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Gait-based gender spoofing detection using depth images

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Abstract
Gender transformation, particularly transgender transitions, has become a significant challenge in biometric security systems, as it complicates the identification of an individual's original gender based on their birth sex. This issue is especially prevalent in gait-based gender identification systems, which can be spoofed by individuals who have undergone gender transformation. To address this challenge, this study proposes a novel gait-based gender spoofing detection method using depth images. Given the absence of publicly available gait-spoofing datasets, a new dataset called spoofing gait dataset (SpooGa) was developed for this research. The SpooGa dataset contains depth images capturing individuals' walking styles, tailored specifically to the study's requirements. The proposed method comprises three main stages: pre-processing, feature extraction, and classification. During the pre-processing stage, the dataset is standardized to ensure uniformity in data dimensions. Feature extraction involves normalizing the depth images using gait energy images (GEI), which are then divided into three parts: the upper body, body, and lower body. This study focuses on the body and lower body parts, which are mapped onto a principal component analysis (PCA) plane to reveal distinctive cyclical patterns indicating changes in viewpoint. Features are subsequently extracted using the leg, toe, hand (LETH) formula. For classification, three independent methods are employed: linear support vector machine (linear SVM), fine decision tree, and weighted k-nearest neighbor (weighted KNN) classifier. The feature dataset is divided into training (70%) and testing (30%) subsets. The performance of the proposed method is evaluated based on its ability to correctly identify the original gender of individual's post-disguise. The experimental results demonstrate the effectiveness of the proposed method, achieving an accuracy of 92.30% with the linear SVM, 96.15% with the weighted KNN, and 92.30% with the fine decision tree classifiers. These findings indicate the potential of the proposed approach to enhance biometric security against gender spoofing attacks.

Keywords
Gait energy images, Gender transformation, Biometric security, Gait-based identification, Gender spoofing detection, Depth images, SpooGa dataset.

1.Introduction
Human gait is a significant biometric characteristic used to identify individuals based on their unique walking patterns. Among biometric features, gait and facial recognition are often considered the most crucial modalities for gender classification [1]. Unlike other biometric characteristics, such as iris [2] or fingerprints [3], gait recognition does not require extensive equipment or high-resolution capture, making it a practical choice for gender classification. The significance of gait analysis in biometric security lies in its ability to recognize individuals from a distance without requiring their direct cooperation, which is particularly useful in surveillance and security applications.

Gender, which fundamentally divides humans into male and female, can be identified by observing physical appearances and unique characteristics associated with each sex. A pioneering study in 1971 by Johansson demonstrated that people could recognize each other solely by their walking patterns when light pointers were attached to their joints in a dark environment [4]. This finding highlighted the potential of gait as a reliable biometric feature.

Gender recognition has a wide range of applications, including security systems [5]. In surveillance systems, effective gender classification can reduce data volume, expedite recognition processes [6], analyze gender relationships [7], and enhance robotic interactions [8]. However, gait-based gender identification systems face several challenges that

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can impact their accuracy. Factors such as low-light environments, varying gait patterns due to changes in clothing or footwear, and intentional attempts to spoof gender can complicate detection. These challenges indicate the need for more robust methods to improve the reliability of gait-based biometric systems.

The motivation for this study is to explore the effectiveness of depth images in detecting gender spoofing. Gait-based gender identification systems can still be deceived by individuals who disguise themselves as a different gender. To address this challenge, gait-based gender spoofing detection aims to identify individuals who attempt to spoof their gender. This method allows for subconscious and indirect gender classification, enhancing the robustness of biometric security systems.

The objective of this research is to classify gender spoofing using depth images obtained from a Kinect sensor. Depth images of silhouettes are captured with a Microsoft Kinect sensor, and the images are processed using the proposed method. For this study, a custom dataset of silhouette images was collected at the University Sultan Zainal Abidin, serving as the primary dataset.

Our key contributions in this study are threefold: First, a novel application of depth imaging for gender spoofing detection is proposed, utilizing depth images to improve the accuracy of gender classification. Second, the performance of this approach is evaluated using three different classifiers—linear support vector machine (linear SVM), fine decision tree, and weighted k-nearest neighbor (weighted KNN)—to assess its effectiveness in various scenarios. Third, a comparative analysis of this method with existing gender spoofing detection techniques is provided, highlighting its advantages and identifying areas for further improvement.

The dataset undergoes training to extract relevant features for classification. Training is essential due to the inherent complexities involved in teaching a computer to recognize gait patterns, as computers lack the cognitive capabilities of the human brain [9]. To maintain consistency, the study focuses on images of individuals aged between 20 to 30 years, as walking styles vary significantly across different age groups [10]. This age range is chosen to ensure that the algorithm remains unaffected by age-related variables, thereby simplifying the identification of unique walking patterns and enhancing the efficiency of the proposed approach.

The rest of this paper is organized as follows: Section 2 reviews related work in the field of gait-based gender classification and spoofing detection. Section 3 presents the dataset and preprocessing techniques used in this study, along with the proposed method, including feature extraction and classification techniques. Section 4 discusses the experimental results and compares them to existing methods. Finally, Section 5 concludes the paper by summarizing the findings.

2.Related work

Gait-based detection methods in biometric identification have been broadly classified into two main categories: model-free techniques and model-based techniques [11]. These categories define the approach used to analyze gait for purposes such as identification, gender recognition, or detecting spoofing attempts.

2.1Model-free techniques

Model-free techniques do not require the modeling of individual body parts; instead, they analyze the entire silhouette to capture the walking pattern in a concise manner [12]. The model-free approach primarily relies on the binary representation of silhouettes [13, 14]. A significant breakthrough in this category was the introduction of the gait energy image (GEI) by Han and Bhanu [15]. The GEI is one of the most effective model-free techniques for capturing gait, providing a way to represent the temporal and spatial information of gait silhouettes in a compact form.

2.1.1Gait energy image (GEI)

GEI is a representation that consolidates temporal and spatial gait information into a single image derived from a sequence of gait silhouettes [15]. The GEI reduces storage requirements for gait data compared to maintaining the full sequence of binary silhouettes [16] and accelerates processing times. Despite its advantages, the GEI technique is influenced by an individual's appearance, which can affect its accuracy [17]. Recent studies have continued to explore GEI for gait analysis, including efforts to improve robustness against variations in clothing and carrying conditions.

Lu and Plataniotis[18] developed the "Gait-CNN-ViT" model, which combines convolutional neural networks (CNNs) with vision transformers (ViT) to enhance gait recognition performance. By combining DenseNet-201, VGG-16, and ViT models, this multi-model framework enhances the ability to recognize gait patterns under various challenging conditions, achieving high accuracy across datasets like CASIA-B and OU-ISIR [18]. This integration addresses complex covariates by encoding salient gait features, significantly improving robustness against factors like clothing and angle variations. A GEI is illustrated in *Figure 1*.

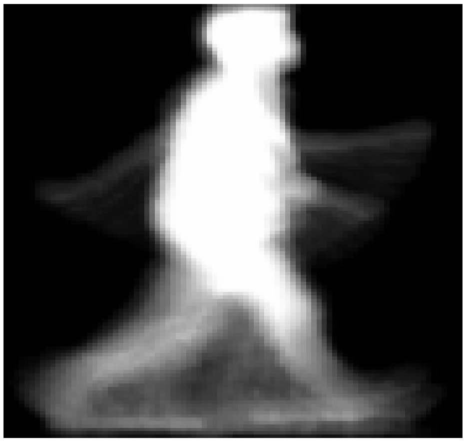

Figure 1 Gait energy image (GEI)

2.2Model-based techniques

In contrast to model-free methods, model-based techniques focus on constructing a detailed model of the human body and its movement. These methods typically involve capturing joint angles, limb lengths, and other body dynamics. Although model-based techniques can provide more detailed insights into gait characteristics, they generally require more complex processing and higher-resolution data.

2.2.1Principal component analysis (PCA)

Principal component analysis (PCA) is a widely used unsupervised linear dimensionality reduction method that can reduce the dimensionality of datasets with high variability [19]. PCA identifies uncorrelated variables that capture the variance in the data by computing the eigenvalues and eigenvectors of the covariance matrix. In gait analysis, PCA has been used to normalize training images and reduce feature dimensionality before further analysis [20]. Through the use of PCA, this method frequently converts high-dimensional data into a lower-dimensional subspace, enabling the extraction of features using techniques such as linear discriminant analysis (LDA) [21].

Recent applications of PCA in gait analysis have focused on enhancing its efficiency and robustness. For instance, Wong and Abas (2017) used PCA combined with sparse coding for gait recognition, which resulted in a 92% accuracy rate on a large public dataset but required careful tuning of parameters [22].

Jain and Kanhangad (2018) used a lifting 5/3 wavelet transform in conjunction with PCA to create a gait representation for person identification and gender classification. This method demonstrated the effectiveness of PCA in obtaining features from gait data, achieving remarkable classification rates of 97.98% on the CASIA-B gait database and 97.5% on the OU-ISIR large population dataset [23]. Similarly, Chiu et al. (2022) employed a hybrid PCA approach with adaptive thresholding, which improved recognition rates but at the expense of increased computational overhead due to the hybrid model's complexity [24].

2.3Deep learning approaches

Gait recognition systems using deep learning are also focusing on improving environmental robustness. For example, Mokhairi et al. (2015) proposed a multi-task learning framework that jointly learns gait recognition and environmental adaptation, achieving high accuracy across different settings but requiring a significant amount of annotated training data [25]. Similarly, a study by Chen et al. (2023) introduced an attention-based recurrent neural networks (RNN) model to dynamically adjust to variations in gait sequences, which enhanced robustness but led to increased training time and model complexity [26].

2.4Hybrid methods

Hybrid methods that combine model-free, model-based, and deep learning approaches are being explored to capitalize on the strengths of each technique. For instance, Hassan et al. (2018) developed a hybrid deep neural network framework that integrates skeleton data, joint angles, and gait parameters to enhance pathological gait recognition [27]. This model effectively combines a graph convolutional network, recurrent neural network, and artificial neural network, achieving an impressive accuracy rate while improving robustness against variations in gait patterns. The proposed approach demonstrated superior performance over single-input models on two different skeleton datasets, setting a new standard in skeleton-based action recognition.

The literature on gait-based gender recognition and spoofing detection demonstrated significant advancements in both model-free and model-based approaches, with deep learning methods showing increasing accuracy in recent studies. However, many existing approaches still struggle with variations in environmental conditions and spoofing attempts. This study addresses these challenges by integrating depth images with gait analysis to improve robustness against spoofing and environmental factors, particularly using the spoofing gait dataset (SpooGa) dataset. By comparing model-free, model-based, and hybrid approaches, this research contributes a novel method with enhanced performance over existing techniques, particularly in terms of gender spoofing detection accuracy.

3.Materials and methods

3.1Dataset

Gender is a significant determinant of an individual's identity and a fundamental aspect in computer vision science, often included in computer-based classification systems [28]. In this study, the SpooGa dataset was developed, which is specifically designed for analyzing gender spoofing in gait patterns. The SpooGa dataset comprises depth images collected from 50 participants, aged between 20 and 30 years, with heights ranging from 150 cm to 180 cm and weights from 50 kg to 100 kg. This demographic range ensures a broad representation of gait patterns and minimizes the influence of age-related postural changes. The data collection took place at the University Sultan Zainal Abidin, Malaysia, using a Kinect sensor. The gait measurement system used in this study is based on the methodology described by He et al. [29]. Participants were instructed to walk along a 6-meter path five times, maintaining a normal walking pace. The Kinect sensor, calibrated to a frame rate of 30 fps and positioned 1.5 meters above the ground, captured the depth images. The sensor's fixed positioning and frame rate ensured consistent and accurate image acquisition. *Figure 2* shows the data collection environment with the Kinect sensor.

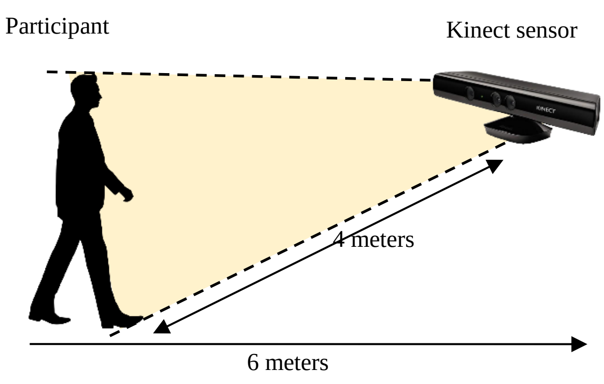

Figure 2 Data collection environment with the Kinect sensor

The dataset is divided into two categories: Original Gender and Gender Spoofing.

Original gender

The original gender dataset consists of 70 depth images of gait silhouettes, with 35 images from male participants and 35 from female participants. Each participant walked according to their natural gender-specific gait style. The data were initially recorded in video format and later extracted into individual depth images. *Figure 3* provides examples of original gender data in depth images. The Gender Spoofing dataset also includes 70 depth images of gait silhouettes, equally divided between male and female participants. For this dataset, participants were instructed to walk in a manner typical of the opposite gender. For instance, female participants mimicked male walking styles and vice versa. The gait data were recorded in video format and converted to depth images. *Figure 4* illustrates examples of gender spoofing data in depth images.

Figure 3 Original gender data in depth images

Figure 4 Gender spoofing data in depth images

3.2Data Preprocessing and Conversion

The depth images were resized to fixed dimensions to ensure uniformity across the dataset. Normalization was performed using min-max scaling to map pixel values to the range [0, 1], standardizing the input for further processing. Data augmentation techniques, including rotation (±10 degrees), scaling (90-110%), and the addition of Gaussian noise, were applied to enhance the dataset's diversity and robustness.

To prepare the data for analysis, video frames were converted to GEIs using a python script. Frames were extracted at one-second intervals to ensure a consistent representation of the gait cycle. This preprocessing and conversion ensure that the SpooGa dataset is well-suited for analyzing and classifying gait patterns, both genuine and spoofed.

3.3Proposed method

In this study, the SpooGa dataset is employed for the detection of gender spoofing in gait patterns. The dataset consists of depth images capturing both original and gender-spoofed gaits. Each silhouette image underwent multiple visual evaluations, and manual adjustments were made when necessary to ensure high-quality silhouette data for accurate gait analysis. The dataset was split into two phases for experimentation: training on the original gender data and testing using the gender spoofing data. The primary goal is to develop a classification model that accurately detects gender spoofing in the testing phase, after being trained on the original gender data. The proposed method follows a structured pipeline consisting of several key stages: preprocessing, GEI computation, part definition, PCA, and feature extraction. Linear SVM, fine decision tree, and weighted KNN were applied to classify the data based on the extracted features.

The proposed method is divided into two main phases: the training phase and the testing phase. In the training phase, the original gender dataset is used to train a classification model. In the testing phase, the model is evaluated using the gender spoofing dataset to classify the spoofed gaits. The objective of the training phase is to create a robust classification model, which is then validated during the testing phase.

Figure 5 illustrates the four main steps of the classification flow: preprocessing, GEI calculation, part definition, and the PCA algorithm.

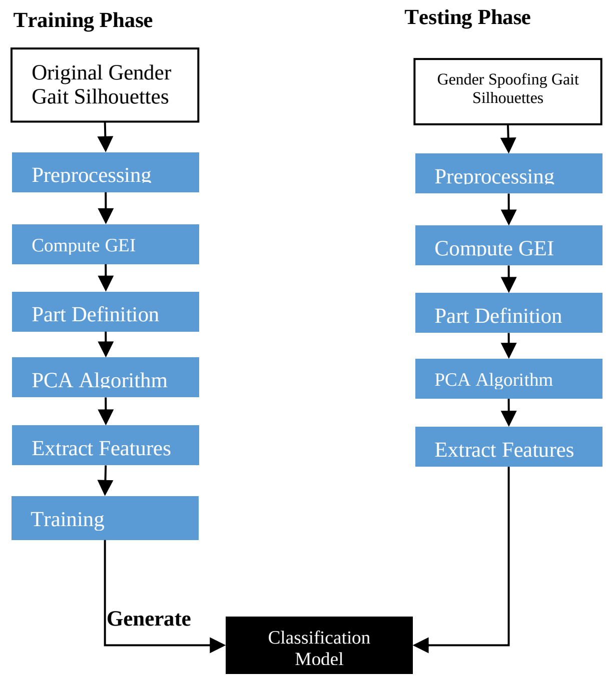

Figure 5 The main steps of the classification process include: preprocessing, GEI calculation, part definition, and the application of the PCA algorithm

Preprocessing

The preprocessing step involves normalizing the depth images to ensure consistency in the silhouette data. Each depth image is resized to fixed dimensions (height and width) [30]. to standardize input across the dataset. This process helps to eliminate variations in image size and ensure that all images are uniformly represented for further analysis (*Figure 6*).

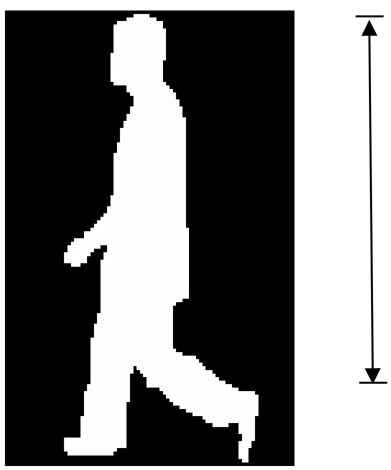

Figure 6 Normalized silhouettes

GEI Computation

Once the images are normalized, the GEI technique is applied. The GEI is computed by averaging the silhouette images over a complete gait cycle. This method captures the dynamic aspects of walking by combining multiple frames into a single image representing the overall gait pattern. The formula for calculating GEI [31] is given as in Equation 1:

$$Gt\ (m, n)= \sum_{t=1}^{Ns} St(m,n) \qquad (11)$$

Here, t indicates the frame number of the sequence, m and n represent the 2D image coordinates, and N is the total number of frames in the cycle (s) of the silhouette sequence.

Part Definition

After computing the GEI, the image is divided into two main parts: the chest and legs. This segmentation aids in targeted feature extraction, as it allows specific regions of the body (i.e., chest and legs) to be analyzed separately for further classification. The separation of these parts is essential for distinguishing between original and spoofed gaits, as certain body segments may exhibit different motion characteristics during gender spoofing. The part definition process is shown in *Figure 7*.

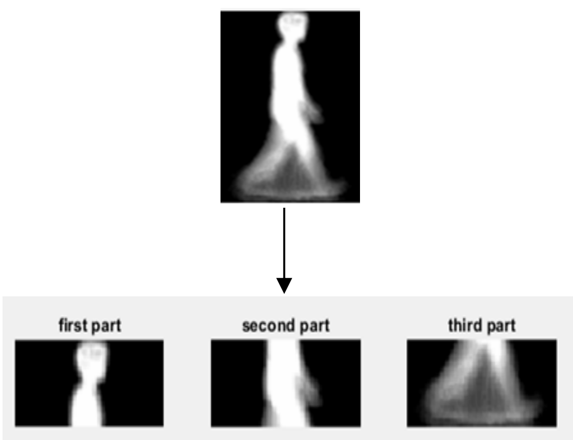

Figure 7 Part definition process

PCA

PCA is an unsupervised learning technique that is used to reduce the dimensionality of images in an effort to improve accuracy [19]. During PCA, principal components that collectively account for 98% of the data's volatility are retained.

PCA algorithm is a helpful technique for identifying trends in data and presenting it in a way that emphasizes similarities and differences [32]. It converts a group of possibly correlated variables into principal components, which are smaller, uncorrelated variables. As much of the data's variation as possible is captured by the first principal component, and the remaining variability is explained by each successive component.

PCA is employed as a dimensionality reduction technique to enhance the classification accuracy and reduce computational complexity. By reducing the number of features, PCA helps retain the most significant components that explain the variance in the data while discarding less important information. The covariance approach to PCA, which was used in this study for every component, is described in detail below [19].

Determine the empirical mean

The first step in PCA is to compute the empirical mean for each dimension of the data. The empirical mean is calculated as in Equation 2:

$$\mu = \frac{1}{M}\sum_{i=0}^{M} Xi \qquad (2)$$

where μ is the mean vector, *Xi* are the individual data points, and *M* is the number of dimensions.

Subtract the mean

The empirical mean is subtracted from each data point to center the data, ensuring that the principal components capture the data's variability more effectively. This step helps to focus on the deviations in the data, which are crucial for feature extraction.

Compute the covariance matrix

The covariance matrix C is computed by multiplying the mean-adjusted data matrix B with its transpose:

$$C = \frac{1}{N} BBT$$

This matrix captures the relationships between different features in the data.

Determine the covariance matrix's eigenvalues and eigenvectors.

The covariance matrix C is diagonalized to compute its eigenvalues and eigenvectors. The eigenvectors represent the directions in the feature space, while the eigenvalues indicate the amount of variance captured along each principal component.

Adjust the eigenvalues and eigenvectors

The eigenvalues and their corresponding eigenvectors are sorted in descending order, with the largest eigenvalues representing the most significant components of the data.

Compute the cumulative energy content for each eigenvector

The cumulative energy content is calculated to determine how much of the variance is captured by the principal components. Typically, components that account for 98% of the total variance are retained. Select a subset of the eigenvectors as basis vectors

A subset of the eigenvectors is selected as basis vectors to reduce the dimensionality of the data while retaining the most important features.

Modification of images

The mean-adjusted the matrix are 88×88 if the initial image's dimensions were 88×88. Moreover, an 88×88 covariance matrix would exist. An eigenvector or principal component is represented by each column in the covariance matrix.

The resulting matrix, also known as the feature matrix, would measure 88 by 44 if it were assumed that about 44 among the 88 basic components, or eigenvectors, are to be kept. Consequently, 44 by 88 would be the whole data matrix's dimensions.

Feature extraction

Specific body parts are measured and their distances calculated. Since the GEI image is separated into two main sections, features are extracted from each component. Three features are used for calculating the distances. The feet distances must be calculated first. The distances between the toes are ranked second and third, respectively.

Feet distances

The distance in feet between the start and finish of a walking step is measured. The two leg distances are computed as the formula is provided below in Equation 3.

$$dl=\sqrt{(y2-y1)^2+(x2-x1)^2} \tag{3}$$

where *dl* is feet distance. The first coordinates representing the start of a walking step are thus defined as $x1$ and $y1$, whereas the second pair of coordinates, represented by x2 and $y2$, indicates the end of the walking step. The feature is calculated and the data is saved in .csv file format. *Figure 8* and *Figure 9* present scatter plot for feet distances feature for normal gender data and gender spoofing data, respectively.

Toes distance

The toe distance is the length of time, measured while walking, between the ground and the tip of the elevated toe. The toe distance computation is expressed in the following formula shown in Equation 4.

$$dT=\sqrt{(Jy2-Jy1)^2+(Jx2-Jx1)^2} \tag{4}$$

where *dT* stands for toe distance. The first set of coordinates for the toe from the ground is then described by $Jx1$ and $Jy1$, and the second set of coordinates that indicate the lifted toe during walking is represented by $Jx2$ and $Jy2$. The feature is calculated and the data is saved in .csv file format. *Figure 10* and *Figure 11* show scatter plot for toes distances feature for normal gender data and gender spoofing data.

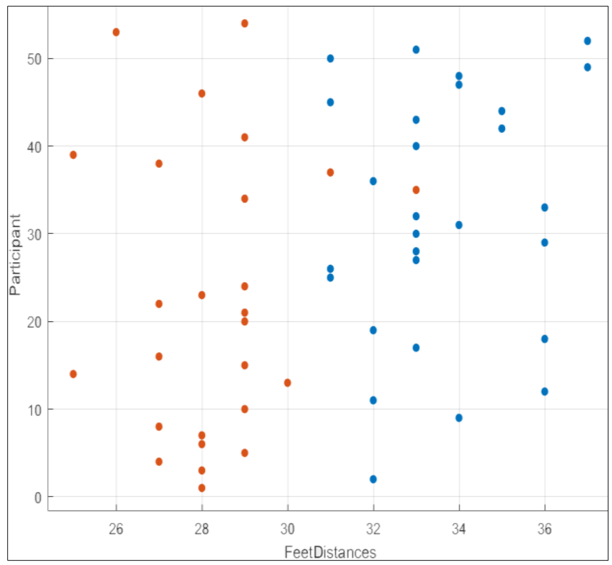

Figure 8 Scatter plot for feet distances normal gender data

Hand swing distances

The point at which the hand tip starts to swing and the finish of the swinging action are used to calculate the hand swing distances. This computation is explained by the formula provided in Equation 5.

$$dT=\sqrt{(Hy2-Hy1)^2+(Hx2-Hx1)^2} \tag{5}$$

where the hand swing distance is denoted by *dH*. Then, $Hx1$ and $Hy1$ represent the hand's initial coordinates as seen from the ground, while $Hx2$ and $Hy2$ represent the hand's second set of coordinates as seen when walking. The feature is calculated and the data is saved in .csv file format. *Figure 12* and *Figure 13* show scatter plot for Hand Swing Distances feature for normal gender data and gender spoofing data. *Figure 14* offers a visual depiction of the pixel-calculated distance features for better understanding about each selected distance.

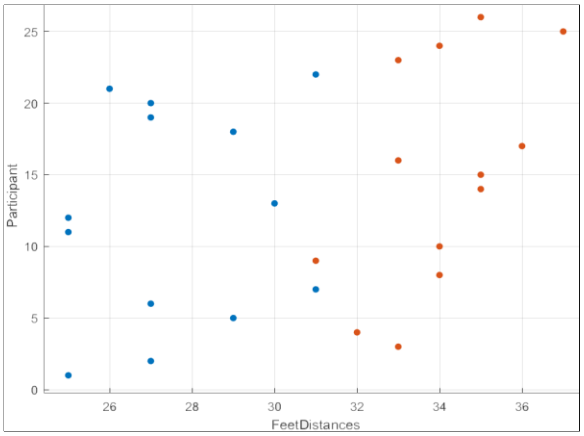

Figure 9 Scatter plot for feet distances gender spoofing data

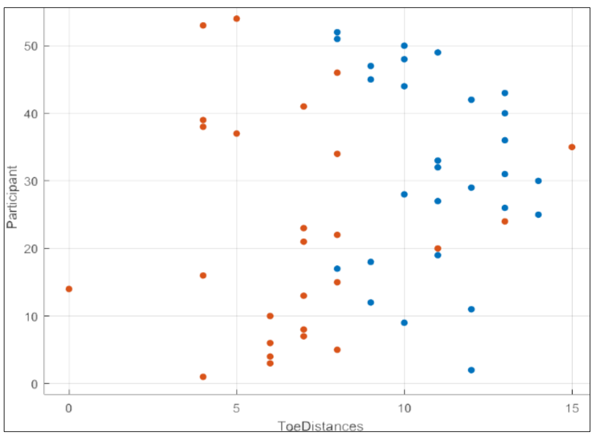

Figure 10 Scatter plot for toes distances normal gender data

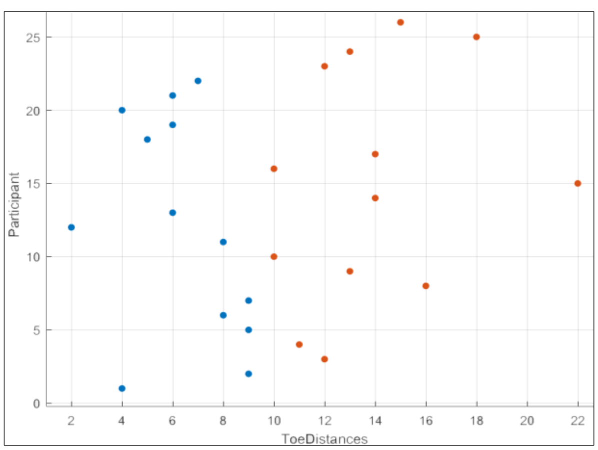

Figure 11 Scatter plot for toes distances gender spoofing data

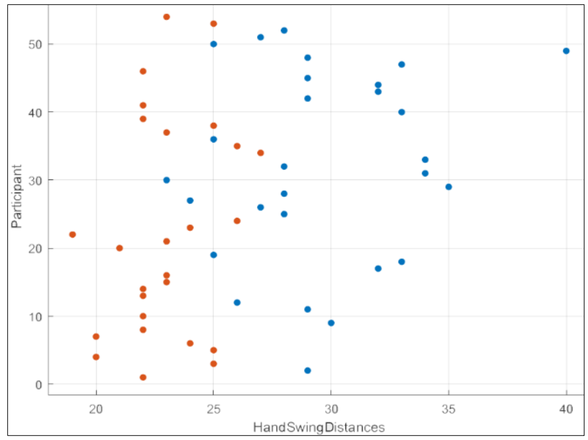

Figure 12 Scatter plot for hand swing distances normal gender data

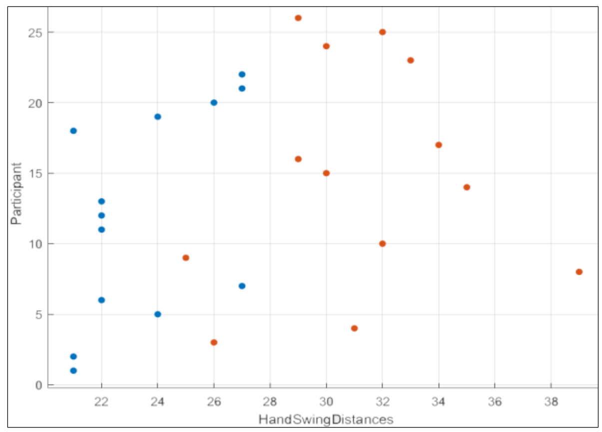

Figure 13 Scatter plot for hand swing distances gender spoofing data

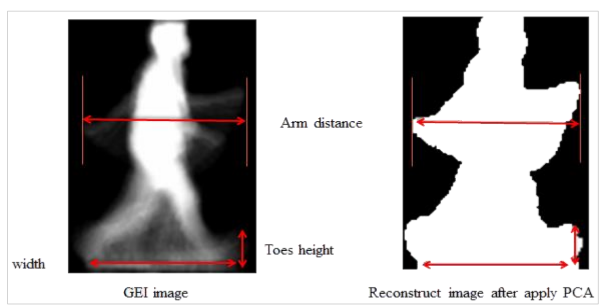

Figure 14 Feature part

For classification, the formula used to compute the features as given in Equations 3, 4 and 5 is combined. One of the most important steps in improving classification accuracy is fusion. The fusion formula is defined by the leg, toe, hand (LETH) formula, shown in Equation 6.

LETH = Equation 3 + Equation 4 + Equation 5 (6)

4.Results and discussion

In this study, the newly collected SpooGa dataset is utilized for gender spoofing detection. The dataset includes depth images capturing gait patterns of individuals between the ages of 20 and 30. For this study, a subset of images depicting individuals between the ages of 20 and 30 is carefully selected. From the original gender and gender spoofing datasets, a total of 82 images are chosen for the experiment. Seventy percent of these images are used for training, while the remaining thirty percent are kept aside for testing.

Each image undergoes feature extraction from its silhouette, creating a unique feature vector for further analysis. This feature extraction process is applied to every image sequence in the dataset, generating feature vectors for each image. The process begins with GEI computation, followed by feature extraction. PCA is then applied to reduce the dimensionality of these feature vectors, retaining only the most significant components for training and testing.

In the training phase, the features extracted from the original gender images are used to train a machine learning classification algorithm to generate a classification model. This trained model is then evaluated in the testing phase, where features from the gender spoofing images are classified using the model. The effectiveness of the proposed gender spoofing detection method using depth images is evaluated based on the classification results.

Three classifiers are used for classification: Linear SVM, fine decision tree, and weighted KNN. Initially, the classifiers are trained using features extracted from the original gender data. *Table 1* shows the training results for the three classifiers, including accuracy, prediction speed, and training time.

Table 1 Training result using normal gender data

Classification algorithm	**Accuracy**	**Prediction speed**	**Training time**
Linear SVM	96.3%	~1100 obs/sec	7.30 sec
Weighted KNN	94.4%	~910 obs/sec	9.72 sec
Fine decision tree	85.2%	~430 obs/sec	7.28 sec

After training, the gender spoofing features are applied to the trained model during the testing phase to classify the spoofed gait patterns. *Table 2* presents the performance measures for the three classifiers based on the testing data, which evaluates the accuracy of gender spoofing detection.

Table 2 Performance measures for SpooGA dataset

Selected feature	**Algorithm**	**Accuracy**
All	Linear SVM	92.30%
All	Weighted KNN	96.15%
All	Fine decision tree	92.30%

The experimental results demonstrated significant accuracy for each of the three classifiers. The best-performing classifier was weighted KNN, which achieved an accuracy of 96.15%, surpassing both linear SVM and fine decision tree, which each achieved 92.30% accuracy. The high performance of weighted KNN can be attributed to its capability as an unsupervised learning approach, which may contribute to better handling of variance in the spoofed gait data compared to supervised methods like SVM and decision tree.

The proposed technique using depth images has proven to outperform many existing methods, particularly those that rely on RGB or skeleton-based images. Depth images provide higher pixel detail, as they capture 3D information about the subject's gait, offering more accurate representations than 2D images or skeletal data. The proposed method for gender spoofing detection was compared with recent skeleton-based gender classification methods using SVM and KNN classifiers.

As shown in *Table 3*, the proposed method, which utilizes depth images from the SpooGa dataset, achieved an accuracy of 92.30% with the SVM classifier and 96.15% with the KNN classifier. These results were compared with recent studies that used body skeleton, including Ahmed and Sabir [13], Andersson and Araujo [33] and Camalan et al. [34]. Ahmed and Sabir [13] reported 90% accuracy using SVM. Andersson and Araujo achieved 84.7% and 85.4% for SVM and KNN respectively, using anthropometric body skeleton [33]. Finally, Camalan et al. [34] achieved the accuracy of 83.87% using linear SVM and 85.48% for KNN. The comparison suggests that the depth image-based approach outperforms or matches the accuracy of skeleton-based methods, particularly with KNN classifiers. *Table 3* highlights that while all methods performed well, the proposed method using depth images is particularly effective, especially when using the KNN classifier. The results suggest that depth images provide a more detailed representation for detecting gender spoofing, and are competitive or superior compared to skeleton-based approaches.

Table 3 Comparison of proposed and existing method

Algorithm	Proposed method	[13]	[33]	[34]
SVM	92.30%	90.0%	84.7%	83.87%
KNN	96.15%	N/A	85.4%	85.48%

The experimental results show that the proposed method using depth images for gender spoofing detection yields high accuracy, surpassing many existing methods. The comparison with skeleton-based images further highlights the advantages of using depth images, which capture more detailed information about gait patterns, contributing to improved classification performance.

Despite the promising results, this study has several limitations. Firstly, the sample size of 82 images is relatively small, which may limit the generalizability of the findings. A larger dataset would provide more robust results. Secondly, the age range of the participants (20-30 years) does not account for potential variations in gait due to age differences, which may impact gender spoofing detection. Future studies should include a more diverse age range to enhance the applicability of the method. Additionally, the use of the SpooGa dataset, while effective for this study, may not represent other gait variations or spoofing attempts outside the dataset, necessitating further testing on larger, more diverse datasets. Finally, the system was tested in a controlled environment, and its performance in real-world, dynamic scenarios, where external factors such as varying lighting conditions and occlusions can affect accuracy, remains to be validated. Future work will need to address these limitations to improve the robustness and applicability of the method in practical deployments.

A complete list of abbreviations is listed in *Appendix I*.

5.Conclusion and future work

In this paper, the concept of gait-based gender spoofing detection using depth images was introduced, utilizing the SpooGa dataset, which was specifically collected for this research. The dataset consists of a comprehensive collection of gait image data, and for this study, 82 depth images of individuals aged between 20 and 30 years were carefully selected. The depth images were divided into two phases: 70% for training and 30% for testing. Original gender depth images were used for training, while gender spoofing images were applied during the testing phase.

The feature extraction process began with the computation of GEIs, followed by part definition, which categorized the GEIs into body and leg segments. PCA was then applied to reduce the dimensionality of the images, resulting in reconstructed feature vectors. The final features extracted included three distinct distance measures: feet, toe, and hand swing distances. These features were used to train classification models.

Three machine learning classification methods were employed for classification: linear SVM, fine decision tree, and weighted KNN. The classification models were trained with original gender data, and during testing, gender spoofing was detected with high accuracy. The experimental results demonstrate that the proposed method performs exceptionally well compared to existing approaches.

In particular, weighted KNN achieved an accuracy of 96.15%, surpassing both linear SVM and fine decision tree, which each achieved 92.30%. The success of the proposed technique can be attributed to the comprehensive feature set, which captures critical physical characteristics of the body structure and gait patterns necessary to differentiate between genders. Depth images, with their ability to capture 3D information, played a crucial role in achieving this high level of accuracy.

These results confirm that using depth images, in combination with effective feature extraction and classification techniques, offers a significant advantage in detecting gender spoofing through gait analysis. The proposed method outperformed equivalent existing techniques, highlighting its potential for practical applications. In future work, this method will be integrated into a full-fledged gender spoofing detection system, which can be deployed in various real-world scenarios. The system contributes positively to society by enhancing security and authentication systems where identity verification through gait analysis is critical.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability statement

The data considered in this study were gathered from the Faculty of Informatics & Computing at Universiti Sultan Zainal Abidin, Malaysia, involving participants who walked normally and abnormally to assess gait-based gender spoofing detection. The data are not publicly available. However, the data may be provided by the corresponding author upon reasonable request.

Author's contribution statement

Muhammad Shazmil bin Mohd Sabilan: Conceptualization, methodology, development of the spooga dataset, data analysis, feature extraction, classification methods development, writing – original draft, writing – review and editing. **Azim Zaliha Abd Aziz:** Conceptualization, supervision, data collection, writing – review and editing.

References

[1] Ng CB, Tay YH, Goi BM. Recognizing human gender in computer vision: a survey. In 12th pacific rim international conference on artificial Intelligence, Kuching, Malaysia, 2012 (pp. 335-46). Springer Berlin Heidelberg.

[2] Bouzouina Y, Hamami L. Multimodal biometric: iris and face recognition based on feature selection of iris with GA and scores level fusion with SVM. In 2nd international conference on bio-engineering for smart technologies (BioSMART) 2017 (pp. 1-7). IEEE.

[3] Hajri S, Kallel F, Hamida AB. Contrast enhancement and feature extraction algorithms of finger knucle print image for personal recognition. In 4th international conference on advanced technologies for signal and image processing 2018 (pp. 1-4). IEEE.

[4] Johansson G. Visual motion perception. Scientific American off prints, Freeman. 1975.

[5] Cai L, Zeng H, Zhu J, Cao J, Hou J, Cai C. Multi-view joint learning network for pedestrian gender classification. In international symposium on intelligent signal processing and communication systems 2017 (pp. 23-7). IEEE.

[6] Yu S, Tan T, Huang K, Jia K, Wu X. A study on gait-based gender classification. IEEE Transactions on Image Processing. 2009; 18(8):1905-10.

[7] Jones IIIRJ, Reilly TM, Cox MZ, Cole BM. Gender makes a difference: investigating consumer purchasing behavior and attitudes toward corporate social responsibility policies. Corporate Social Responsibility and Environmental Management. 2017; 24(2):133-44.

[8] Ramey A, Salichs MA. Morphological gender recognition by a social robot and privacy concerns: late breaking reports. In proceedings of the international conference on human-robot interaction 2014 (pp. 272-3). ACM.

[9] Iqtait M, Mohamad FS, Mamat M. Feature extraction for face recognition via active shape model (ASM) and active appearance model (AAM). In IOP conference series: materials science and engineering 2018 (pp. 1-8). IOP Publishing.

[10] Reimann H, Ramadan R, Fettrow T, Hafer JF, Geyer H, Jeka JJ. Interactions between different age-related factors affecting balance control in walking. Frontiers in Sports and Active Living. 2020; 2:1-19.

[11] Han J, Bhanu B. Statistical feature fusion for gait-based human recognition. In proceedings of the computer society conference on computer vision and pattern recognition 2004. IEEE.

[12] Wang J, She M, Nahavandi S, Kouzani A. A review of vision-based gait recognition methods for human identification. In international conference on digital image computing: techniques and applications 2010 (pp. 320-7). IEEE.

[13] Ahmed MH, Sabir AT. Human gender classification based on gait features using kinect sensor. In 3rd international conference on cybernetics 2017 (pp. 1-5). IEEE.

[14] Liu W, Zhang C, Ma H, Li S. Learning efficient spatial-temporal gait features with deep learning for human identification. Neuroinformatics. 2018; 16:457-71.

[15] Han J, Bhanu B. Individual recognition using gait energy image. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2005; 28(2):316-22.

[16] Gupta SK, Sultaniya GM, Chattopadhyay P. An efficient descriptor for gait recognition using spatio-temporal cues. In emerging technology in modelling and graphics: proceedings of IEM graph 2020 (pp. 85-97). Springer Singapore.

[17] Liu T, Sun B, Chi M, Zeng X. Gender recognition using dynamic gait energy image. In 2nd information technology, networking, electronic and automation control conference 2017 (pp. 1078-81). IEEE.

[18] Lu H, Plataniotis KN, Venetsanopoulos AN. MPCA: multilinear principal component analysis of tensor objects. IEEE Transactions on Neural Networks. 2008; 19(1):18-39.

[19] Nanaa K, Rizon M, Abd RMN, Ibrahim Y, Abd AAZ. Detecting mango fruits by using randomized hough transform and backpropagation neural network. In 18th international conference on information visualisation 2014 (pp. 388-91). IEEE.

[20] Hongye X, Zhuoya H. Gait recognition based on gait energy image and linear discriminant analysis. In international conference on signal processing, communications and computing 2015 (pp. 1-4). IEEE.

[21] Xu C, Makihara Y, Ogi G, Li X, Yagi Y, Lu J. The OU-ISIR gait database comprising the large

population dataset with age and performance evaluation of age estimation. IPSJ Transactions on Computer Vision and Applications. 2017; 9:1-4.
[22] Wong PL, Abas ZA. An analysis of human silhouettes with normalised silhouettes images and shape fourier descriptors. International Journal of Human and Technology Interaction. 2017; 1(1):31-6.
[23] Jain A, Kanhangad V. Gender classification in smartphones using gait information. Expert Systems with Applications. 2018; 93:257-66.
[24] Chiu HJ, Li TH, Kuo PH. Breast cancer–detection system using PCA, multilayer perceptron, transfer learning, and support vector machine. IEEE Access. 2020; 8:204309-24.
[25] Mokhairi M, Engku FHSA. Comparison of image classification techniques using CALTECH 101 dataset. Journal of Theoretical and Applied Information Technology. 2015; 71(1):79-86.
[26] Chen H, Lareau C, Andreani T, Vinyard ME, Garcia SP, Clement K, et al. Assessment of computational methods for the analysis of single-cell ATAC-seq data. Genome Biology. 2019; 20:1-25.
[27] Hassan OM, Abdulazeez AM, Tiryaki VM. Gait-based human gender classification using lifting 5/3 wavelet and principal component analysis. In international conference on advanced science and engineering 2018 (pp. 173-8). IEEE.
[28] Kumar G, Singh UP, Jain S. An adaptive particle swarm optimization-based hybrid long short-term memory model for stock price time series forecasting. Soft Computing. 2022; 26(22):12115-35.
[29] He Y, Zhang J, Shan H, Wang L. Multi-task GANs for view-specific feature learning in gait recognition. IEEE Transactions on Information Forensics and Security. 2018; 14(1):102-13.
[30] Singh B, Patel S, Vijayvargiya A, Kumar R. Analyzing the impact of activation functions on the performance of the data-driven gait model. Results in Engineering. 2023; 18:101029.
[31] Jun K, Lee K, Lee S, Lee H, Kim MS. Hybrid deep neural network framework combining skeleton and gait features for pathological gait recognition. Bioengineering. 2023; 10(10):1-20.
[32] Mogan JN, Lee CP, Lim KM, Ali M, Alqahtani A. Gait-CNN-ViT: multi-model gait recognition with convolutional neural networks and vision transformer. Sensors. 2023; 23(8):1-15.
[33] Andersson V, Araujo R. Person identification using anthropometric and gait data from kinect sensor. In proceedings of the AAAI conference on artificial intelligence 2015 (pp. 425-31). AAAI.
[34] Camalan S, Sengul G, Misra S, Maskeliūnas R, Damaševičius R. Gender detection using 3d anthropometric measurements by kinect. Metrology and Measurement Systems. 2018; 25(2):253-67.

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Appendix I

S. No.	Abbreviation	Description
	CNN	Convolutional Neural Networks
1	GEI	Gait Energy Images
2	KNN	k-Nearest Neighbor
3	LETH	leg, toe, hand
4	LDA	Linear Discriminant Analysis
5	PCA	Principal Component Analysis
6	RNN	Recurrent Neural Networks
7	SpooGa	Spoofing Gait Dataset
8	SVM	Support Vector Machine