



Comparative Study of Machine Learning and Deep Learning Techniques for Gait Recognition: Advances in Feature Extraction, Reduction, Transformation, and Classification

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ABSTRACT

Gait recognition, a biometric technique used to identify individuals based on their unique walking patterns, has become increasingly prominent in fields such as security, surveillance, healthcare, and rehabilitation. This paper provides a detailed comparative analysis of machine learning and deep learning techniques in gait recognition, focusing on feature extraction, reduction, and transformation methods. Traditional machine learning models like Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) are examined for their reliance on handcrafted features, while advanced deep learning architectures, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are explored for their ability to automatically learn feature representations. The study highlights how each approach performs under challenging conditions such as occlusions, variations in clothing, and differing camera views. Preprocessing techniques and dimensionality reduction methods are also reviewed to demonstrate their impact on improving recognition accuracy. Furthermore, the potential of using generative adversarial networks (GANs) and other feature selection methods to enhance robustness is discussed. By comparing the strengths and limitations of both machine learning and deep learning, this paper provides valuable insights for researchers to make informed decisions when developing gait recognition systems. The study concludes by suggesting future research directions that include the integration of multimodal data and addressing ethical concerns in gait recognition applications.

1. Introduction

Biometric recognition systems have seen substantial advancements over the last few decades, offering increasingly sophisticated tools for identification and surveillance. Among these technologies, gait recognition has emerged as a critical non-intrusive biometric approach, capable of identifying individuals from a distance by analyzing their walking patterns. The appeal of gait recognition lies in its unobtrusiveness; it can be performed without requiring the subject's direct cooperation or knowledge, unlike other biometric systems such as fingerprint or facial recognition. Gait is a behavioral and physiological trait that remains relatively stable across various environments, making it a powerful identifier in fields such as security, surveillance, healthcare, and even rehabilitation. The fundamental challenge in gait recognition is to extract meaningful features that accurately capture the unique characteristics of an individual's gait. These features must then be transformed into a representation that enables reliable classification. In traditional machine learning approaches, which were dominant in the early 2000s, feature extraction relied heavily on handcrafted techniques. However, with the advent of deep learning (DL), there has been a shift towards automatic feature extraction methods, which have significantly enhanced recognition performance.

In early approaches, classification relied heavily on traditional machine learning algorithms, such as k-Nearest Neighbors (KNN) and Support Vector Machines (SVM). These models primarily used handcrafted features—such as step length, cadence, and body symmetry—extracted through labor-intensive methods. Classification in these systems depended on mapping the extracted features to predefined classes, where SVM classified based on optimal hyperplanes, and KNN relied on distance metrics to identify the closest match in the feature space. With the introduction of deep learning, classification techniques evolved. Deep learning architectures, such as Convolutional Neural Networks (CNNs), brought a paradigm shift by automating feature extraction and classification. CNNs were able to learn hierarchical feature representations, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks captured temporal dependencies in gait sequences, leading to more robust classification even under varying conditions. The use of softmax and sigmoid layers for

classification enabled these networks to output multi-class and binary classification results, respectively, further enhancing gait recognition performance. GANs also contributed by augmenting data and enhancing the classification of occluded or degraded gait patterns. This paper delves into the evolution of these classification methods, contrasting the accuracy and reliability of traditional ML techniques with state-of-the-art DL approaches, and highlighting how each method performs under diverse conditions.

2. Gait Recognition Methods: Approaches and Techniques

In figure 1 expanded view of the comparative analysis between Machine Learning (ML) and Deep Learning (DL) techniques for gait recognition. Here's a more detailed breakdown of each section:

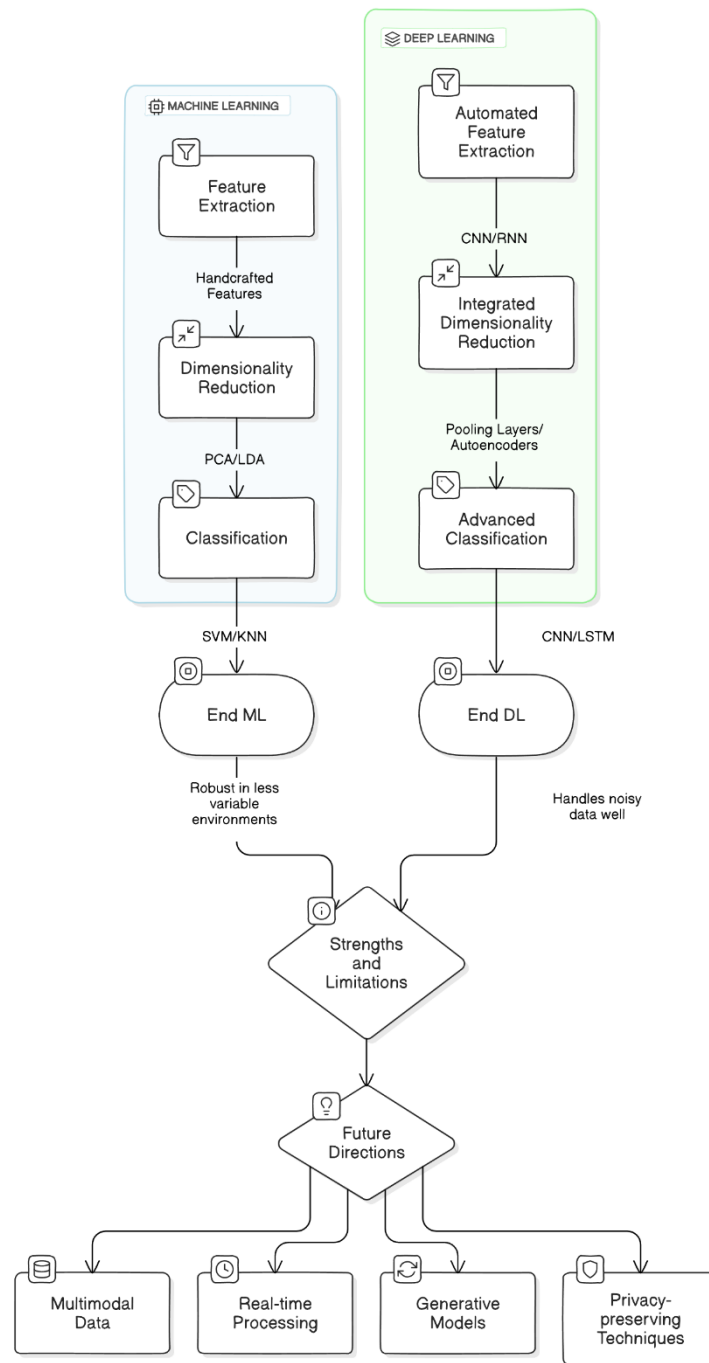


Figure 1: Comparative Analysis of Machine Learning and Deep Learning Techniques for Gait Recognition

Machine Learning (ML) Workflow

- **Feature Extraction:** In ML approaches, feature extraction is primarily performed manually, relying on handcrafted features like step length, body symmetry, and cadence. These features require domain expertise and are often created based on human observation and understanding of gait patterns.
- **Dimensionality Reduction:** After feature extraction, dimensionality reduction techniques such as PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis) are applied. These methods aim to reduce the high-dimensional feature space into a lower-dimensional representation while retaining the most important features for classification.
- **Classification:** Once the dimensionality has been reduced, ML models such as SVM (Support Vector Machines) or KNN (k-Nearest Neighbors) are used for classification. These algorithms rely heavily on the features provided and often perform well in controlled, less variable environments.
- **End of ML Process:** The ML workflow concludes with classification, where models typically show robustness in environments with fewer variations. However, these methods struggle with noisy data or real-world challenges like occlusion or varying lighting conditions.

Deep Learning (DL) Workflow

- **Automated Feature Extraction:** In contrast to ML, DL techniques such as CNN (Convolutional Neural Networks) and RNN (Recurrent Neural Networks) automate the feature extraction process. This allows the model to learn hierarchical feature representations from raw data like gait sequences, eliminating the need for manual feature crafting.
- **Integrated Dimensionality Reduction:** DL models inherently include dimensionality reduction within their architecture. Pooling layers (e.g., max pooling, average pooling) or autoencoders are used to reduce spatial dimensions, focusing on the most critical aspects of the data. This integration streamlines the process, making DL more scalable.
- **Advanced Classification:** Once the features are extracted and reduced, advanced classification layers, such as softmax for multi-class classification, are applied. LSTMs (Long Short-Term Memory Networks) are particularly effective in capturing temporal dependencies in sequential data, which is important for video-based gait recognition tasks.
- **End of DL Process:** DL techniques excel in handling complex, noisy, and real-world environments where data may be occluded, incomplete, or contain significant variations. Their ability to automatically learn and adapt to varying conditions is a key strength over traditional ML approaches.

Both ML and DL have distinct strengths and limitations, highlighted in the center of the diagram. ML is robust in controlled, less variable environments but struggles with noisy or unpredictable data. On the other hand, DL methods, especially CNNs and LSTMs, are well-equipped to handle noisy data and can adapt to more challenging real-world scenarios with minimal manual intervention.

In the early stages of gait recognition research, traditional machine learning methods dominated, particularly from the year 2000 to 2020. During this period, researchers focused on manually extracting features from gait data, a process that was both labor-intensive and required domain expertise [154]. Handcrafted features, such as step length, cadence, and symmetry, were among the key traits used to model gait [155]. One widely used approach was the Gait Energy Image (GEI), which condensed an entire gait cycle into a single image by averaging the silhouette frames across time [156]. This method effectively captured the spatial distribution of body movements, simplifying the recognition process for traditional machine learning models such as Support Vector Machines (SVMs) [157] and k-Nearest Neighbors (KNN) [158]. Similarly, Motion History Images (MHI) and Gait Flow Images (GFI) were also employed to represent the temporal dynamics of gait, further enhancing the recognition capabilities of machine learning classifiers [159]. These features, along with Gait Silhouette Images (GSI), were effective in extracting spatial and temporal information from gait sequences. Hidden Markov Models (HMMs) were frequently used to handle the sequential nature of gait data, enabling the classification of individuals based on the temporal evolution of their gait features [160]. Despite their success in controlled environments, these machine learning methods struggled with real-world variability. Changes in clothing, different footwear, and objects carried by individuals often introduced noise into the system, reducing the accuracy of traditional models [161]. Furthermore, occlusions and variations in camera angles added additional complexity, making handcrafted features less reliable in diverse scenarios [162]. These limitations underscored the need for more robust feature extraction and representation methods, which ultimately led to the rise of deep learning in the field [163].

The advent of deep learning between 2016 and 2020 brought about a paradigm shift in gait recognition. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), began to outperform traditional machine learning methods by automatically learning features directly from raw gait data [1] [3]. Unlike handcrafted feature extraction, which required domain expertise and extensive preprocessing, CNNs could automatically extract spatial hierarchies of features from silhouette images or raw

video sequences [5] [7]. These models significantly improved recognition accuracy, especially in scenarios where environmental factors like lighting or occlusion varied widely [10]. For instance, CNN-based models were able to process Gait Silhouette Images (GSI) and Gait Energy Images (GEI) more effectively by capturing fine-grained spatial patterns and learning relevant feature maps through multiple layers of abstraction [12]. Deep learning architectures also proved more robust against covariate conditions, such as changes in clothing or varying viewpoints, that had previously hindered traditional machine learning models [15]. RNNs, specifically Long Short-Term Memory (LSTM) networks, provided an added advantage by capturing temporal dependencies in gait sequences [18]. By processing the sequential data inherent in walking patterns, RNNs offered better performance in video-based gait recognition tasks [19].

The use of Generative Adversarial Networks (GANs) from 2016 onwards brought new possibilities for handling occluded or degraded gait data. GANs enabled the generation of synthetic gait data, which was used to augment training datasets and improve the robustness of models in real-world environments [20] [22]. By reconstructing missing or occluded gait sequences, GANs made it possible to recognize individuals under challenging conditions where traditional models failed [25]. These models also facilitated view-invariant recognition, which was essential for identifying individuals across different camera perspectives [30]. Alongside feature extraction, feature reduction and transformation were crucial for improving the performance of gait recognition models, particularly in the early 2000s. Traditional machine learning approaches relied heavily on dimensionality reduction techniques to simplify the high-dimensional gait data while retaining the most discriminative features [236] [237]. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were two of the most widely used methods for this purpose [240] [241].

PCA was employed to reduce the dimensionality of silhouette images or Gait Energy Images (GEI), projecting the data into a lower-dimensional space while preserving the variance in the dataset [237] [242]. This allowed for faster processing and reduced the computational burden on machine learning models, making real-time gait recognition feasible. LDA, on the other hand, was used to maximize class separability by projecting the data onto a subspace where the differences between individuals' gait patterns were more pronounced [239]. This technique was particularly useful in scenarios where the dataset contained multiple classes, as it improved the classifier's ability to distinguish between different individuals [243]. Moreover, techniques such as Independent Component Analysis (ICA) and Multilinear Principal Component Analysis (MPCA) were employed to handle more complex, multi-dimensional gait data. ICA, for instance, helped separate mixed signals caused by background noise or variations in camera angles, allowing the model to focus on the underlying gait patterns [245]. MPCA extended the capabilities of traditional PCA by allowing for the reduction of multidimensional tensors, making it suitable for 3D gait sequences [246] [247]. However, despite these advancements, traditional feature reduction techniques had their limitations. By discarding some variability in the data, models became less adaptable to real-world conditions, such as changes in walking speed or the presence of occlusions. This further highlighted the need for more integrated and flexible approaches, which were later realized with the adoption of deep learning models [249] [251].

Deep learning models incorporated feature reduction directly into their architectures, eliminating the need for external dimensionality reduction techniques like PCA or LDA [50] [70]. CNNs, for example, used pooling layers to reduce the spatial dimensions of feature maps while preserving essential information [80] [85]. Max pooling, average pooling, and global pooling layers allowed CNNs to focus on the most important features while reducing computational complexity [100]. Autoencoders, a specific type of neural network, were also employed for feature reduction in deep learning-based gait recognition [105] [110]. Autoencoders compressed gait data into a lower-dimensional latent space, effectively learning a more compact representation of the input data while preserving critical features [120] [125]. This approach was particularly useful for unsupervised learning, where the goal was to learn meaningful representations from unlabeled gait data [140]. Furthermore, GANs continued to play a vital role in augmenting and transforming gait data during this period, enhancing the diversity and robustness of training datasets [145] [150]. By integrating feature extraction, reduction, and transformation within the network, deep learning models achieved higher accuracy and scalability than traditional machine learning methods. These models were better equipped to handle the complexities of real-world environments, where variations in walking speed, clothing, and environmental factors introduced significant challenges [150] [235].

3. Feature Extraction in Machine Learning and Deep Learning Techniques for Gait Recognition

Gait recognition has evolved through various machine learning (ML) and deep learning (DL) approaches as given in table 1 and 2 respectively, each contributing significantly to improving the accuracy and robustness of recognition systems. The ML approaches have traditionally focused on manually crafted feature extraction methods to enhance the representation of gait data for classification tasks. Techniques like Accumulated Prediction Image and Accumulated Flow Image [151] and Gradient Histogram Energy Image [152] combine different image and flow representations to address challenges such as silhouette corruption. These methods rely on the regularity or irregularity of human motion for identifying individuals, as demonstrated by Periodic Human Motion [153] and Aperiodic Features [154]. Additionally, methods like Entropy Volumes [155] and Gait

Recognition Depth Image [156] incorporate entropy-based measures and depth features, respectively, to provide richer 3D spatial representations, improving overall recognition accuracy.

Further ML approaches have explored different ways of representing motion and energy in gait sequences. Techniques like Active Energy Image [157] and Gait Flow Image [158] focus on using energy-based and motion flow features, while Motion Energy Image and Motion History Image [159] emphasize temporal information to capture changes over time. More refined methods, such as Gait Energy Image Partitioning [160], break down traditional Gait Energy Images (GEI) into smaller segments to improve the classification process, while Gait Information Image [161] creates compact representations from silhouette images. Temporal aspects are also captured through methods like Temporal Self-Similarities [162] and Gait Entropy Image [163], which analyze the self-similar properties and entropy of gait patterns, respectively.

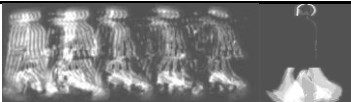
In addition to silhouette-based methods, ML approaches have also incorporated texture, depth, and 3D spatial information for enhanced feature extraction. Gabor Features [167], Curvelet Sub-Band of Masked Gait Energy Image [174], and Pose Depth Volume Extraction [179] apply texture filters, depth features, and spatial representations to offer more detailed information for classifiers. Techniques such as Binary Motion Image [164] and Model-Based Gait Cycle Features [184] simplify the silhouette into binary or structured representations for easier processing by ML models, while Local Binary Pattern [192] captures texture details from gait images. Furthermore, Relative Distance Features [182], Gait Fluctuation Image [200], and Radial Sampling [216] measure specific body part movements, shape fluctuations, and spatial variations, adding robustness to ML-based recognition systems.

Deep learning (DL) approaches have revolutionized gait recognition by automating feature extraction and significantly improving performance, particularly in real-world scenarios with more variability. Convolutional Neural Networks (CNNs) [1, 6, 8] have emerged as the leading models for extracting hierarchical spatial features from gait silhouettes, outperforming traditional ML methods in accuracy and generalization. CNN-based architectures like 3D CNNs [33] extend this by capturing spatio-temporal features from 3D gait data, which is especially useful in video-based recognition. These models automatically learn meaningful features, eliminating the need for handcrafted extraction methods. In addition to CNNs, techniques like Encoder-Decoder Networks [4-5] compress and reconstruct gait data, preserving key features even in noisy or degraded input.

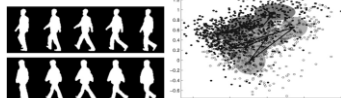
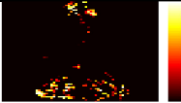


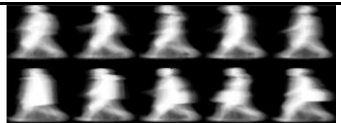
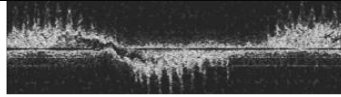



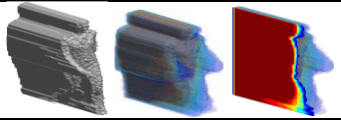
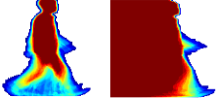
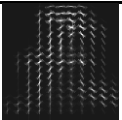

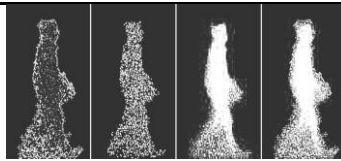

Generative models, particularly Generative Adversarial Networks (GANs) [3, 26], have also played a crucial role in augmenting gait recognition datasets by generating synthetic gait data. GAN-based methods, such as Reconstructed Gait Energy Image [26], can even restore missing or degraded data, enhancing the input quality for DL models. Other feature extraction methods, such as Stacked Sparse Autoencoders [31], focus on compressing and extracting key latent features from gait data, allowing for improved classification in challenging conditions. Moreover, DL approaches like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks [29, 68] are particularly effective at capturing temporal dependencies in sequential gait data, such as video footage. These networks allow for a better understanding of dynamic gait patterns over time. Skeleton-Based Recognition [17, 137] has also emerged as a powerful DL approach, leveraging skeletal data rather than silhouettes, which is particularly beneficial in cases of occlusion or incomplete data.



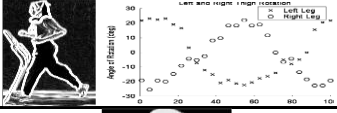

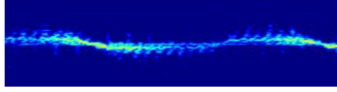

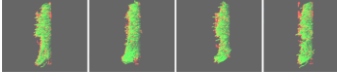



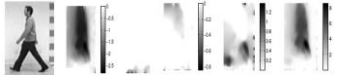

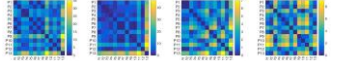

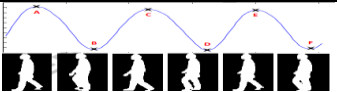

Deep learning models further improve recognition by extracting invariant features that are resilient to variations in viewpoint, clothing, or occlusion. For instance, Invariant Feature Extraction [28] and Discriminant Projection [55] focus on improving the robustness of gait features under these conditions. More advanced methods like Sequence-Pose Encoder-Decoder Networks [32] combine pose estimation with sequence learning, allowing for detailed analysis of joint movements and spatial relationships over time.





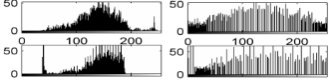
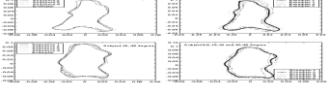





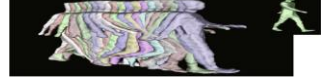


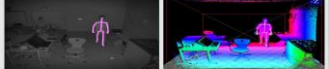
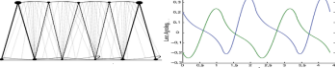
Table 1. Feature Extraction of ML approaches

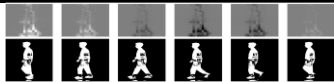



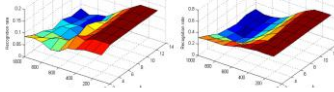
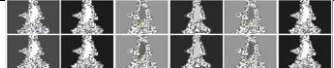

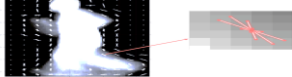

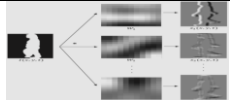
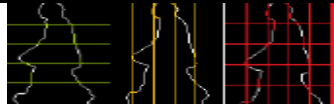
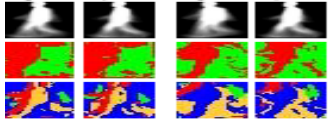
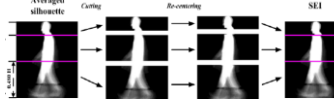
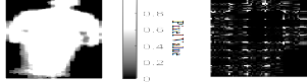
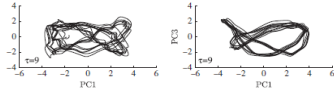

S. No	Cite	Year	Technique	Image
1	[151]	2017	Accumulated Prediction Image and Accumulated Flow Image, Edge Masked Active Energy Image	

2	[152]	2017	Gradient Histogram Energy Image from corrupted silhouettes	
3	[153]	2012	Periodic Human Motion	
4	[154]	2017	Aperiodic Feature	
5	[155]	2015	Entropy Volumes	
6	[156]	2019	Gait Recognition Depth Image	
7	[157]	2010	Active Energy Image	
8	[158]	2011	Gait Flow Image	
9	[159]	2001	Motion Energy Image, Motion History Image	
10	[160]	2020	Gait Energy Image Partitioning	
11	[161]	2018	Gait Information Image	
12	[162]	2011	Temporal Self-Similarities	
13	[163]	2009	Gait Entropy Image (GEnI)	
14	[164]	2015	Binary Motion Image	
15	[165]	2006	Gait Energy Image	
16	[166]	2010	Masked Gait Energy Image	

17	[167]	2012	Gabor Features	
18	[168]	2013	Feature Subset Selection	
19	[169]	2006	Frequency Domain Feature, Gait silhouette volume	
20	[170]	2017	Global GERF gait energy response functions, GERF	
21	[171]	2018	Average Energy Silhouette Image	
22	[172]	2015	Time Frequency Distribution	
23	[173]	2010	Optical Flow	
24	[174]	2017	Curvelet sub band of masked Gait Energy Image	
25	[175]	2020	Local Optimal Oriented Pattern Binary	
26	[176]	2011	Gait Energy Volumes	
27	[177]	2012	2.5 D The Backfilled GEI	
28	[178]	2012	Depth Gradient Histogram Energy Image	
29	[179]	2014	Pose Depth Volume Extraction	
30	[180]	2014	2D Color Gait Feature Image	
31	[181]	2006	Linear Time Normalized Gait Walking Cycles	

32	[182]	2016	Relative Distance Features	
33	[183]	2015	Gaussian Gait Image	
34	[184]	2004	Model based Gait cycle Features	
35	[185]	2017	Gait Energy Response Function	
36	[186]	2009	Time frequency image	
37	[187]	2007	Gait History Image	
38	[188]	2017	Fisher Motion Descriptor	
39	[189]	2016	Optical Flow Image	
40	[190]	2018	Discriminative Features	
41	[191]	2020	Region of Interest	
42	[192]	2013	Local Binary Pattern	
43	[193]	2019	Model based silhouettes, contours, spatio-temporal motion	
44	[194]	2017	Pressure Features	
45	[195]	2020	Binary, Edge, Skeleton, FFT of Skeleton	
46	[196]	2014	Gait Probability Image	
47	[197]	2012	Silhouette Contour	

48	[198]	2018	Shadow Features	
49	[199]	2018	Spatially Dependent Gait Energy Response Function	
50	[200]	2014	Gait Fluctuation Image	
51	[201]	2007	Feature Extraction Transforms	
52	[202]	2017	Spatiotemporal Subspace Learning	
53	[203]	2003	Statistical Shape Analysis	
54	[204]	2012	Style Adaptive Contour	
55	[205]	2013	Procrustes Mean Shape	
56	[206]	2010	Joint Extraction	
57	[207]	2010	Multiple-Projections Normalization	
58	[208]	2012	Group Sparse Representation	
59	[209]	2014	Curved Trajectories	
60	[210]	2014	Spatio-Temporal Dissimilarity	
61	[211]	2017	Hypergraph Partition	
62	[212]	2015	3D Skeleton Joint Features	
63	[213]	2009	Hybrid Dynamical Models	

64	[214]	2004	Oscillations in Pixel Intensities	
65	[215]	2014	Pyramidal Fisher Motion	
66	[216]	2007	Radial Sampling	
67	[217]	2015	Frequency-Domain Gait Entropy Termed	
68	[218]	2017	Coupled Locality Preserving Projections	
69	[219]	2018	Gabor wavelets	
70	[220]	2014	Generic Entity Resolution Framework	
71	[221]	2019	Histogram of Oriented Gradient	
72	[222]	2014	Histogram of Oriented Flow	
73	[223]	2020	Histograms of Temporal Gradients	
74	[224]	2016	Pooled Segmented Statistical Features	
75	[225]	2014	Motion Co-Clustering	
76	[226]	2012	Shifted Energy Image and Structural Feature	
77	[227]	2019	Depth Features	
78	[228]	2013	Box Geometry Reconstructed in Latent Space	
79	[229]	2014	Dynamic Distance Shape	

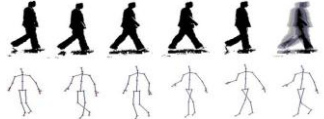
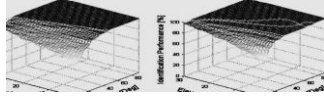
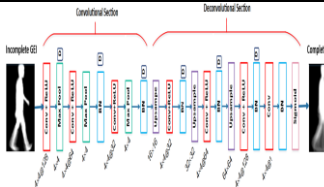
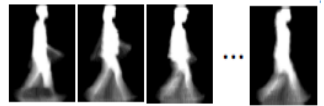
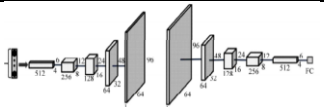
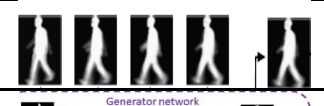
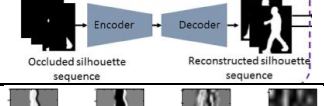
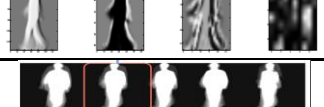
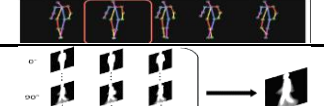
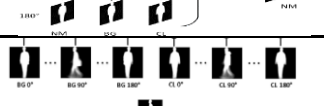
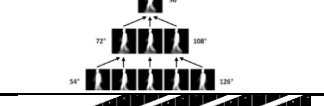


80	[230]	2018	similarity leg swing motion (step length, gait cycle with zero-crossing)	
81	[231]	2005	Motion sequences onto the 3D model	

Table 2. Feature Extraction of DL approaches

Deep Learning				
S. No	Year	Cite	Technique	Image
1	2018	[1] [6] [8] [10-13] [16] [19-22] [24] [27] [29-30] [34] [37-41] [43-44] [46-53] [56-57] [60-64] [66] [72-73] [76-78] [80-83] [85-86] [88-92] [94-96] [98] [102-105] [109] [111-120] [124-130] [132-134] [136] [138-144] [146-150]	CNN	
2	2019	[3]	Generator	
3	2019	[4-5] [7] [15] [23] [25] [35] [69] [74] [84] [135]	Encoder	
4	2019	[8]	Mean-pooling	
5	2019	[9] [18] [45] [121]	Encoder, Decoder	
6	2017	[14]	DCNN	
7	2019	[17]	Skeleton	
8	2019	[26]	Reconstructed Gait Energy Image	
9	2017	[28]	Invariant feature extraction	
10	2017	[29] [68] [95]	Long Short Term Memory	
11	2018	[31]	Stacked autoencoder	

12	2019	[32]	Encoder Sequence pose	Decoder;	
13	2019	[33]	3-D CNN		
14	2020	[36]	Gait descriptors		
15	2017	[42]	VGG-D		
16	2019	[54]	Color mapped Contour		
17	2020	[55]	Discriminant projection		
18	2019	[59]	Multi-level features	sequence	
19	2020	[65]	NDNN		
20	2019	[67]	Multi-level features	sequence	
21	2017	[70]	Optical Flows		
22	2017	[71]	Savitzky-Golay smoothing filter		
23	2018	[75]	Detection, COG		
24	2019	[79]	Gaussian low-pass filter with 0 mean		
25	2017	[87]	Descriptor		
26	2020	[93]	Optical flow		
27	2020	[97]	OF, average pooling		
28	2020	[99]	3D Gait Estimation		

3.1 Machine Learning Approaches for Gait Recognition:

The Accumulated Prediction Image and Accumulated Flow Image method, proposed in 2017, combines active energy images with accumulated flow images to enhance gait data representation, which boosts classification accuracy, though it is computationally expensive and less robust in noisy conditions [151]. Similarly, the Gradient Histogram Energy Image from Corrupted Silhouettes (2017) creates energy images based on gradient histograms, which improves robustness when dealing with corrupted silhouettes but remains sensitive to large variations in the data [152]. The Periodic Human Motion approach (2012) leverages periodic features extracted from human motion sequences, which works effectively in regular gait patterns but struggles when the walking patterns are irregular or non-periodic [153]. On the other hand, the Aperiodic Features method (2017) focuses on capturing non-periodic characteristics in gait sequences, which is useful for irregular gait detection but may be limited when handling more periodic gaits [154].

The Entropy Volumes technique, introduced in 2015, uses entropy-based metrics to capture variability in gait sequences, enabling differentiation among individuals. However, this approach is sensitive to noise and requires large datasets for accuracy [155]. The Gait Recognition Depth Image (2019) leverages depth-based features to enhance 3D spatial representation, providing accurate data but requiring specialized sensors, which may not always be available [156]. The Active Energy Image (2010) method uses energy images derived from silhouettes for fast and lightweight classification, but it struggles to capture dynamic aspects of gait [157]. Similarly, the Gait Flow Image (2011) technique uses motion flow information to capture dynamic gait features but is sensitive to noise and occlusions [158]. The Motion Energy Image and Motion History Image method (2001) applies motion-based techniques to extract energy and temporal changes, though it is now outdated and struggles with the variability of modern gait patterns [159].

The Gait Energy Image Partitioning (2020) improves traditional Gait Energy Images by partitioning them, offering better feature separation but facing limitations in handling dynamic gaits [160]. Gait Information Image (2018) processes silhouette images into compact representations that allow for efficient classification, although it is sensitive to noise [161]. The Temporal Self-Similarities (2011) method captures self-similar properties of gait over time, improving temporal feature extraction but at the cost of being computationally expensive and less robust to noise [162]. Similarly, the Gait Entropy Image (2009) uses entropy-based representations to handle variations in silhouettes but remains sensitive to noise [163].

The Binary Motion Image (2015) simplifies gait classification by creating a binary representation of motion, which is efficient for low-resolution data but loses important details in more complex gaits [164]. Gait Energy Image (2006), a foundational method for averaging images of gait cycles, is simple and effective in traditional ML models, though it is less effective for dynamic and occluded gaits [165]. The Masked Gait Energy Image (2010) applies masks to focus on key areas of the silhouette, improving classification accuracy but requiring precise masking to be effective [166]. The Gabor Features (2012) method uses Gabor filters to extract texture-based features from gait images, capturing fine details but being sensitive to noise and computationally expensive [167]. Feature Subset Selection (2013) identifies the most discriminative features in gait sequences, reducing feature space and improving accuracy, although suboptimal feature selection could lead to the loss of important information [168].

The Frequency Domain Feature Gait Silhouette Volume (2006) transforms gait silhouettes into the frequency domain for analysis, offering detailed insights into movement patterns but requiring careful handling to avoid losing spatial features [169]. Global Gait Energy Response Function (2017) uses energy response functions for robust feature representation but may struggle with occlusions and noisy data [170]. The Average Energy Silhouette Image (2018) simplifies data representation to enhance computational efficiency, though oversimplification may lead to the loss of important details [171]. Time Frequency Distribution (2015) combines time and frequency domain features to offer a comprehensive analysis of gait patterns, though it is computationally expensive [172]. The Optical Flow (2010) method captures motion dynamics in gait sequences, providing detailed motion information but remaining sensitive to motion noise [173]. The Curvelet Sub-Band of Masked Gait Energy Image (2017) enhances Gait Energy Images with curvelet sub-band filtering to preserve details, though the process is computationally intensive [174].

The Local Optimal Oriented Pattern Binary (2020) applies local binary patterns to capture texture details from gait images, improving classification accuracy but remaining sensitive to noise [175]. The Gait Energy Volumes (2011) technique extracts volumetric energy features from gait sequences, providing 3D information but requiring large amounts of data for processing [176]. 2.5D Backfilled GEI (2012) adds depth information to 2D Gait Energy

Images, offering a more detailed 3D representation but requiring depth sensors [177]. The Depth Gradient Histogram Energy Image (2012) method uses depth gradient histograms to enhance 3D feature extraction, but it is limited by the availability of depth sensors [178]. Pose Depth Volume Extraction (2014) extracts pose-related depth information for improved recognition, though specialized hardware is required [179]. The 2D Color Gait Feature Image (2014) adds color features to silhouettes, enhancing classification but being sensitive to lighting conditions [180].

The Linear Time Normalized Gait Walking Cycles (2006) method normalizes gait sequences over time to improve consistency and recognition, though its effectiveness is limited when dealing with irregular gait patterns [181]. The Relative Distance Features (2016) approach measures relative distances between body parts to provide key discriminative features but is sensitive to pose variations and occlusions [182]. Gaussian Gait Image (2015) uses Gaussian filtering to smooth silhouette images, providing more consistent feature sets but potentially oversmoothing and losing details [183]. Model-Based Gait Cycle Features (2004) uses a model-based approach to capture gait cycles, offering a structured representation of gait but struggling in noisy real-world scenarios [184]. The Gait Energy Response Function (2017) uses energy response functions to produce reliable representations, though it is computationally complex when applied to large datasets [185].

The Time Frequency Image (2009) combines time and frequency features to provide a robust representation, though this method is computationally expensive [186]. Gait History Image (2007) tracks silhouettes over time to capture temporal features, but it remains sensitive to noise and occlusions [187]. The Fisher Motion Descriptor (2017) applies Fisher motion descriptors to improve representation, though careful tuning is required to avoid overfitting [188]. Optical Flow Image (2016) captures motion information, particularly effective in dynamic environments, though it is sensitive to noise and variations [189]. The Discriminative Features (2018) technique enhances feature separation for better classification, though it requires a large dataset to perform optimally [190]. Region of Interest (2020) focuses on key areas of gait silhouettes to isolate critical features, though its accuracy is dependent on precise region selection [191].

The Local Binary Pattern (2013) method extracts texture-based features from silhouettes using LBP, which is fast and efficient but sensitive to noise and lighting variations [192]. Model-Based Silhouettes Contours (2019) focuses on extracting silhouette contours for classification, offering improved spatial representation but struggling with occlusions [193]. Pressure Features (2017) introduces pressure-based features, adding additional data points but requiring specialized equipment [194]. The Binary Edge Skeleton FFT of Skeleton (2020) technique applies Fourier transforms to skeletal gait data for frequency-domain feature extraction, though this method is computationally expensive [195]. Gait Probability Image (2014) uses probability-based methods to create robust representations, though large datasets are required for accurate results [196]. Silhouette Contour (2012) extracts contours for classification, effective for spatial analysis but sensitive to occlusions and lighting variations [197].

Shadow Features (2018) captures shadow-based features, adding context to silhouette-based approaches but remaining sensitive to lighting variations [198]. Spatially Dependent Gait Energy Response Function (2018) improves spatial resolution for Gait Energy Images, offering better accuracy but at a high computational cost [199]. The Gait Fluctuation Image (2014) technique tracks fluctuations in gait patterns to capture temporal and spatial features, though it is sensitive to motion variations [200]. Feature Extraction Transforms (2007) combines multiple transform-based methods for feature extraction, providing comprehensive feature sets but being computationally complex [201]. Spatiotemporal Subspace Learning (2017) combines spatial and temporal features for more comprehensive representation, though it is computationally demanding [202]. Statistical Shape Analysis (2003) uses shape analysis to derive key features, offering structured analysis but being sensitive to outliers and variations [203].

The Style Adaptive Contour (2012) method adapts contour shapes to different walking styles, improving adaptability, though careful tuning is required to avoid errors [204]. Procrustes Mean Shape (2013) aligns gait silhouettes using Procrustes analysis to provide a consistent representation, though it assumes shape consistency, which may not always hold [205]. Joint Extraction (2010) focuses on extracting joint data from gait sequences, providing granular motion data but requiring detailed motion capture data [206]. Multiple-Projections Normalization (2010) normalizes silhouettes across multiple projections to improve consistency, though it is limited to well-structured datasets [207]. Group Sparse Representation (2012) uses sparse representation to reduce the dimensionality of gait data, providing efficient dimensionality reduction but being sensitive to sparsity parameters [208].

The Curved Trajectories (2014) approach analyzes curved trajectories in gait sequences, providing more detailed motion features but being computationally expensive [209]. Spatio-Temporal Dissimilarity (2014) measures dissimilarity in spatio-temporal features, capturing subtle variations but remaining sensitive to noise [210]. The Hypergraph Partition (2017) technique segments gait sequences using hypergraph partitioning, which improves feature extraction but is computationally expensive [211]. 3D Skeleton Joint Features (2015) extracts 3D joint-based features, providing rich data for classification but requiring advanced sensors [212]. Hybrid Dynamical Models (2009) combines multiple dynamical models to extract temporal features, though it is complex and computationally expensive [213]. Oscillations in Pixel Intensities (2004) tracks pixel intensity oscillations to capture motion features, though it remains sensitive to noise [214].

The Pyramidal Fisher Motion (2014) method applies Fisher motion descriptors using a pyramidal approach, enhancing detail extraction but being computationally expensive [215]. Radial Sampling (2007) captures spatial variations in gait sequences through radial sampling, providing detailed spatial features but being computationally expensive [216]. Frequency-Domain Gait Entropy (2015) combines frequency-domain analysis with entropy-based features, capturing both frequency and variability information, though it is sensitive to noise and computationally heavy [217]. Coupled Locality Preserving Projections (2017) projects gait data into a lower-dimensional space while preserving locality, though it is sensitive to outliers [218]. The Gabor Wavelets (2018) method extracts texture-based features using Gabor wavelets, though it is computationally expensive and sensitive to noise [219]. The Generic Entity Resolution Framework (2014) resolves gait sequences into simpler entities, providing a compact feature representation but being limited by the accuracy of entity resolution [220].

Histogram of Oriented Gradient (2019) extracts local shape information using histograms of oriented gradients, though it is sensitive to noise and lighting variations [221]. The Histogram of Oriented Flow (2014) method extends this approach to capture flow information in gait sequences, improving temporal feature extraction but being sensitive to motion noise [222]. Histograms of Temporal Gradients (2020) combines histograms of gradients with temporal information, improving accuracy but at the cost of increased computational expense [223]. Pooled Segmented Statistical Features (2016) pools statistical features from segmented silhouettes, enhancing spatial representation but remaining sensitive to segmentation accuracy [224]. Motion Co-Clustering (2014) uses co-clustering to extract motion features, improving feature extraction efficiency but remaining computationally complex [225]. The Shifted Energy Image and Structural Feature (2012) technique combines energy images with structural feature extraction, improving representation but being limited by the accuracy of structural extraction [226].

Depth Features (2019) enhance silhouette representation using 3D depth features, though depth sensors are required for optimal results [227]. The Box Geometry Reconstructed in Latent Space (2013) method reconstructs gait silhouettes in a latent space for better representation, though it is computationally expensive [228]. Dynamic Distance Shape (2014) tracks dynamic shape changes in gait sequences to capture motion patterns, though it is sensitive to noise [229]. Similarity Leg Swing Motion (2018) focuses on leg swing motion to provide key features for classification, though it may be limited by variations in leg movement patterns [230]. Lastly, the Motion Sequences onto the 3D Model (2005) method projects gait sequences onto a 3D model for spatial analysis, providing detailed 3D spatial features but being computationally expensive [231].

3.2 Deep Learning Approaches for Gait Recognition:

Convolutional Neural Networks (CNNs) [1, 6, 8, 10-13, 16, 19-22] are widely used in deep learning for automatically extracting hierarchical spatial features from gait silhouettes. These networks offer high classification accuracy and reduce the need for manual feature engineering, making them ideal for complex tasks. However, CNNs require large datasets and significant computational resources for training, which can be a limitation. Generator models, such as GANs [3], are used to create synthetic gait data for augmentation, improving the robustness of models by reducing overfitting. Despite their usefulness, GANs are challenging to train and may produce unrealistic data.

Encoder networks [4-5, 7, 15, 23] compress gait data into lower-dimensional representations, which improves efficiency and accuracy by reducing data complexity. However, critical information can be lost if the encoder is not properly tuned. Similarly, mean-pooling [8] reduces the size of feature maps in CNNs, focusing on significant features to reduce computational complexity. Nevertheless, finer details may be lost during this process. Encoder-Decoder Networks [9, 18, 45] compress and reconstruct gait sequences, preserving key features for classification. However, these networks tend to be computationally intensive.

3D CNNs [33] extend the functionality of 2D CNNs by processing 3D data, capturing both spatial and temporal features, which leads to robust recognition. Despite their effectiveness, 3D CNNs demand more computational power and memory compared to their 2D counterparts. Discriminant projection [55] enhances class separability in deep learning frameworks, leading to higher classification accuracy, but the training process can be computationally expensive.

The Reconstructed Gait Energy Image [26] technique uses GANs to reconstruct gait energy images from incomplete or degraded data, improving the input quality and leading to better classification results. However, this method is computationally intensive, and GAN-generated artifacts can affect the output. Stacked Sparse Autoencoders [31] are used to compress gait data while extracting essential features, reducing noise and improving classification accuracy, though training autoencoders requires careful tuning and can be difficult.

Sequence-Pose Encoder-Decoder networks [32] combine pose estimation and sequence analysis, capturing temporal and pose information for improved gait recognition. However, these networks are computationally demanding, particularly for long sequences. Recurrent Neural Networks (RNNs) [29, 68, 95], including LSTMs, are highly effective at capturing temporal dependencies in gait sequences, making them suitable for handling sequential data like video frames. However, RNNs are prone to vanishing gradient problems and can be computationally expensive.

The Invariant Feature Extraction method [28] focuses on extracting features that remain invariant to viewpoint or occlusion, improving robustness in challenging environments. However, it requires large datasets to be trained effectively. Skeleton-Based Recognition [17, 137] uses skeletal data to improve recognition, especially in scenarios where silhouettes are occluded or incomplete. This method is robust in such cases, but it requires skeletal tracking, which may not always be available.

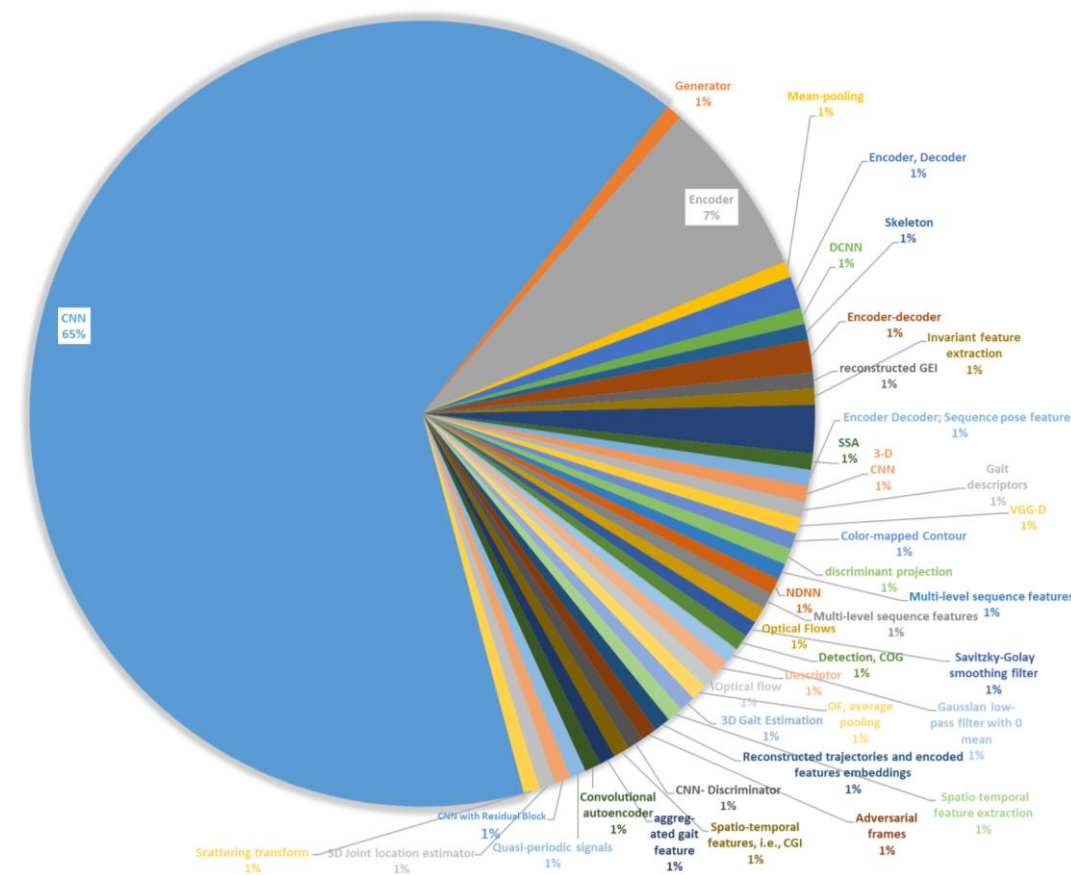


Figure 2. Ratio of Most Adopted Feature Extraction Techniques in Gait Recognition

Gait Energy Images [26, 83] are processed using deep learning methods to extract hierarchical feature maps automatically, which is more effective than traditional methods. However, the process is computationally expensive and requires large amounts of training data. Similarly, Pose-Based Recognition [135] uses pose-based models to capture joint movements and relationships, providing detailed analysis of joint movements. While this method improves recognition, it is sensitive to inaccuracies in pose estimation. Lastly, GAN-based feature generation [16, 27, 29, 30] generates synthetic gait data to augment training datasets, increasing data diversity and reducing overfitting. However, GANs are difficult to train, and the synthetic data they produce may not always accurately represent real-world patterns, potentially reducing effectiveness in some scenarios. This summary captures the deep learning approaches' strengths and limitations, highlighting how these advanced techniques enhance gait recognition while noting the computational and training challenges that may arise.

As illustrated in Figure 2, Convolutional Neural Networks (CNNs) dominate the feature extraction techniques for gait recognition, accounting for 65% of the adopted methods. Other approaches, such as Encoder methods (7%) and Generative Adversarial Networks (GANs), which contribute 1%, reflect the diversity in handling gait data through dimensionality reduction, data augmentation, and automatic feature extraction. This wide range of techniques emphasizes the flexibility required to manage the complexities in gait recognition systems.

4. Feature reduction and transformation

In the context of feature reduction and transformation as given in table 3 and 4, machine learning approaches have traditionally relied on techniques like Principal Component Analysis (PCA) [236, 238] and Linear Discriminant Analysis (LDA) [240], which focus on projecting high-dimensional gait data into lower-dimensional spaces to enhance computational efficiency. PCA is used to reduce the dimensionality of silhouette images or Gait Energy Images (GEI), maintaining the variance within the dataset while simplifying the feature set. This approach has been particularly useful in real-time gait recognition by reducing the computational burden. LDA, on the other hand, projects gait data into a subspace where class separability is maximized, improving recognition accuracy by distinguishing between individuals' gait patterns.

Other advanced methods like Kernel Principal Component Analysis (KPCA) [237], Multilinear Principal Component Analysis (MPCA) [238], and Multilinear Discriminant Analysis (MLDA) [243] handle more complex, multi-dimensional data by extending traditional PCA techniques to tensors, making them suitable for 3D gait sequences. Techniques such as Independent Component Analysis (ICA) [242] help address challenges like background noise or camera angle variations, enhancing feature extraction by isolating gait-related signals.

Deep learning models, however, have shifted towards integrating feature reduction directly into network architectures. For instance, Convolutional Neural Networks (CNNs) incorporate pooling layers (e.g., Max Pooling, Average Pooling) [36, 59, 83] to reduce the spatial dimensions of feature maps while retaining critical information. This makes the feature extraction process more efficient, especially in large-scale datasets. Additionally, Autoencoders [105] compress gait data into a latent space, learning compact representations of the input data without the need for manual feature engineering. The adoption of Generative Adversarial Networks (GANs) has further improved feature augmentation and transformation by generating synthetic data for training, addressing the challenge of limited real-world data for model training.

By automating the feature reduction process and embedding it within the network architecture, deep learning models have demonstrated better scalability and accuracy in handling real-world gait recognition tasks compared to traditional machine learning methods.

Table 3. Feature reduction and transformation in Machine Learning

Machine Learning			
S. No	Cite	Year	Technique
1	[236]	2007	Principal Component Analysis
	[238]	2003	
2	[237]	2007	Kernal Principal Component Analysis
3	[238]	2006	Multilinear Principal Component Analysis
4	[239]	2006	Two-Stage Principal Component Analysis

5	[240]	2004	Linear Discriminant Analysis
6	[241]	2013	Multiple Discriminant Analysis
7	[242]	2005	Independent Component Analysis
8	[243]	2017	Multilinear Laplacian Discriminant Analysis
9	[244]	2014	Local Binary Pattern
10	[245]	2010	Modified Independent Component Analysis
11	[246]	2016	Multilinear Analysis
12	[247]	2008	Kernel Fisher Discriminant Analysis
13	[248]	2003	Regularized Local Tensor Discriminant Analysis
14	[249]	2017	Joint-Direct Linear Discriminant Analysis
15	[250]	2018	Euclidian Norm
16	[251]	2012	Discrete Cosine Transform

Table 4. Feature reduction and transformation in Deep Learning

Deep Learning			
S. No	Year	Feature reduction and transformation	Cite
1	2018	Up-sampling	[1]
2	2019	Discriminator	[3] [19] [38] [45-46] [48] [62] [105]
3	2019	Sparse representation	[4]
4	2019	Unsamplng	[5]
5	2019	Principal Component Analysis	[5] [7] [15] [28] [41-42] [65] [87] [88] [97] [100] [111]
6	2019	View transform	[8]
7	2019	Flip, Rotation, Zoom, Clip, Translation, Adding Noise	[10]
8	2017	LDA	[12] [43] [92] [94]
9	2020	Decoder	[23] [25] [26] [35] [84] [98] [100] [122] [135]
10	2018	Gaussian distribution	[30]
11	2019	Optical flow computation	[34]
12	2020	Pooling	[36] [79]
13	2020	YCbCr Transformation	[37]
14	2018	pooling by a rectifier	[43]
15	2019	Linear interpolation	[54]
16	2019	Max pooling	[58]
17	2019	Set pooling	[59] [67]
18	2019	Ablation	[60]
19	2020	FFD geometric transformation	[66]
20	2016	Linear transformation	[69] [120]
21	2017	Local Directional Pattern	[70]
22	2018	Euclidian distance	[75]
23	2020	Horizontal Pooling	[83]
24	2019	Deconvolutional layer	[91]
25	2020	Aggregation	[93]
26	2020	Temporal displacement	[100]
27	2019	Deconvolution Layer	[104]
28	2018	Gated Recurrent Units	[127]

29	2019	Average pooling	[129]
30	2019	TF Transform	[133]
31	2019	F- score	[137]
32	2020	Gaussian noise; Scaling	[138]
33	2020	DCT; Scattering transform; PCA	[145]
34	2020	Batch normalization	[148]
35	2020	Doppler Fourier Transform	[149]

Here is the detailed breakdown of feature reduction and transformation methods in machine learning (ML) and deep learning (DL) approaches, along with advantages and disadvantages:

In machine learning approaches, Principal Component Analysis (PCA) [236] is widely used for reducing the dimensionality of gait data by retaining the most important variance, which enhances computational efficiency and is crucial for real-time processing. However, PCA is limited by its assumption of linearity, making it less effective in capturing complex, nonlinear gait patterns. Kernel Principal Component Analysis (KPCA) [237] addresses this limitation by capturing nonlinear relationships in gait data through kernel methods, improving performance in complex datasets. However, KPCA is computationally intensive and requires careful tuning of kernel parameters. Multilinear Principal Component Analysis (MPCA) [238] extends PCA to multi-dimensional tensors, making it suitable for 3D gait data by preserving spatial-temporal features, though it has high computational complexity, limiting its use in real-time applications. Two-Stage PCA [239] refines feature reduction by applying PCA in multiple stages, improving accuracy, but at the cost of additional computational overhead.

Linear Discriminant Analysis (LDA) [240] maximizes class separability by projecting gait data onto a lower-dimensional space, improving classification accuracy. However, it assumes Gaussian distribution within classes, which may not hold in real-world datasets, reducing its effectiveness. Multiple Discriminant Analysis (MDA) [241] extends LDA for multi-class problems, optimizing class separability, but it is prone to overfitting and suffers from the curse of dimensionality in smaller datasets. Independent Component Analysis (ICA) [242] decomposes gait data into independent components, effectively isolating gait-related features from noise, though it is sensitive to variations and requires careful preprocessing. Multilinear Laplacian Discriminant Analysis (MLDA) [243] applies LDA to tensor-based data, making it suitable for 3D gait recognition, though it is computationally expensive and can overfit on small datasets.

Local Binary Pattern (LBP) [244] is a simple, fast, and effective texture-based method for transforming gait silhouettes into binary patterns for classification, but it is sensitive to lighting variations, reducing its robustness in uncontrolled environments. Modified ICA [245] introduces additional constraints to ICA, improving feature isolation in noisy datasets, though it increases computational complexity and requires careful tuning. Multilinear Analysis [246] efficiently handles multi-dimensional gait data, preserving spatial relationships, but it requires high memory and computational resources, limiting its use in real-time systems. Kernel Fisher Discriminant Analysis (KFDA) [247] uses kernel methods to capture nonlinear separability in gait data, but like KPCA, it is computationally intensive and requires careful kernel parameter tuning.

Regularized Local Tensor Discriminant Analysis [248] improves robustness to variations in gait sequences by applying regularization, though this adds computational cost. Joint-Direct LDA [249] combines joint-based features with LDA for more accurate recognition but is limited by LDA's inability to capture nonlinear data. Euclidean Norm [250] simplifies the representation of gait data by focusing on distance-based features, which makes computations faster but may not fully capture complex gait variations. Finally, Discrete Cosine Transform (DCT) [251] reduces dimensionality by transforming data into the frequency domain, capturing significant features but being sensitive to noise and potentially discarding critical spatial information.

In deep learning approaches, Up-sampling [1] is used to enhance the spatial resolution of gait features, improving feature extraction accuracy, though overuse can lead to overfitting. Discriminators in GANs [3, 19, 38, 45-46, 48, 62, 105] are employed to differentiate between real and synthetic data, improving the quality of learned features. However, GANs are notoriously difficult to train and achieve stable convergence. Sparse Representation [4] reduces redundancy in feature maps, making models more efficient, though excessive sparsity risks losing critical details. PCA in DL architectures [5, 7, 15, 28, 41-42, 65, 87, 88, 97, 100, 111] helps reduce the dimensionality of

high-level features, enhancing computational efficiency and reducing overfitting, but PCA's assumption of linearity limits its ability to capture complex, nonlinear relationships in deep learning models. View Transform [8] normalizes gait features across different camera angles, improving robustness in multi-camera setups, though poorly tuned parameters can introduce distortions. Flip, Rotation, Zoom [10] data augmentation techniques improve model generalization by introducing variations during training, though overreliance on these transformations may cause overfitting to augmented data instead of focusing on real-world variations.

LDA in DL [12, 43, 92, 94] enhances class separability at the final classification stages, improving accuracy, though its linear nature may limit effectiveness in nonlinear deep learning models. Encoder-Decoder Networks [23, 25, 26, 35, 84, 98, 100, 122, 135] compress gait data into latent space and reconstruct it, reducing noise and dimensionality, though the computational cost is high, especially for large datasets.

This structured breakdown captures the various ML and DL approaches to feature reduction and transformation in gait recognition, detailing how they enhance classification performance while considering the associated computational and practical challenges.

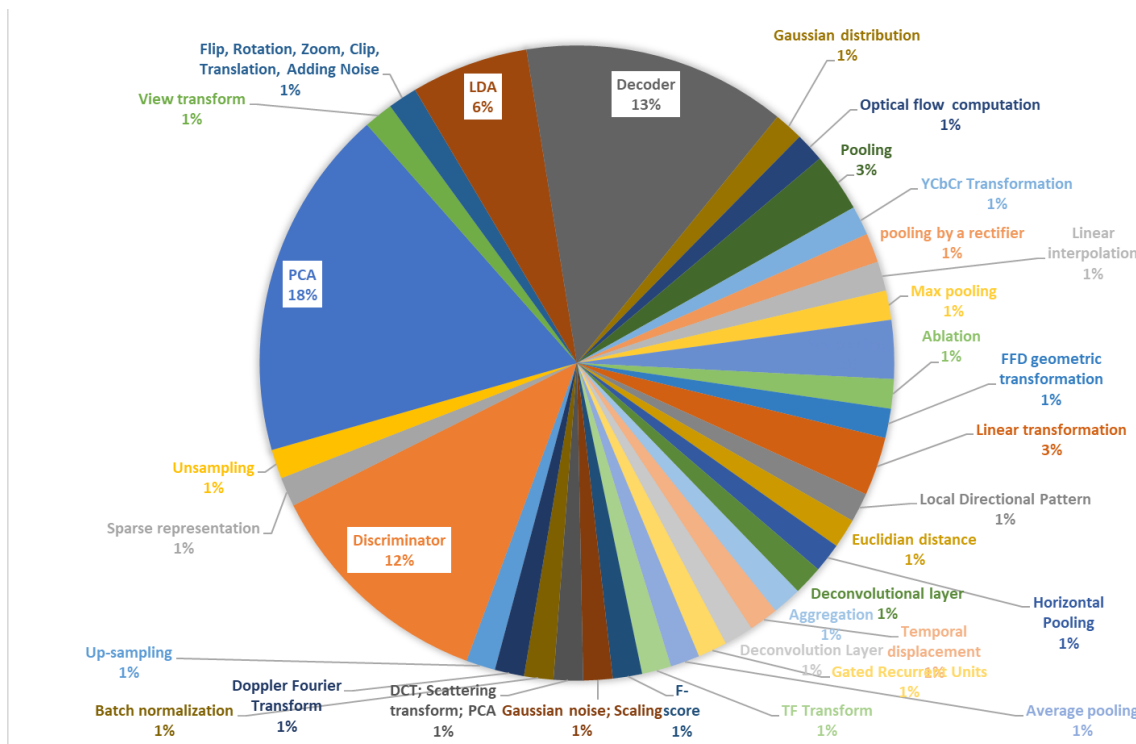


Figure 3. Ratio of Most Adopted Feature Reduction and Transformation Techniques in Gait Recognition

As shown in Figure 3, Principal Component Analysis (PCA) leads the feature reduction and transformation methods with 18%, followed by Decoder methods at 13%, and Discriminators (12%) commonly used in GANs. These techniques highlight the balance between traditional methods like PCA and more advanced deep learning approaches such as Encoder-Decoder architectures for efficiently processing gait data.

5. Classification

Classification plays a pivotal role in the domain of gait recognition, serving as a critical component in translating extracted gait features into meaningful, discriminative outputs. Through classification, systems are equipped to identify individuals based on the unique patterns inherent in their walking styles. The efficacy of gait recognition systems largely depends on the choice of classification technique, which can significantly impact both accuracy and computational efficiency.

Machine Learning (ML) and Deep Learning (DL) represent two principal paradigms for classification in gait recognition. ML approaches traditionally rely on manually engineered features and classical algorithms, offering interpretability and often requiring less computational power. In contrast, DL techniques enable automatic

feature extraction and hierarchical representation learning, often achieving superior performance on complex datasets due to their capacity to model non-linear and high-dimensional patterns.

The classification techniques used in both ML and DL frameworks are diverse and have evolved over time. In ML, techniques such as Bayesian Frameworks, Hidden Markov Models, and Support Vector Machines have been widely applied, each contributing different strengths such as probabilistic modeling, temporal dynamics handling, and margin-based separation. Similarly, DL methods utilize a range of strategies such as Sigmoid and Softmax functions, Backpropagation, and adversarial training methods like Wasserstein GANs, which leverage deep architectures for robust performance.

Tables 5 and 6 summarize the classification techniques employed in Machine Learning and Deep Learning for gait recognition, respectively. These tables illustrate the progression and variation in classification strategies, emphasizing how the field has evolved from early probabilistic and ensemble-based models to contemporary approaches rooted in neural optimization and deep generative modeling.

Table 5. Classification of Machine Learning (ML) Techniques in Gait Recognition

Machine Learning			
S.No	Cite	Year	Classification Techniques
1	[252]	2006	Bayesian Framework
2	[253]	2008	Hidden Markov Models
3	[254]	2008	Neural Network Ensemble
4	[255]	2008	Manifold Learning
5	[256]	2009	Soft Computing
6	[257]	2009	Support Vector Machine
7	[258]	2009	Neural Network Ensemble with Probabilistic Fusion
8	[259]	2009	Recurrent Neural Network
9	[260]	2010	Probabilistic Approach
10	[261]	2010	Swarm Optimization
11	[262]	2012	Boosting
12	[263]	2013	Regression Method
13	[264]	2014	Probabilistic Support Vector Machine
14	[265]	2014	Incremental Support Vector Machine
15	[266]	2014	Classifier Ensemble Method
16	[267]	2015	Regularized
17	[268]	2017	Subspace ensemble learning via totally corrective boosting
18	[269]	2016	Random Forests
19	[270]	2017	K Nearest Neighbor, Artificial Neural Network, Deep Neural Network
20	[271]	2017	Set-Collaboration Metric Learning
21	[272]	2017	Subspace Ensemble Learning Framework via Totally Corrective Boosting and Tensor-Based
22	[273]	2016	Local Nearest Neighbor Embedding
23	[274]	2018	Semi- and weakly-supervised
24	[275]	2018	Collaborative Representation Classification

Table 6. Classification of Deep Learning (DL) Techniques in Gait Recognition

Deep Learning			
S. No	Year	Classification	Cite
1	2018	Sigmoid	[1] [15] [35] [78] [84] [132]
2	2019	Binary classification	[3] [6] [76] [110]

3	2019	Back-propagation	[4] [24] [70] [91]
4	2019	Nearest neighbor	[5] [8] [28] [41-45] [87-88]
5	2019	Regression based	[6]
6	2019	Random Forest	[7]
7	2019	Wasserstein GAN	[9]
8	2019	Softmax	[8] [10] [12-13] [16-17] [20] [22] [27] [30-31] [33-34] [38-40] [44] [47-51] [54] [56-58] [61] [64] [68] [71-72] [74-75] [77-78] [81-82] [85-86] [88-90] [93] [95-96] [99-103] [105] [111] [113] [118-120] [122] [124-125] [127-131] [133] [136] [139] [140 -144] [147 - 150]
9	2016	Linear SVM	[11]
10	2017	Nearest Centroid	[12]
11	2017	SVM	[13] [16] [18] [65] [73] [92] [94] [116] [117] [121] [125] [137]
12	2017	Logistic regression loss	[14] [56]
13	2019	Latent semantic analysis	[19]
14	2020	Cross-reconstruction	[21]
15	2020	Discriminator	[23] [25] [26] [62] [109]
16	2019	Auto encoder	[32]
17	2020	KNN	[37] [82] [92] [97] [138] [147]
18	2020	Directed Acyclic Graph	[36]
19	2020	Multi SVM	[37]
20	2018	Decision based	[43]
21	2019	Triplet loss	[46] [52] [53]
22	2020	Metric learning	[55]
23	2019	Horizontal pyramid pooling	[59]
24	2019	Fully Connected layer	[63]
25	2020	Triplet ranking loss	[66]
26	2019	Horizontal pyramid pooling	[67] [80]
27	2016	Recurrent attention model	[69]
28	2017	Back propagation	[70]
29	2019	supervised classification through LSTM	[79]
30	2020	Euclidean distance	[83]
31	2019	Back propagation	[91]
32	2020	Fine Tree	[92]
33	2019	Histogram distance	[104]
34	2020	GaitSet (DNN)	[106]
35	2020	Linear layer	[107]
36	2019	Margine layer	[108]
37	2018	Adaptive late fusion	[112]
38	2016	One-class Softmax	[113]
39	2017	Multi channels DCNN	[114]
40	2017	One-class SVM	[115]
41	2018	RBF network estimators	[123]
42	2018	Gradient boosting	[126]
43	2019	Semi-supervised	[135]
44	2020	Log softmax	[139]
45	2020	Hidden Markov Model	[145]
46	2020	Linear regression	[146]
47	2020	Multilayer Perceptron	[147]
48	2020	Artificial Neural Network	[147]

In the realm of machine learning approaches, the Bayesian Framework [252] leverages prior knowledge to estimate posterior probabilities for gait classification. Its strength lies in providing a robust probabilistic foundation, particularly effective when prior knowledge is available, but it demands significant prior data and is computationally expensive. Hidden Markov Models (HMM) [253] are well-suited for modeling temporal dynamics in gait sequences, capturing the transitions between successive feature vectors. HMMs excel at handling sequential data but are computationally intensive, especially for large datasets. The Neural Network Ensemble [254] approach combines multiple neural networks, improving classification performance by handling complex and nonlinear data. However, it requires significant computational resources and can be challenging to train.

Manifold Learning [255] offers an efficient method to reduce the dimensionality of gait data while preserving its geometric properties, making classification more efficient. This method is suitable for handling high-dimensional data, but it struggles with highly nonlinear or noisy datasets. Soft Computing [256] approaches integrate various computational techniques, such as fuzzy logic and genetic algorithms, to classify gait data. These techniques are flexible and adaptable to noisy or imprecise data, but they tend to be slower and require extensive fine-tuning. Support Vector Machines (SVMs) [257] find an optimal hyperplane that maximizes the margin between gait classes, excelling in high-dimensional spaces and binary classification tasks. However, SVM performance is sensitive to the choice of kernel and can degrade in the presence of noisy data.

The Recurrent Neural Network (RNN) [259] method is commonly used for sequence-based data like gait, as it captures long-range temporal dependencies within the gait cycle. RNNs are highly effective in such tasks but are prone to vanishing gradient problems and are computationally expensive. A Probabilistic Approach [260] models the likelihood of different gait patterns, offering robustness in handling uncertainties but requiring extensive computation for larger datasets. Swarm Optimization [261] techniques, such as particle swarm optimization, optimize classifier parameters for more effective classification of complex, nonlinear gait data. This method is effective for optimization tasks but can be slow to converge and is sensitive to parameter settings. Finally, boosting [262] improves the performance of weak classifiers by combining them into a stronger classifier, enhancing classification accuracy and handling imbalanced data effectively, though it is prone to overfitting when applied to noisy data.

In deep learning approaches, the Sigmoid Classifier [1, 15, 35, 78, 84, 132] is commonly used for binary classification tasks, offering smooth gradient properties and computational efficiency in such problems. However, it is not ideal for multi-class classification due to its binary nature. Similarly, Binary Classification methods [3, 6, 76, 110] simplify the classification process by distinguishing between two classes, such as identifying whether a subject belongs to a specific group or not. This approach is fast but limited to binary problems and requires adaptation for multi-class scenarios. Backpropagation [4, 24, 70, 91] is the key algorithm used to train neural networks by adjusting the weights to minimize error. It is a powerful method for training deep networks, though it is computationally intensive, especially as networks become deeper.

The Nearest Neighbor Classifier (KNN) [5, 8, 28, 41-45, 87-88] classifies gait data by evaluating the nearest neighbors in the feature space and using a majority vote. KNN is simple to implement and effective for small datasets, but it becomes computationally expensive with large datasets and is sensitive to noise. Regression-Based Classifiers [6] predict continuous values in gait recognition tasks, which are effective for continuous prediction but not ideal for categorical classification problems. Random Forest [7] uses multiple decision trees to improve classification accuracy by averaging the predictions from multiple trees. This technique reduces the risk of overfitting and is robust to noise, but it is computationally expensive due to the large number of trees required.

The Softmax Classifier [8, 10, 12-13, 16-17, 20] is frequently used in multi-class classification tasks within deep learning models, providing probabilistic outputs for each class. Softmax performs well in multi-class classification but is sensitive to outliers and requires careful model optimization. Similarly, SVM in DL [13, 16, 18, 65, 73] is used in some deep learning models as the final classifier, effectively handling high-dimensional and complex data but being computationally expensive and sensitive to parameter tuning.

These approaches, whether leveraging traditional machine learning methods or more advanced deep learning techniques, offer diverse strategies for gait classification, each with distinct advantages and disadvantages depending on the complexity of the dataset and the specific application requirements.

6. Future Prospects in Gait Recognition: Challenges and Opportunities

Gait recognition has made significant strides in recent years, especially with the advent of advanced deep learning techniques. However, the field still faces challenges that need to be addressed to fully realize its potential. In this section, we will discuss the future prospects and emerging trends under several key themes.

1. Multimodal Gait Recognition

Combining Different Modalities for Robust Recognition

One of the most promising future directions is the integration of multimodal data, such as combining visual data with depth, infrared, or thermal imaging, as well as skeletal and pressure-based gait patterns. Each modality brings its unique strengths:

- Depth information can provide accurate 3D spatial representation, improving recognition under varying conditions.
- Thermal imaging helps in low-light or dark environments where traditional RGB cameras fail.
- Skeletal data captures motion dynamics, which is crucial in scenarios with occlusions or non-standard walking patterns.

Challenges: While multimodal approaches offer more robust recognition, they require specialized sensors, which may not be available in all environments. The increased complexity in data fusion and processing also poses computational challenges.

2. Real-Time Processing and Edge Computing

Gait Recognition in Real-World Applications

One of the major goals of future gait recognition systems is to enable real-time processing for dynamic environments such as surveillance, healthcare, or smart homes. Current systems, particularly deep learning models, often require substantial computational resources, which limits their real-time applicability.

Hardware Acceleration: With advancements in GPU and TPU technologies, real-time gait recognition systems are becoming more feasible. Leveraging edge computing, where data processing happens locally on devices rather than cloud servers, can significantly reduce latency.

Challenges: Even with hardware advancements, the real-time deployment of deep learning models requires optimizing both algorithm efficiency and hardware-software integration. Achieving this balance is essential for real-world applicability.

3. Generative Models and Data Augmentation

Handling Missing, Occluded, and Limited Data

Generative Adversarial Networks (GANs) are emerging as powerful tools for creating synthetic gait data, handling missing frames, or augmenting datasets with realistic variations. GANs can help:

- Overcome challenges of limited training data by generating diverse and augmented samples.
- Restore incomplete or occluded gait sequences, enabling more accurate recognition in real-world conditions.

Challenges: Training GANs is notoriously difficult due to convergence issues, and synthetic data must be carefully validated to ensure it accurately represents real-world scenarios.

4. Privacy-Preserving Gait Recognition

Addressing Ethical and Privacy Concerns

With the widespread adoption of gait recognition, especially in surveillance and security, concerns about privacy and ethical implications are growing. Future gait recognition systems need to ensure that biometric data is collected, stored, and used in a manner that respects privacy rights.

Techniques such as:

- Federated learning, which enables training models on local devices without transferring sensitive data to central servers, may play a key role in privacy-preserving gait recognition.
- Differential privacy can also be employed to anonymize gait data, protecting individuals' identities while maintaining the utility of the data.

Challenges: Balancing privacy preservation with recognition accuracy is an ongoing challenge. Techniques like federated learning introduce communication overhead, while differential privacy can degrade model performance if not applied carefully.

5. Cross-Domain Gait Recognition

Generalizing Across Domains and Conditions

A critical future challenge for gait recognition is ensuring that models generalize well across different domains (e.g., varying lighting, camera angles, clothing changes). This remains a bottleneck for deploying these systems across diverse environments.

Domain Adaptation techniques, which allow models to transfer learned representations from one domain to another, are crucial in ensuring robust performance across different conditions. Models can be pre-trained on large, diverse datasets and fine-tuned to new environments with minimal labeled data.

Challenges: Cross-domain recognition requires building models that can adapt to unseen environments while maintaining high accuracy. Achieving this may require combining domain adaptation techniques with multimodal data.

6. Human Gait as a Behavioral Biomarker

Applications Beyond Security and Surveillance

Gait recognition has traditionally been used for security and surveillance, but its future applications extend to healthcare and behavioral analytics. Gait is increasingly being used to assess an individual's health, cognitive state, or even mood. Potential applications include:

- Early detection of neurodegenerative diseases (e.g., Parkinson's or Alzheimer's) through gait analysis.
- Monitoring physical rehabilitation progress by tracking improvements in walking patterns.

Challenges: These healthcare applications require highly precise and sensitive models capable of detecting subtle gait variations over time. Further research is needed to develop specialized models for such use cases.

6. Conclusion

This review highlights the advances made in gait recognition through machine learning and deep learning approaches, with a particular focus on feature extraction, reduction, transformation, and classification techniques. While traditional machine learning methods relied heavily on handcrafted features and external dimensionality reduction, deep learning has revolutionized the field by automating feature extraction and integrating feature reduction directly into network architectures. Despite the progress made, challenges such as handling occlusions,

clothing variations, and camera viewpoint changes still persist. The incorporation of multimodal data, advancements in real-time processing, and the use of GANs for data augmentation and restoration represent exciting future directions for improving gait recognition systems. Ultimately, the choice between machine learning and deep learning techniques should be guided by the specific application, dataset size, and computational resources available.

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