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Data Preprocessing and Feature Selection Techniques in Gait Recognition: A Comparative Study of Machine Learning and Deep Learning Approaches

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ABSTRACT

The study of gait recognition, a biometric application that identifies individuals based on their unique walking patterns, is an evolving field. In this paper, we conduct a literature review to compare the performance of machine learning and deep learning approaches in covariate conditions, focusing on the specific aspects of deep learning pipelines in gait recognition. We highlight commonly used strategies and open problems in identification based on behavioral traits and propose future perspectives for researchers in this field. Through our investigation, we aim to provide insights that will aid researchers in developing informed decisions when to take which data preprocessing technique in designing gait recognition systems. Our paper provides a comprehensive exposition of machine learning versus deep learning architectures and pipelines for biometric applications using human gait and serves as a valuable resource for researchers in this area.

1. Introduction

Gait recognition is a biometric technique that has been gaining increasing attention in recent years. It involves the identification of individuals based on their unique walking patterns, which can be captured and analyzed using various technologies such as cameras, sensors, and accelerometers [1]. The basic principle behind gait recognition is that everyone has a distinct gait or walking pattern, which is determined by a range of physical and behavioral factors such as body size, shape, and posture [2].

One of the key advantages of gait recognition over other biometric techniques is that it doesn't require any external intervention [3]. Unlike fingerprint or facial recognition, for example, gait recognition can be performed from a distance and without the individual's knowledge or consent. This makes it a potentially powerful tool for security and surveillance applications, as well as for healthcare and rehabilitation purposes [6] [8] [9]. Gait recognition has also been shown to be highly effective even when dealing with low-resolution images or video footage. This is because the characteristics of an individual's gait are relatively stable over time and can be captured from a range of different viewpoints and lighting conditions [12] [14].

In this review paper, we will explore the current state-of-the-art in gait recognition technology. We will begin by discussing the history and development of gait recognition, including the key challenges and limitations that researchers have faced in this field. We will then examine the different technologies that are currently being used to capture and analyse gait data, including the advantages and disadvantages of each approach.

We will also provide a comprehensive overview of the various algorithms and models that have been developed for gait recognition, including both deep learning and machine learning techniques. We will analyse the performance of these models in different scenarios and identify the strengths and weaknesses of each approach. In addition, we will explore the various applications of gait recognition technology, including security and surveillance. We will examine the ethical and legal considerations surrounding the use of gait recognition and discuss the potential impact of this technology on society.

This paper presents an overview of the importance and applications of gait recognition in biometric identification and surveillance, along with a review of the various techniques used for gait recognition. The paper begins with a brief overview of the importance and applications of gait recognition in biometric identification and surveillance, and an outline of the paper in section 1. This is followed by a description of the characteristics of human gait and the factors that influence gait patterns, including physiological and behavioural aspects in section 2. Next, a review of the various techniques used for gait recognition is provided, including deep learning and machine learning approaches in section 3. This is followed by a discussion of the advantages and limitations of deep learning and machine learning methods in section 4. The paper concludes with a summary of the main findings and contributions of the paper, and concludes the paper as a reflection on the potential of gait recognition as a biometric identification and surveillance tool in section 5.

2. Gait recognition methods

The utilization of machine learning and deep learning models has become increasingly popular in gait recognition due to their capability to extract features and learn from large datasets. This section provides an overview of various models used in gait recognition, including their architectures and pipelines. In gait recognition, SVM extracts features such as step length [127], step time, and velocity from gait data and uses them as input to train the model (Wang et al., 2011).

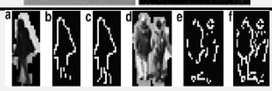
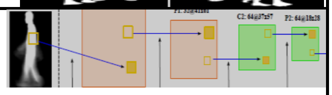
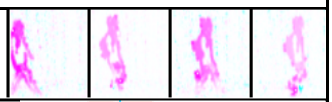
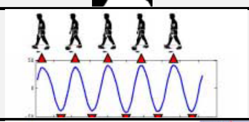
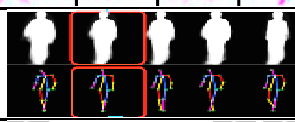
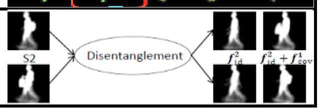
Another machine learning model utilized in gait recognition is the k-nearest neighbors (KNN) algorithm. In gait recognition [125], KNN measures the similarity between different gait patterns using Euclidean distance (Jing et al., 2008). CNNs are neural networks that are specifically designed for image recognition tasks and have been adapted for gait recognition by using gait images or video frames as input to the model (Yu et al., 2017). Recurrent neural networks (RNNs) have also been employed in gait recognition, capable of capturing the temporal dependencies in gait patterns over time (Zhang et al., 2016). Hidden Markov models (HMMs), a generative model, have also been utilized in gait recognition. HMM is a probabilistic model that can be used for classification and sequence analysis. In gait recognition [126], HMM models the temporal sequence of gait features and uses this model to classify gait patterns (Makihara et al., 2011). Autoencoders are another deep learning model that has been used for gait recognition. Autoencoders are neural networks trained to reconstruct their own inputs and have been used for gait recognition by learning to encode gait images or video frames into a low-dimensional feature space (Zhang et al., 2018). Other machine learning and deep learning models employed in gait recognition include decision trees [128], random forests, and deep belief networks (DBNs) (Xu et al., 2016). In terms of model pipelines, pre-processing and feature extraction are important steps in gait recognition. Pre-processing involves removing noise and artifacts from gait data, while feature extraction involves extracting meaningful features from gait data such as step length, step time, and velocity. Feature selection is also a crucial step in model pipelines, as it involves selecting the most relevant features for classification.

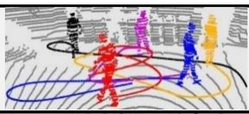
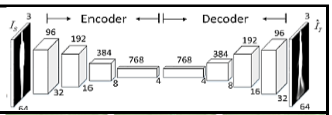
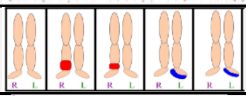
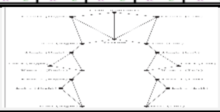
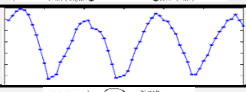
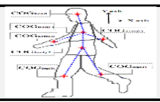
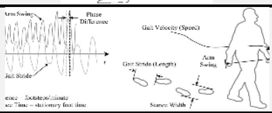
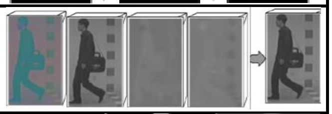
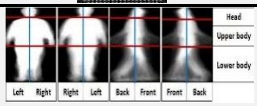
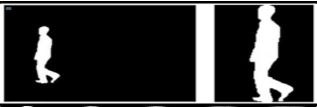
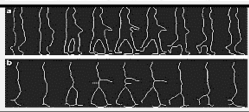
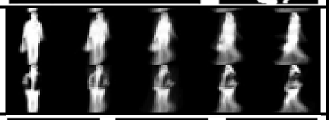
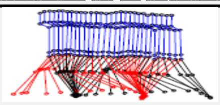
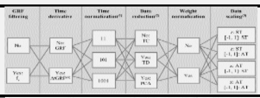
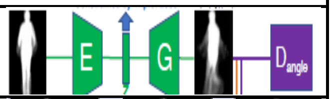
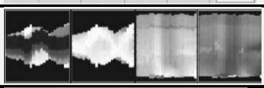
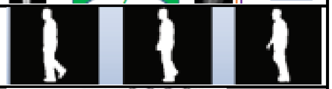
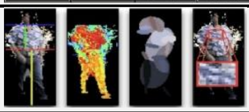
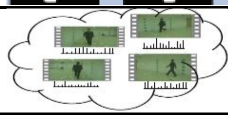
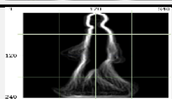
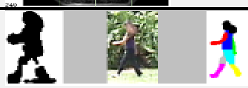
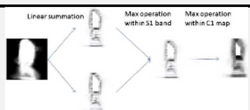
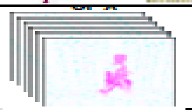
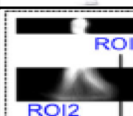
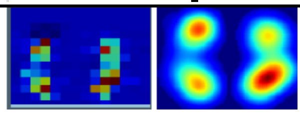
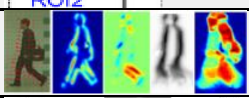
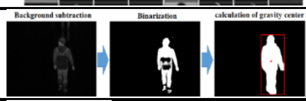
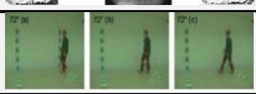
Gait recognition has seen a surge in popularity due to the use of machine learning and deep learning models that can extract features from large datasets. Convolutional neural networks (CNNs) have been widely adopted as they are designed for image recognition tasks and can be applied to gait recognition by treating gait images or video frames as input to the model. Recurrent neural networks (RNNs) are also used to capture temporal dependencies in gait patterns over time. Hidden Markov models (HMMs) have been employed to model the temporal sequence of gait features and classify gait patterns. Autoencoders have also been utilized to encode gait images or video frames into a low-dimensional feature space. Other machine learning and deep learning models used in gait recognition include decision trees, random forests, and deep belief networks (DBNs). In terms of model pipelines, pre-processing and feature extraction are crucial steps to extract meaningful features from gait data. Feature selection is also important to select the most relevant features for classification.

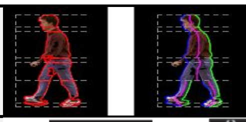
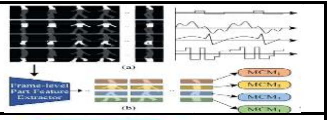
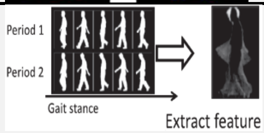
3 Data preprocessing and feature selection of ML and DL techniques in gait recognition

The preprocessing of data and selection of features are crucial aspects of building accurate machine learning and deep learning models for gait recognition. Table 1 presents an overview of the various techniques utilized for data preprocessing and feature selection in gait recognition. Data preprocessing involves cleaning and transforming raw data to facilitate analysis. In gait recognition, this process involves techniques such as normalization, filtering, segmentation, and alignment. Normalization scales the data to a uniform range to eliminate variances due to differences in sensor placement and individual walking styles. Filtering removes noise from the data, segmentation isolates individual gait cycles, and alignment aligns gait data across multiple trials. Feature selection involves identifying the most relevant features from the data to enhance model performance. Gait recognition employs techniques such as principal component analysis (PCA), which determines the most significant features by reducing the dimensionality of the data. Other techniques include linear discriminant analysis (LDA), which identifies features that discriminate between different individuals, and wavelet transform, which is used to extract time-frequency features.

Table 1. Data preprocessing and feature selection of ML and DL techniques in gait recognition

Machine Learning						Deep Learning			
S.No	Cite	Year	Data Preprocessing	Image	Method	Year	Data Preprocessing	Cite	Image
1	[15]	1984	Background subtraction		Adaptive Mixture of Gaussians	2019	Background Subtraction	[4] [54]	
2	[16]	2002	Background and foreground modelling		Color-Based Body Part Segmentation	2019	Gait Energy Image	[5] [10] [24] [25] [32] [34] [51] [64]	
3	[18]	2007	Background-subtraction using contour-based		Gradient map from the foreground gradients	2019	Zero centered Gaussian noise	[7]	
4	[19]	2009	Outlier detection		Dynamic shape model factorizes the body posture	2016	Spatiotemporal representation	[11]	
5	[20]	2008	Unsupervised Feature Selection		Standard deviations	2017	Spatial-temporal Optical Flow	[13]	
6	[22]	2002	Gait Cycle Analysis		Silhouette width (zero centered)	2019	Coordinates concatenation	[17]	
7	[23]	2002	Height and Stride estimation		Local minima of silhouette signature	2020	Euclidean distance	[21]	

8	[27]	2015	Tracker, Projection, Tangent, Trajectory		Color Gait Curvature Image	2019	Encoder	[26]	
9	[28]	2016	Frequency domain features		Euclidean Distance Scores	2017	Coordinate Extraction	[29]	
10	[36]	2019	Leg length and distal mass		Center rotation at the knees	2018	Skeleton extraction	[30]	
11	[39]	2016	Genetic Algorithm for feature selection		Skeleton body	2018	Silhouette extraction	[31]	
12	[40]	2019	Centre of Mass		Morphology using dilation	2019	Silhouette stereo map	[33]	
13	[42]	2013	Centre of Gravity		Angle between the vectors and y-axis.	2019	Canonical and Pose features	[35]	
14	[43]	2003	Gait velocity, stance width, stride length, stance times		Soft kinematic	2020	Remove noise; resize data	[37]	
15	[44]	2019	Centroid		Centroid Descriptor	2014	GEI Reconstruction through GAN	[38]	
16	[50]	2010	Local feature		Region of Interest	2017	Region of Interest	[41]	
17	[53]	2011	Global feature		Contour and skeleton motion	2019	GAN generator	[45 -48] [62]	
18	[54	2006	Stride length, cycle time, speed		Joint angles and body points	2017	Background Subtraction based on Gaussian mixture model	[49]	
19	[55]	2020	3D Ground Reaction Forces		GRF filtering, time derivative, time and weight normalization.	2018	Angle Sensitive Discriminator	[52]	
20	[56]	2014	Genetic algorithm for spatial temporal pattern		Distance vector	2019	Object region segmentation	[58]	
21	[57]	2013	Symmetry-driven Local features accumulation		Weighted HSV histogram	2020	Cross-view gait descriptor	[65]	
22	[59]	2020	Haralick texture descriptor		Gait Gradient Magnitude Image	2016	Heatmaps	[68]	
23	[60]	2003	Automated Scaled Silhouette		Overlay Image for the Ground truth Frames	2017	Mean subtracting	[71]	
24	[61]	2010	Biologically Inspired Feature		Discriminative locality alignment	2017	Optical Flows	[72]	
25	[63]	2019	Multiscale Feature		Gabor filter, Multiscale Local Binary Pattern	2019	Spatial Temporal	[73]	
26	[76]	2018	Optical Flow		Local optical flow features	2017	Cartesian distance	[74]	
27	[77]	2018	Weighted Adaptive Center Symmetric		Local binary pattern	2018	binarization	[75]	
28	[78]	2015	Marker less Motion		Gait period, key positions of body	2020	Segmentation, alignment	[81]	

29	[79]	2019	Cross-speed		Skeleton segmentation algorithm	2020	Frame-level Part Extractor	[83]	
30	[80]	2014	Inter-Period Gait Fluctuations		Temporal fluctuation as gait fluctuation image and trajectory fluctuations as spatial fluctuation features	2016	Optical flow	[86]	

Data preprocessing techniques are necessary to ensure that the data is appropriately formatted for input into the CNN. Effective machine learning and deep learning models for gait recognition require crucial steps such as data preprocessing and feature selection.

3.2 Feature extraction and representation of ML and DL techniques in gait recognition

Gait recognition is the method of recognizing individuals based on their walking styles. Table 2 presents a summary of the techniques utilized for this purpose. Feature extraction involves selecting pertinent information from the gait data that can differentiate between individuals. The following are some commonly used feature extraction techniques in gait recognition:

- Histogram of Oriented Gradients (HOG): This technique extracts features that describe the shape and texture of objects within an image. In gait recognition, HOG can be utilized to depict the human body's shape and leg movements.
- Principal Component Analysis (PCA): PCA is a method that projects the data onto a lower-dimensional space to reduce its dimensionality. In gait recognition, PCA can be used to reduce the dimensionality of the gait data while retaining the most significant information.
- Dynamic Time Warping (DTW): DTW measures the similarity between two time-series data. In gait recognition, DTW can be employed to compare the resemblance between the gait patterns of different individuals.

Gait recognition has benefited from the application of deep learning techniques, which enable the automatic learning of distinctive features. Several deep learning techniques have been utilized in gait recognition, including:

- Convolutional Neural Networks (CNNs): These networks are frequently employed in image recognition tasks. In gait recognition, CNNs can automatically extract features from gait images.
- Recurrent Neural Networks (RNNs): These networks are often used to analyze sequential data. In gait recognition, RNNs can analyze the temporal sequence of gait data.
- Autoencoders: These neural networks can perform unsupervised learning. In gait recognition, autoencoders can learn a low-dimensional representation of gait data that is suitable for classification purposes.

4. Exploring the Performance of Machine Learning and Deep Learning Approaches for Gait Recognition

Recent research has found that DL techniques outperform ML techniques in gait recognition tasks. Li et al. (2020) compared CNNs and SVMs for gait recognition and found that CNNs had better accuracy. Similarly, Yang et al. (2021) found that RNNs outperformed k-NN in gait recognition. However, DL approaches require a large amount of data for training and can be computationally expensive. On the other hand, ML approaches can achieve good performance with a smaller amount of data and are computationally efficient. Thus, the choice of approach depends on available resources and specific application requirements.

Variability in gait patterns can affect the performance of gait recognition systems. Variability can arise from different walking speeds, clothing, shoes, and walking surfaces. Researchers have proposed various approaches to improve the robustness of gait recognition systems, such as data augmentation, transfer learning, and fusion of multiple modalities. In summary, gait recognition is a promising biometric technique with various applications. Both ML and DL approaches are commonly used for gait recognition, and their performance depends on various factors such as the choice of algorithm, feature extraction method, and dataset. DL techniques have shown better performance than ML techniques in recent studies, but they require a large amount of data and computational resources. Researchers continue to explore new approaches to improve the robustness and accuracy of gait recognition systems.

4.1 Evaluating the Effectiveness of Machine Learning and Deep Learning Methods

Gait recognition utilizes both ML and DL algorithms for pattern recognition. ML algorithms such as SVMs, RF, and k-NN have been widely used due to their simplicity and less computational requirements. However, they may not be able to capture the complex patterns in gait data as effectively as DL algorithms such as CNNs, RNNs, and LSTM networks, which have shown better performance in various gait recognition tasks.

The performance of both ML and DL methods also depends on the quality and size of the dataset used for training. A larger and more diverse dataset can improve the performance of these methods. Additionally, the choice of algorithm and features affects their effectiveness. Traditional ML algorithms can achieve comparable performance to DL algorithms with a smaller amount of data in some cases. Features such as stride length, stride time, step width, and angular velocity have been used for gait recognition. While DL algorithms can automatically extract relevant features from the gait data, traditional ML algorithms may require manual feature engineering. The computational resources available play a crucial role in the effectiveness of these methods. DL algorithms require a larger dataset and significant computational resources, such as high-performance GPUs, to achieve superior performance. Conversely, traditional ML algorithms can attain good performance with a smaller dataset and are computationally efficient. Availability of computational resources also affects the effectiveness of these methods. DL algorithms require a large amount of data and computational resources such as high-performance GPUs to achieve better performance, while traditional ML algorithms can achieve good performance with a smaller amount of data and are computationally efficient.

Interpretability of models is another factor affecting the effectiveness of ML and DL methods in gait recognition. DL algorithms like CNNs and RNNs are less interpretable than traditional ML algorithms such as Decision Trees and SVMs. Interpretable models are critical in various fields like healthcare, where decisions made from models could significantly impact human life. In conclusion, the effectiveness of ML and DL methods in gait recognition depends on factors such as dataset quality and size, algorithm choice, gait data type, feature selection, and computational resources. Although DL algorithms can capture complex patterns in gait data and perform better than traditional ML algorithms in several gait recognition tasks, they require more data and computational resources. Traditional ML algorithms can achieve comparable performance to DL algorithms using smaller data and are more computationally efficient. The choice of approach depends on the specific requirements of the application and the available resources.

4.2 Why DL models outperforms ML models in gait recognition

Deep learning (DL) approaches have shown better performance than traditional machine learning (ML) approaches in gait recognition tasks. This is because DL algorithms can automatically extract relevant features from raw gait data, whereas traditional ML algorithms require manual feature engineering. DL algorithms can capture complex patterns in gait data, which can be difficult or impossible to identify using traditional ML algorithms. These algorithms can learn hierarchical representations of gait data by stacking multiple layers of nonlinear transformations. This allows the model to capture complex spatiotemporal patterns in the data, such as the relationship between different joint angles during walking.

In contrast, traditional ML algorithms such as SVMs and k-Nearest Neighbors (k-NN) require manual feature engineering. This involves selecting relevant features from the raw data, such as stride length or step width, and then using these features as input to the algorithm. Feature engineering can be time-consuming and may not capture all the relevant information in the data. DL algorithms can also learn from a larger and more diverse dataset than traditional ML algorithms. This is because DL algorithms can automatically extract features from raw data, whereas traditional ML algorithms require manually engineered features. A larger and more diverse dataset can improve the performance of DL algorithms by providing more examples of different gait patterns.

However, DL approaches also have some drawbacks compared to traditional ML approaches. DL algorithms require a larger amount of data and computational resources, such as high-performance GPUs, to achieve better performance. In contrast, traditional ML algorithms can achieve good performance with a smaller amount of data and are computationally efficient. DL algorithms can also be more difficult to interpret than traditional ML algorithms, which can be important in applications such as healthcare. In conclusion, DL approaches are better than traditional ML approaches in gait recognition tasks because they can automatically extract relevant features from raw gait data, capture complex patterns in the data, and learn from a larger and more diverse dataset. However, the choice of approach depends on the specific requirements of the application and the available resources. Traditional ML approaches can be more computationally efficient and easier to interpret, while DL approaches can achieve better performance with larger datasets and more complex tasks.

4.3 Advantage and disadvantage of deep learning and machine learning approach in gait recognition

For the traditional ML approach, the advantages can include lower computational resources and interpretability of the model. The disadvantages can include the need for manual feature engineering, which can be time-consuming and may not capture all relevant information in the data. For the DL approach, the advantages can include the ability to automatically extract relevant features from raw data, learn from a larger and more diverse dataset, and capture complex patterns in the data. The disadvantages can include the need for a larger amount of data and computational resources, as well as the difficulty in interpreting the model.

There are several advantages and disadvantages of using deep learning (DL) and machine learning (ML) approaches in gait recognition.

Advantages of DL approach:

- Automatic feature extraction: DL algorithms can automatically extract relevant features from raw gait data without requiring manual feature engineering. This reduces the amount of time and effort required to prepare the data for analysis.
- Improved accuracy: DL algorithms can capture complex patterns in the data, which can improve the accuracy of gait recognition compared to traditional ML algorithms.
- Better performance with large and diverse datasets: DL algorithms can learn from a larger and more diverse dataset, which can improve their performance in gait recognition tasks.
- Transfer learning: DL algorithms can be fine-tuned using transfer learning, which allows the model to learn from a pre-trained network on a related task. This can improve the performance of the model in gait recognition tasks by leveraging the knowledge learned from the pre-trained network.

Disadvantages of DL approach:

- Computationally expensive: DL algorithms require a larger amount of data and computational resources, such as high-performance GPUs, to achieve better performance.
- Difficulty in interpretation: DL algorithms can be more difficult to interpret than traditional ML algorithms, which can be important in applications such as healthcare.

Advantages of ML approach:

- Lower computational resources: ML algorithms can achieve good performance with a smaller amount of data and are computationally efficient.
- Interpretable models: ML algorithms are generally easier to interpret than DL algorithms, which can be important in applications where interpretability is important.

Disadvantages of ML approach:

- Manual feature engineering: ML algorithms require manual feature engineering, which can be time-consuming and may not capture all the relevant information in the data.
- Limited complexity: ML algorithms are limited in their ability to capture complex patterns in the data, which can limit their performance in gait recognition tasks.

In conclusion, both DL and ML approaches have their advantages and disadvantages in gait recognition tasks. The choice of approach depends on the specific requirements of the application and the available resources. DL approaches are better suited for tasks that require the capture of complex patterns in the data, while ML approaches are better suited for tasks that require interpretable models and lower computational resources.

1.4 Applications of ML and DL in Gait Recognition

The use of machine learning (ML) and deep learning (DL) techniques has facilitated the development of robust gait recognition systems with high accuracy and performance. Here are some of the specific applications of ML and DL in gait recognition:

- Fall detection: Gait analysis can be used to detect falls in elderly people, reducing the risk of injury and providing timely assistance. ML and DL techniques can be used to analyze gait patterns and identify abnormal movements that could indicate a fall.
- Biometric identification: Gait recognition can be used as a biometric identification method, providing a non-invasive and reliable way to verify the identity of individuals. ML and DL methods can be used to extract gait features and match them to a database of known individuals.

- Rehabilitation: Gait analysis can be used to monitor the progress of patients undergoing rehabilitation and to provide feedback on their performance. ML and DL techniques can be used to analyse gait patterns and provide personalized recommendations for improvement.
- Security: Gait recognition can be used in security systems for surveillance and access control.
- Sports performance analysis: Gait analysis can be used to monitor the performance of athletes and provide feedback on their technique. ML and DL methods can be used to analyse gait patterns and provide personalized recommendations for improvement.
- Medical diagnosis: Gait analysis can be used to diagnose medical conditions such as Parkinson's disease and cerebral palsy. ML and DL techniques can be used to analyze gait patterns and identify abnormalities that could indicate the presence of these conditions.
- Human-computer interaction: Gait recognition can be used in human-computer interaction systems, allowing users to control devices and applications using their gait patterns. ML and DL methods can be used to analyze gait patterns and translate them into computer commands.

Overall, the applications of ML and DL in gait recognition are diverse and have the potential to improve many aspects of human life. The ongoing development of these techniques is likely to lead to even more applications in the future.

4.5 Challenges and limitations of current methods.

ML and (DL) approaches have shown promise in gait recognition, there are also challenges and limitations associated with current methods. Here are some of the main challenges and limitations:

- Dataset size and diversity: Many gait recognition datasets are small and not representative of the general population. This can limit the generalizability of ML and DL models and lead to overfitting.
- Variability in gait patterns: Gait patterns can vary significantly between individuals and can be affected by factors such as age, health status, and footwear. This can make it difficult to develop accurate and robust models that can work across a diverse range of individuals.
- Computational resources: DL methods require large amounts of computational resources and may not be practical for use on low-power devices or in real-time applications. ML methods may be more suitable for these applications but may not achieve the same level of accuracy as DL methods.
- Interpretability: DL models can be difficult to interpret and may not provide insights into the specific features that are being used to make predictions. This can limit their usefulness in some applications where interpretability is important.
- Privacy concerns: Gait recognition systems can raise privacy concerns, particularly in public spaces where individuals may not want to be identified. There is also a risk that the data used to train ML and DL models could be used for nefarious purposes.
- Adversarial attacks: DL models are vulnerable to adversarial attacks, where small changes to input data can cause the model to make incorrect predictions. This can be a particular concern in security applications where the consequences of incorrect predictions can be severe.

Overall, while ML and DL approaches have shown promise in gait recognition, there are also significant challenges and limitations that need to be addressed. Future research will need to focus on developing more robust and accurate models that can work across a diverse range of individuals and applications, while also addressing issues such as privacy and interpretability.

5. Conclusion

In conclusion, machine learning and deep learning techniques are driving the rapid evolution of gait recognition as a promising technology with diverse applications. With advancements in algorithms and data processing capabilities, machine learning and deep learning approaches have shown potential in improving the accuracy and robustness of gait recognition systems. This has led to increased interest in utilizing gait recognition in areas such as law enforcement, security, healthcare, and personal fitness tracking. However, it is essential to acknowledge the ethical and privacy implications of gait recognition powered by machine learning and deep learning. There are concerns about potential biases, discrimination, and misuse of the technology in surveillance applications, which must be addressed through responsible and transparent development and use. Proper data collection, model training, and validation methodologies should be employed to ensure fairness and prevent biased outcomes. Additionally, measures such as data encryption, consent mechanisms, and strict access controls should be in place to protect individuals' privacy and prevent unauthorized use of gait recognition data.

As machine learning and deep learning continue to advance, there is a need for ongoing collaboration between researchers, policymakers, and stakeholders to establish guidelines, regulations, and best practices for the responsible deployment of gait recognition technology. This includes considerations for data privacy, security, accountability, and transparency. By ensuring that gait recognition is developed and used in an ethical and responsible manner, we can maximize its potential benefits while minimizing risks, and promote the responsible advancement of this evolving field.

References

[1] Rida, Imad, Noor Almaadeed, and Somaya Almaadeed. "Robust gait recognition: a comprehensive survey." IET Biometrics 8.1 (2019): 14-28..

[2] Rida, Imad, Somaya Almaadeed, and Ahmed Bouridane. "Gait recognition based on modified phase-only correlation." Signal, Image and Video Processing 10 (2016): 463-470..

[3] Parashar, Anubha, et al. "Intra-class variations with deep learning-based gait analysis: a comprehensive survey of covariates and methods." Neurocomputing (2022).19-Septe, pp. 2596–2600, doi: 10.1109/ICIP.2019.8803236.

[4] L. min Xia, H. Wang, and W. ting Guo, "Gait recognition based on Wasserstein generating adversarial image inpainting network," *J. Cent. South Univ.*, vol. 26, no. 10, pp. 2759–2770, Oct. 2019, doi: 10.1007/s11771-019-4211-7.

[5] M. Babaee, L. Li, and G. Rigoll, "Person identification from partial gait cycle using fully convolutional neural networks," *Neurocomputing*, vol. 338, pp. 116–125, Apr. 2019, doi: 10.1016/j.neucom.2019.01.091.

[6] Rida, Imad, Somaya Al Maadeed, and Ahmed Bouridane. "Unsupervised feature selection method for improved human gait recognition." 2015 23rd European Signal Processing Conference (EUSIPCO). IEEE, 2015.

[7] D. Das, A. Agarwal, P. Chattopadhyay, and L. Wang, "RGait-NET: An Effective Network for Recovering Missing Information from Occluded Gait Cycles," *Arxiv*, pp. 1–10, Dec. 2019, [Online]. Available: http://arxiv.org/abs/1912.06765.

[8] Parashar, Anubha, et al. "Deep learning pipelines for recognition of gait biometrics with covariates: a comprehensive review." Artificial Intelligence Review (2023): 1-65.

[9] Rida, Imad, et al. "Improved model-free gait recognition based on human body part." Biometric Security and Privacy: Opportunities & Challenges in The Big Data Era (2017): 141-161.

[10] K. Wang, L. Liu, Y. Lee, X. Ding, and J. Lin, "Nonstandard Periodic Gait Energy Image for Gait Recognition and Data Augmentation," in *Chinese Conference on Pattern Recognition and Computer Vision (PRCV)*, 2019, pp. 197–208, doi: 10.1007/978-3-030-31723-2_17.

[11] T. Yeoh, H. E. Aguirre, and K. Tanaka, "Clothing-invariant gait recognition using convolutional neural network," in *2016*

International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS), Oct. 2016, pp. 1–5.

[12] Rida, Imad, et al. "Robust model-free gait recognition by statistical dependency feature selection and globality-locality preserving projections." 2016 39th International Conference on Telecommunications and Signal Processing (TSP). IEEE, 2016.

[13] F. M. Castro, M. J. Marín-Jiménez, N. Guil, and N. P. de la Blanca, "Automatic learning of gait signatures for people identification," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10306 LNCS, 2017, pp. 257–270.

[14] Rida, Imad, Xudong Jiang, and Gian Luca Marcialis. "Human body part selection by group lasso of motion for model-free gait recognition." IEEE Signal Processing Letters 23.1 (2015): 154-158..

[15] J. T. Grant, "Background subtraction techniques in surface analysis," J. Vac. Sci. Technol. A Vacuum, Surfaces, Film., vol. 2, no. 2, pp. 1135–1140, Apr. 1984, doi: 10.1116/1.572689.

[16] A. Elgammal, R. Duraiswami, D. Harwood, and L. S. Davis, "Background and foreground modeling using nonparametric kernel density estimation for visual surveillance," Proc. IEEE, vol. 90, no. 7, pp. 1151–1163, Jul. 2002, doi: 10.1109/JPROC.2002.801448.

[17] F. Yang, X. Jiang, T. Sun, and K. Xu, "Gait recognition with clothing and carrying variations based on GEI and CAPDS features," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11858 LNCS, 2019, pp. 632–643.

[18] J. W. Davis and V. Sharma, "Background-subtraction using contour-based fusion of thermal and visible imagery," Comput. Vis. Image Underst., vol. 106, no. 2–3, pp. 162–182, May 2007, doi: 10.1016/j.cviu.2006.06.010.

[19] C.-S. Lee and A. Elgammal, "Dynamic shape outlier detection for human locomotion," Comput. Vis. Image Underst., vol. 113, no. 3, pp. 332–344, Mar. 2009, doi: 10.1016/j.cviu.2008.10.003.

[20] C.-S. Lee and A. Elgammal, "Dynamic shape outlier detection for human locomotion," Comput. Vis. Image Underst., vol. 113, no. 3, pp. 332–344, Mar. 2009, doi: 10.1016/j.cviu.2008.10.003.

[21] X. Li, Y. Makihara, C. Xu, Y. Yagi, and M. Ren, "Gait Recognition via Semi-supervised Disentangled Representation Learning to Identity and Covariate Features," *IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2020.

[22] J. Luo and T. Tjahjadi, "View and Clothing Invariant Gait Recognition via 3D Human Semantic Folding," *IEEE Access*, vol. 8, pp. 100365–100383, 2020, doi: 10.1109/ACCESS.2020.2997814.

[23] K. Bashir, T. Xiang, and S. Gong, "Feature selection on gait energy image for human identification," in ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, Mar. 2008, pp. 985–988, doi: 10.1109/ICASSP.2008.4517777.

[24] C. Yan, B. Zhang, and F. Coenen, "Multi-attributes gait identification by convolutional neural networks," in *Proceedings - 2015 8th International Congress on Image and Signal Processing, CISP 2015*, Oct. 2016, no. Cisp, pp. 642–647, doi: 10.1109/CISP.2015.7407957.

[25] S. Yu, H. Chen, E. B. G. Reyes, and N. Poh, "GaitGAN: Invariant Gait Feature Extraction Using Generative Adversarial Networks," in *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jul. 2017, vol. 87, pp. 532–539, doi: 10.1109/CVPRW.2017.80.

[26] S. Yu *et al.*, "GaitGANv2: Invariant gait feature extraction using generative adversarial networks," *Pattern Recognit.*, vol. 87, pp. 179–189, 2019, doi: 10.1016/j.patcog.2018.10.019.

[27] R. T. Collins, R. Gross, and Jianbo Shi, "Silhouette-based human identification from body shape and gait," in Proceedings of Fifth IEEE International Conference on Automatic Face Gesture Recognition, 2002, no. March 2005, pp. 366–371, doi: 10.1109/AFGR.2002.1004181.

[28] C. BenAbdelkader, R. Cutler, and L. Davis, "View-invariant Estimation of Height and Stride for Gait Recognition," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 2359 LNCS, 2002, pp. 155–167.

[29] R. Liao, C. Cao, E. B. Garcia, S. Yu, and Y. Huang, "Pose-Based Temporal-Spatial Network (PTSN) for Gait Recognition with Carrying and Clothing Variations," in *Chinese Conference on Biometric Recognition*, vol. 10568, no. c, J. Zhou, Y. Wang, Z. Sun, Y. Xu, L. Shen, J. Feng, S. Shan, Y. Qiao, Z. Guo, and S. Yu, Eds. Cham: Springer International Publishing, 2017, pp. 474–483.

[30] L. Yao, W. Kusakunniran, Q. Wu, J. Zhang, and Z. Tang, "Robust CNN-based Gait Verification and Identification using Skeleton Gait Energy Image," in *2018 Digital Image Computing: Techniques and Applications (DICTA)*, Dec. 2018, pp. 1–7.

[31] I. Cheheb, N. Al-Maadeed, S. Al-Madeed, and A. Bouridane, "Investigating the Use of Autoencoders for Gait-based Person Recognition," in *2018 NASA/ESA Conference on Adaptive Hardware and Systems, AHS 2018*, Aug. 2018, pp. 148–151, doi: 10.1109/AHS.2018.8541447.

[32] Z. Zhang *et al.*, "Gait Recognition via Disentangled Representation Learning," *2019 IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, vol. 2019-June, pp. 4705–4714, Apr. 2019, doi: 10.1109/CVPR.2019.00484.

[33] D. Thapar, G. Jaswal, A. Nigam, and C. Arora, "Gait metric learning siamese network exploiting dual of spatio-temporal 3D-CNN intra and LSTM based inter gait-cycle-segment features," *Pattern Recognit. Lett.*, vol. 125, pp. 646–653, Jul. 2019, doi: 10.1016/j.patrec.2019.07.008.

[34] A. R. Hawas, H. A. El-Khobby, M. Abd-Elnaby, and F. E. Abd El-Samie, "Gait identification by convolutional neural networks and optical flow," *Multimed. Tools Appl.*, vol. 78, no. 18, pp. 25873–25888, Sep. 2019, doi: 10.1007/s11042-019-7638-9.

[35] Z. Zhang, L. Tran, F. Liu, and X. Liu, "On Learning Disentangled Representations for Gait Recognition," *Arxiv*, pp. 1–15, Sep. 2019, [Online]. Available: http://arxiv.org/abs/1909.03051.

[36] B. Gálai and C. Benedek, "Feature selection for Lidar-based gait recognition," in 2015 International Workshop on Computational Intelligence for Multimedia Understanding, IWCIM 2015, Oct. 2015, pp. 1–5, doi: 10.1109/IWCIM.2015.7347076.

[37] A. Mehmood *et al.*, "Prosperous Human Gait Recognition: an end-to-end system based on pre-trained CNN features selection," *Multimed. Tools Appl.*, 2020, doi: 10.1007/s11042-020-08928-0.

[38] W. Swee, C. Dave, and S. Bingquan, "GAIT RECOGNITION FOR PERSON TRACKING ACROSS CAMERA," *Comput. Vis. - ECCV 2014 Work.*, vol. volume 892, 2014, [Online]. Available: https://link.springer.com/book/10.1007%2F978-3-319-16181-5?page=1#toc.

[39] N. Al-Naffakh, N. Clarke, P. Haskell-Dowland, and F. Li, "A Comprehensive Evaluation of Feature Selection for Gait Recognition Using Smartwatches," Int. J. Inf. Secur. Res., vol. 6, no. 3, pp. 691–700, Sep. 2016, doi: 10.20533/ijisr.2042.4639.2016.0080.

[40] M. Schlafly, Y. Yilmaz, and K. B. Reed, "Feature selection in gait classification of leg length and distal mass," Informatics Med. Unlocked, vol. 15, no. January, p. 100163, 2019, doi: 10.1016/j.imu.2019.100163.

[41] X. Zhang, S. Sun, C. Li, X. Zhao, and Y. Hu, "DeepGait: A Learning Deep Convolutional Representation for Gait Recognition," in *Biometric Recognition. CCBR 2017. Lecture Notes in Computer Science, vol 10568. Springer, Cham*, vol. 1, no. c, 2017, pp. 447–456.

[42] R. Altilio, L. Liparulo, A. Proietti, M. Paoloni, and M. Panella, "A genetic algorithm for feature selection in gait analysis," in 2016 IEEE Congress on Evolutionary Computation (CEC), Jul. 2016, pp. 4584–4591, doi: 10.1109/CEC.2016.7744374.

[43] Y.-F. Tsao, W.-T. Liu, and C.-T. Chiu, "Human gait analysis by body segmentation and center of gravity," in 2013 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, Oct. 2013, pp. 1–5, doi: 10.1109/APSIPA.2013.6694128.

[44] S. L. Dockstader, M. J. Berg, and A. M. Tekalp, "Stochastic kinematic modeling and feature extraction for gait analysis," IEEE Trans. Image Process., vol. 12, no. 8, pp. 962–976, Aug. 2003, doi: 10.1109/TIP.2003.815259.

[45] P. Zhang, Q. Wu, and J. Xu, "VN-GAN: Identity-preserved Variation Normalizing GAN for Gait Recognition," *Proc. Int. Jt. Conf. Neural Networks*, vol. 2019-July, no. July, pp. 1–8, 2019, doi: 10.1109/IJCNN.2019.8852401.

[46] P. Zhang, Q. Wu, and J. Xu, "VT-GAN: View Transformation GAN for Gait Recognition across Views," *Proc. Int. Jt. Conf. Neural Networks*, vol. 2019-July, no. July, pp. 1–8, 2019, doi: 10.1109/IJCNN.2019.8852258.

[47] M. Deng, T. Fan, J. Cao, S. Y. Fung, and J. Zhang, "Human gait recognition based on deterministic learning and knowledge fusion through multiple walking views," *J. Franklin Inst.*, vol. 357, no. 4, pp. 2471–2491, 2020, doi: 10.1016/j.jfranklin.2019.12.041.

[48] Y. Wang, C. Song, Y. Huang, Z. Wang, and L. Wang, "Learning view invariant gait features with Two-Stream GAN," *Neurocomputing*, vol. 339, pp. 245–254, Apr. 2019.

[49] Z. Wu, Y. Huang, L. Wang, X. Wang, and T. Tan, "A Comprehensive Study on Cross-View Gait Based Human Identification with Deep CNNs," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 2, pp.

209–226, 2017, doi: 10.1109/TPAMI.2016.2545669.
[50] S. K. and R. G., “An Efficient HOG-Centroid Descriptor for Human Gait Recognition,” in 2019 Amity International Conference on Artificial Intelligence (AICAI), Feb. 2019, pp. 355–360, doi: 10.1109/AICAI.2019.8701366.
[51] Y. Huang, J. Zhang, H. Zhao, and L. Zhang, “Attention-Based Network for Cross-View Gait Recognition,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11307 LNCS, no. ii, Springer International Publishing, 2018, pp. 489–498.
[52] B. Hu, Y. Gao, Y. Guan, Y. Long, N. Lane, and T. Ploetz, “Robust Cross-View Gait Identification with Evidence: A Discriminant Gait GAN (DiGGAN) Approach on 10000 People,” *Arxiv*, 2018, [Online].
[53] W. Kusakunniran, Q. Wu, J. Zhang, and H. Li, “Support vector regression for multi-view gait recognition based on local motion feature selection,” Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., pp. 974–981, 2010, doi: 10.1109/CVPR.2010.5540113.
[54] M. Arantes and A. Gonzaga, “Human gait recognition using extraction and fusion of global motion features,” Multimed. Tools Appl., vol. 55, no. 3, pp. 655–675, Dec. 2011, doi: 10.1007/s11042-010-0587-y.
[55] J.-H. Yoo and M. S. Nixon, “Feature Extraction and Selection for Recognizing Humans by Their Gait,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 4292 LNCS, 2006, pp. 156–165.
[56] J. Burdack, F. Horst, S. Giesselbach, I. Hassan, S. Daffner, and W. I. Schöllhorn, “Systematic Comparison of the Influence of Different Data Preprocessing Methods on the Performance of Gait Classifications Using Machine Learning,” Front. Bioeng. Biotechnol., vol. 8, no. April, pp. 1–12, Apr. 2020.
[57] F. Tafazzoli, G. Bebis, S. Louis, and M. Hussain, “Improving Human Gait Recognition Using Feature Selection,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 8888, 2014, pp. 830–840.
[58] X. Wang, J. Zhang, and W. Q. Yan, “Gait recognition using multichannel convolution neural networks,” *Neural Comput. Appl.*, vol. 0123456789, Oct. 2019, doi: 10.1007/s00521-019-04524-y.
[59] L. Bazzani, M. Cristani, and V. Murino, “Symmetry-driven accumulation of local features for human characterization and re-identification,” Comput. Vis. Image Underst., vol. 117, no. 2, pp. 130–144, Feb. 2013, doi: 10.1016/j.cviu.2012.10.008.
[60] R. Anusha and C. D. Jaidhar, “Human gait recognition based on histogram of oriented gradients and Haralick texture descriptor,” Multimed. Tools Appl., vol. 79, no. 11–12, pp. 8213–8234, Mar. 2020, doi: 10.1007/s11042-019-08469-1.
[61] L. H. Malavã, “Silhouette based gait recognition : Research resource and limits,” 2003.
[62] R. Zhang, D. Yin, Z. Zhou, Z. Cao, F. Meng, and B. Hu, “Improving Cross-View Gait Recognition With Generative Adversarial Networks Rui,” in 2019 Scientific Conference on Network, Power Systems and Computing (NPSC 2019), 2019, vol. 3, no. Npsc, pp. 43–47, [Online]. Available: https://iecscience.org/ppapers/2019120901/NPSC_A11.
[63] Y. Mu and D. Tao, “Biologically inspired feature manifold for gait recognition,” Neurocomputing, vol. 73, no. 4–6, pp. 895–902, Jan. 2010, doi: 10.1016/j.neucom.2009.09.017.
[64] X. Wang and W. Q. Yan, “Human Gait Recognition Based on Frame-by-Frame Gait Energy Images and Convolutional Long Short-Term Memory,” Int. J. Neural Syst., vol. 30, no. 1, p. 1950027, Jan. 2020, doi: 10.1142/S0129065719500278.
[65] M. H. Khan, M. S. Farid, and M. Grzegorzek, “A non-linear view transformations model for cross-view gait recognition,” Neurocomputing, vol. 402, no. xxxx, pp. 100–111, Aug. 2020, doi: 10.1016/j.neucom.2020.03.101.
[66] A. O. Lishani, L. Boubchir, E. Khalifa, and A. Bouridane, “Human gait recognition using GEI-based local multi-scale feature descriptors,” Multimed. Tools Appl., vol. 78, no. 5, pp. 5715–5730, Mar. 2019.
[67] Z. Mahfouf, H. F. Merouani, I. Bouchrika, and N. Harrati, “Investigating the use of motion-based features from optical flow for gait recognition,” Neurocomputing, vol. 283, pp. 140–149, Mar. 2018, doi: 10.1016/j.neucom.2017.12.040.
[68] J. W. Davis and V. Sharma, “Background-subtraction using contour-based fusion of thermal and visible imagery,” *Comput. Vis. Image Underst.*, vol. 106, no. 2–3, pp. 162–182, May 2007, doi: 10.1016/j.cviu.2006.06.010.
[69] S. Zhang and L. Zhang, “Combining weighted adaptive CS-LBP and local linear discriminant projection for gait recognition,” Multimed. Tools Appl., vol. 77, no. 10, pp. 12331–12347, May 2018, doi: 10.1007/s11042-017-4884-6.
[70] W. Kusakunniran, “Extracting Gait Figures in a Video Based on Markerless Motion,” in 2015 Seventh International Conference on Knowledge and Systems Engineering (KSE), Oct. 2015, pp. 306–309, doi: 10.1109/KSE.2015.16.
[71] R. T. Collins, R. Gross, and Jianbo Shi, “Silhouette-based human identification from body shape and gait,” in *Proceedings of Fifth IEEE International Conference on Automatic Face Gesture Recognition*, 2002, no. March 2005, pp. 366–371, doi: 10.1109/AFGR.2002.1004181.
[72] C. BenAbdelkader, R. Cutler, and L. Davis, “View-invariant Estimation of Height and Stride for Gait Recognition,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 2359 LNCS, 2002, pp. 155–167.
[73] B. Gálai and C. Benedek, “Feature selection for Lidar-based gait recognition,” in *2015 International Workshop on Computational Intelligence for Multimedia Understanding, IWCIM 2015*, Oct. 2015.
[74] N. Al-Naffakh, N. Clarke, P. Haskell-Dowland, and F. Li, “A Comprehensive Evaluation of Feature Selection for Gait Recognition Using Smartwatches,” *Int. J. Inf. Secur. Res.*, vol. 6, no. 3, pp. 691–700, Sep. 2016, doi: 10.20533/ijisr.2042.4639.2016.0080.
[75] M. Schlafly, Y. Yilmaz, and K. B. Reed, “Feature selection in gait classification of leg length and distal mass,” *Informatics Med. Unlocked*, vol. 15, no. January, p. 100163, 2019, doi: 10.1016/j.imu.2019.100163.
[76] J. Kovač, V. Štruc, and P. Peer, “Frame–based classification for cross-speed gait recognition,” Multimed. Tools Appl., vol. 78, no. 5, pp. 5621–5643, Mar. 2019, doi: 10.1007/s11042-017-5469-0.
[77] M. R. Aqmar, Y. Fujihara, Y. Makihara, and Y. Yagi, “Gait recognition by fluctuations,” Comput. Vis. Image Underst., vol. 126, pp. 38–52, Sep. 2014, doi: 10.1016/j.cviu.2014.05.004.
[78] Y.-F. Tsao, W.-T. Liu, and C.-T. Chiu, “Human gait analysis by body segmentation and center of gravity,” in *2013 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference*, Oct. 2013, pp. 1–5, doi: 10.1109/APSIPA.2013.6694128.
[79] S. L. Dockstader, M. J. Berg, and A. M. Tekalp, “Stochastic kinematic modeling and feature extraction for gait analysis,” *IEEE Trans. Image Process.*, vol. 12, no. 8, pp. 962–976, Aug. 2003, doi: 10.1109/TIP.2003.815259.
[80] S. K. and R. G., “An Efficient HOG-Centroid Descriptor for Human Gait Recognition,” in *2019 Amity International Conference on Artificial Intelligence (AICAI)*, Feb. 2019, pp. 355–360, doi: 10.1109/AICAI.2019.8701366.
[81] W. Kusakunniran, Q. Wu, J. Zhang, and H. Li, “Support vector regression for multi-view gait recognition based on local motion feature selection,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 974–981, 2010.
[82] Jing, X., Yan, W., Lai, J., & Zhang, D. (2008). Gait recognition based on weighted KPCA and SVM. Pattern Recognition Letters, 29(12), 1741-1745.
[83] J.-H. Yoo and M. S. Nixon, “Feature Extraction and Selection for Recognizing Humans by Their Gait,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 4292 LNCS, 2006, pp. 156–165.
[84] Makihara, Y., Yagi, Y., & Yachida, M. (2011). Gait recognition using a hidden Markov model. Pattern Recognition Letters, 32(3), 378-382.
[85] F. Tafazzoli, G. Bebis, S. Louis, and M. Hussain, “Improving Human Gait Recognition Using Feature Selection,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 8888, 2014, pp. 830–840.
[86] A. Al-Tayyan, K. Assaleh, and T. Shanableh, “Decision-level fusion for single-view gait recognition with various carrying and clothing conditions,” Image Vis. Comput., vol. 61, pp. 54–69, May 2017, doi: 10.1016/j.imavis.2017.02.004.
[87] Xu, C., Zhang, Y., Chen, H., & He, H. (2016). Gait recognition using random forests and deep belief networks. IEEE Transactions on Cybernetics.