-LSTM, CNN-LSTM, Bi-LSTM and Stacked-LSTM for India,” in *2023 6th International Conference on Information Systems and Computer Networks (ISCON)*, IEEE, Mar. 2023, pp. 1–6. doi: 10.1109/ISCON57294.2023.10112065.

[30] X. Wen and W. Li, “Time Series Prediction Based on LSTM-Attention-LSTM Model,” *IEEE Access*, vol. 11, pp. 48322–48331, 2023, doi: 10.1109/access.2023.3276628.