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Report: Human Gait Recognition Using Deep Learning

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Table of Contents

Abstract	3
Introduction	4
Background	5
Problem Statement.....	5
Research Objectives	6
Scope of the Project	6
Literature Review	7
Critical Analysis:.....	10
Connections	10
Conflict among Methods	11
Proposed Methodology	15
Expected Results	15
Plan of the Work: Gantt Chart	16
References	17

Human Gait Recognition Using Deep Learning

Abstract

There are several methods for the identification and authentication of people. Human gait recognition uses the walking pattern of a person for authentication and recognition. This is considered an efficient and reliable method of biometric identification. However, some factors degrade the recognition rate of the human gait recognition methods such as variation of clothes, carrying, clothing, etc. This work aims to propose a two-phase human gait recognition technique for the recognition of individuals. Phase-1 is based on the data preparation such as frame extraction, resining, augmentation, and normalization of data. Phase-2 aims to design a CNN model based on an attention mechanism for feature extraction and classification. The performance of the model will be tested using different datasets and computing different evaluation measures such as accuracy, loss, and confusion matrix. The proposed method will also be compared with recent methods for recognition rate.

Introduction

In the past few years, human gait recognition (HGR) has gotten the attention of researchers due to its vital role in security purposes. There are several techniques being used for the identification and authentication of people including iris [1], face [2], fingerprints, etc. The gait is considered the most suitable due to easy availability and acquisition of data. As the cameras are installed in different areas such as streets, buildings, banks, airports, and embassies the cooperation of individuals is not required to capture the data. In the gait, the attributes of the walk are used to recognize an individual. The gait is also used for several other purposes such as medical diagnosis, security, and surveillance [3].

In the HGR, the features of gait are used for recognition that is easy to obtain but some alarming factors can minimize the performance of the HGR method. These factors include variations in clothes [4], walking speed, view, carrying [5], etc. The low light and shadows of feet can also affect the gait pattern acquisition.

The HGR approaches can be divided into two categories such as model-based [6] and model-free [7] using different techniques such as machine learning or deep learning. The human body structure is utilized for recognition in the model-based approach while the model-free approach uses the silhouette of the human body. The first technique works well on different factors such as variations of cloth, views, and carrying but faces the problems of high computation [8]. The second approach has low computational cost but is prone to various factors [9, 10].

A generic model of HGR is based on several steps such as data preprocessing, segmentation, feature extraction, optimization, and classification or recognition.

In the preprocessing, the data is normalized to make it suitable for further processing [4]. This step can be based on different methods such as noise removal, background elimination, and contrast enhancement. and many more. This step is important to feed the suitable data to the segmentation in which the relevant information of the input data is obtained. This step includes different approaches such as thresholding and watershed [9]. The segmented data is passed to the HGR system for feature extraction in which the important attributes of the data are obtained. The feature extraction step is crucial because it needs to extract the relevant features of the input data. There are several methods for feature extraction such as shape[11], color[12], texture, and geometric[13]. The irrelevant feature extraction may fail the HGR method. Therefore, the refinement of features is performed using a suitable feature selection or optimization technique. After feature extraction,

these features need to be optimized so that the HGR method performance is not compromised in accuracy and computational cost. This step includes the selection of relevant features and eliminating the irrelevant. There are several feature optimization methods such as nature-inspired, Principle Component Analysis [14], entropy [15], etc. [16]. The last step in the HGR system is classifying the data which gives the final output. The classification can be performed using different approaches such as machine learning classifiers including SVM, KNN, and Decision Tree.

Background

In the HGR, the human gait is utilized for recognition purposes. Many methods are being used for person authentication, but HGR is considered a better option due to its data acquisition procedure. In data acquisition, there is no need for personal cooperation because data is captured from a distance. There are many methods designed by authors for HGR. Some are based on classical feature extraction such as HOG; some are based on deep features. This project offers a CNN model based on the attention mechanism which tends to obtain good features and offer better accuracy. Moreover, the proposed model evaluation aims to check the performance of different gait datasets such as CASIA-A and CASIA-B.

Problem Statement

In HGR, the walking style of a person is utilized for recognition or behavioral analysis. This is also used to diagnose medical problems. There are many methods introduced by researchers for HGR but faced the degradation of performance due to different factors such as clothing variations, view variations, and different carrying conditions. Some techniques perform well on a specific dataset but their performance is minimized on other datasets so the generalization is not achieved [17, 18]. Many methods are based on multiple streams and perform well but their computational cost is high so cannot be used in real-world environments [19]. In some methods feature selection approach is employed but fails due to relevant information loss [20, 21]. Furthermore, the methods that use feature optimization and data augmentation are less flexible [22]. This research aims to design an HGR method that overcomes these problems and offers efficiency, adaptivity, generalizability, and flexibility.

Research Objectives

1. **To expand the feature extraction and combination of methods** with the help of spatial and temporal features and also ensure the recognition rate and computational efficiency.
2. **To develop a strong HGR method** that effectively overcomes the problems of variation in angle, clothing, and background variability and also ensures generalizability to improve the system performance.
3. **To evaluate the efficacy of the single and multi-stream methods by extracting such** features that are discriminative, conducting analysis to adapt the trade-offs in terms of performance, flexibility, and computational cost of the HGR.
4. **To inspect the impression of feature selection and optimization methods'** using entropy or skewness-based selection of features on the recognition rate and stability of the HGR method, by eliminating the feature loss and improving results.
5. **To carry out a comparison of the HGR method performance utilizing multiple datasets**, such as CASIA-A, B, and C, to ensure its generalizability and robustness in real-world environments.

These objectives will offer such an HGR method that is generalized. Optimized, robust, and adaptable.

Scope of the Project

The project scope is based on the implementation of an attention-based CNN HGR method. This method aims to conduct experiments on different HGR datasets to test its generalization capabilities. The method is based on a robust preprocessing, feature extraction, and classification architecture based on the attention mechanism making it efficient for person authentication. The method can be implemented in different areas such as banks, airports, or health care units. This model can be used for both biometrics and healthcare abnormalities.

Literature Review

Researchers have carried out a lot of work on human gait recognition (HGR) to address different factors affecting the recognition technique's performance.

The authors presented a new method based on a two-stream network. The technique is comprised of five steps such as frames acquisition from video data, conversion of frames into Grayscale, designing of a two-stream network for feature extraction, feature fusion obtained from both streams and classification using machine learning algorithms. A 55-layer CNN model is designed from scratch to design both streams. The optical flow is obtained using the Horn and Schunk algorithm, and temporal features are obtained using the CNN model in stream-1. While the frames are directly passed to the CNN model for feature extraction in the stream-2. The method is validated using CASIA-B and more than 90% accuracy is obtained on each angle. The method gives good outcomes on the CASIA-B dataset but shows degraded performance on the CIFAR-100 dataset on which it was originally trained [17].

A method based on deep learning feature extraction is proposed to overcome the recognition problem in HGR. The method is comprised of several steps such as the processing of input data, the region of interest segmentation, feature extraction using the VGG model, and classification. The input image of 128×128 is given as input to the model and features are obtained using the transfer learning technique. The model has different layers and can be divided into five distinct groups such as a group having two convolution layers and the second type of group is based on three convolution layers. The feature extraction is performed using convolution layers and classification is performed using a fully connected or dense layer. The method is evaluated with the help of a publicly available dataset called CASIA-A and a maximum accuracy of 97.80% is obtained. The method performed well on the CASIA-A dataset but the generalizability is not validated [18].

The assurance of correctness and safety is carried out by introducing an HGR method using the CNN model. The method includes several steps such as video-to-frame conversion, GEI's extraction by applying to preprocess, and ROI identification such as the knee, hip, angle of the knee, etc, feature extraction using original and ROI data, feature vector fusion, and classification of data. The data of 150×150 is taken as input and preprocessing is applied using Grayscale conversion and background removing. After preprocessing, the model-based and appearance-based feature extraction is carried out. In the next step, the Fused Gait Feature

Representation (FGFR) model is designed to concatenate both extracted feature vectors. In the last step, the classification of the data is carried out. The model is tested using CASIA-A-A and CASIA-B datasets and accuracy of 99.60% and 99.80% is obtained. The model performed very well by aggregation of the features by is computationally intensive due to the fusion of features. Moreover, the model-based approach is also dependent on the data and may fail if the RIO is not correct [19].

To overcome the angle, view, and clothing variations problem in HGR, a new method is proposed based on four steps. The features are obtained with the help of two pre-trained models such as AlexNet and VGG19. In the next step, features fusion is carried out selecting higher index values. Moreover, entropy and skewness-based techniques are employed during the feature optimization and the best subset of the feature vector is selected. In the last step, various machine learning algorithms are utilized to classify the data. The method is assessed with the help of CASIA-A, B, C, and AVAMVG gait, and the accuracy of 99.70%, 93.30%, 92.20%, and 99.80%. The performance of the method is good on the gait data but the feature extraction process is complex and there may be a loss of features during the feature selection process [20].

The variation problem of human gait is addressed using a CNN model. The method is based on the hybrid technique of feature extraction and selection. This method includes four steps such as frame acquisition from input videos, feature extraction using a pre-trained model such as VGG-16, Kurtosis and Principal Score approach-based feature selection, serial feature fusion, and classification using an SVM classifier. The method is validated using six CASIA-B angles and obtained an accuracy of 95.80% on the 00 angle, 96.0% on the 18 angle, 95.90% on the 36 angle, 96.20% on the 54 angle, 95.60% on 72 angle, and 95.50% on 90 angle [21].

A HGR approach is presented to handle huge data tasks based on a deep learning approach. The method is designed to overcome variations of gait data problems such as clothes, view, and carrying conditions. The method includes preprocessing using data augmentation with the help of a three-flip operation, feature extraction Inception-NASNet Mobile and ResNet-V2, feature optimization using a whale optimization, feature fusion using serial fusion based on modified mean absolute deviation, and clarification using machine learning algorithms. The proposed method is validated with the help of the CASIA-B dataset and an average accuracy of 89.0% is obtained. The proposed method is efficient and effective but is less flexible as compared to multi-stream techniques [22].

In [23], authors introduced an HGR method based on the limited images-based 3-D shape generation. They aim to develop an efficient method by addressing the 3D shape generation task for silhouette data. The method is based on gathering the human body information using a single RGB image frame and construction of body shape by transferring the information sequence of the silhouette. The method is tested for different camera positions to assess the performance. To check the viability of the technique, CASIA-B and OUMVLP datasets are used and an average accuracy of 89.80% using OUMVLP and 92.13% using CASIA-B. The method works well for normal walking and carrying conditions, but the performance is degraded in clothing variation.

The authors designed an HGR system based on temporal and spatial features called GaitSTAR [24]. The method uses the channel-wise structure and obtains the dynamic weights of features. The distortion of the silhouette is addressed using flow representation dynamically. Moreover, the feature set transformation is performed using transformer-based architecture. The features are transformed with the help of integration into a set level from the image level and reweighting of dynamic features is performed to capture the interaction of long range. The purpose of reweighting is to improve the contextual understanding which ultimately improves the results. The GaitSTAR is tested with the help of CASIA-B, CASIA-C, and Gait3D which achieved accuracy of 96.40%, 67.30%, and 54.21%, respectively. The accuracy of the method is promising using CASIA-B, but performance is compromised on CASIA-C and Gait-3D datasets.

To evaluate the performance of different CNN models on gait data, a detailed experimental analysis is carried out [25]. The analysis is based on various deep learning models such as VGG16, VGG19, NASNetMobile, NASNetLarge, Xception, and EfficientNetB0. They used the CASIA-B dataset and used various evaluation measures such as accuracy and loss. The highest accuracy of 97.17% is obtained using the Xception model. The accuracy for the rest of the models lies between 9.78% and 93.85%. The analysis of the model selection is good, but the experiments need to be conducted on various datasets to assess the generalizability of different models.

A hybrid HGR technique based on deep learning feature extraction and Bayesian optimization presented by authors [26]. Initially, the fine-tuning of EfficientNet-B0 is performed using the optical flow data extracted regions. The training of the model is also performed by passing the enhanced video data. The tuning of the hyperparameters is performed using a Bayesian Optimization algorithm instead of a static approach. After feature extraction, the fusion of features is performed using a parallel approach. A modified tiger optimization is used for feature

optimization and final classification is performed using [an extreme learning machine](#) classifier. the method obtained 92.04% and 94.97% using CASIA-B and CASIA-C datasets respectively. The method works well on the dataset but may be computationally intensive due to Bayesian optimization.

Critical Analysis:

In the literature, various HGR methods are proposed by authors based on different feature extraction techniques and feature selection/optimization methods. The method worked well on the gait data for human recognition on different datasets. The accuracy of the models is promising but includes additional overhead due to feature fusion and feature selection process. Moreover, some models are not assessed to validate the generalizability by conducting experiments on different datasets.

Connections

Following are some connections among different HGR methods discussed above.

Feature Extraction for Gait Recognition: All HGR techniques consider the feature extraction step as an important task. Different deep learning models are used to obtain relevant features such as AlexNet, VGG, etc.

Dataset-Specific Performance: These methods used famous gait datasets such as CASIA-A, B, and C and showed improved results. While the generalizability problem is still a gap.

Multi-Stream and Hybrid Approaches: Various HGR methods are based on a hybrid of multi-stream techniques and obtain the spatiotemporal features from the gait data. These methods address the problem of variation in gait data such as carrying, clothing, and walking variations.

Feature Fusion and Optimization: Most of the methods utilize the feature optimization techniques such as nature-inspired algorithms, entropy, and kurtosis-based methods. The methods are comprised of a combination of feature extraction and optimization which offers good results.

Resource Efficiency and Complexity: Various HGR methods tried to address the computation problem due to its application in the real world. They aim to develop such as method that is lightweight and has fewer parameters.

Conflict among Methods

Following are some conflicts among the different HGR methods discussed above.

Model Complexity vs. Resource Constraints: Some methods focus on higher computational costs by designing complex gait models while others focus on developing weight methods to address the computational problem. This shows that the trade-off between accuracy and computational cost is important.

Single vs. Multi-Model Feature Extraction: Some methods use a single CNN model for feature extraction while others use more than one model such as AlexNet and VGG19. The method based on multiple models is good at the extraction of robust features but may be complex to some extent.

Rule-Based vs. Machine Learning-Based Classification:

Some methods are based on machine learning classification while some use rule-based methods and use different deep learning models for feature extraction. The selection is based on the data type and results.

Generalization vs. Dataset-Specific Optimization:

Some HGR method uses only one data to test the models and have a lack of generalizability while some method uses more than one gait dataset to make a generalized model.

Feature Selection vs. Comprehensive Fusion:

There are various methods that focus on the feature optimization process to obtain relevant features and eliminate redundancy. Some method uses the fusion method to take all features as input for classification to eliminate the feature loss problem. The literature review summary is also given in Table 1.

Table 1: Summary of Literature Review of Recent HGR Methods

Ref#	Year	Research Design	Key Findings/Results	Methodology	Limitations
Mehmood et al. [17]	2024	Experimental	Method obtained more than 90% accuracy	Frame Acquisitions, RGB to Gray Scale conversion, spatiotemporal feature	The accuracy of CIFAR-100 is not promising

				extraction, feature optimization, classification	
Rani et al. [18]	2024	Experimental	The method was tested using the CASIA-A dataset and achieved an accuracy of 97.8%	Preprocessing, image segmentation, feature extraction, and classification	The method is tested on a small dataset which does not reflect the generalizability
Yousef et al. [19]	2023	Experimental	The model is tested using CASIA-A and B and achieved 99.60% and 99.80% accuracy	Video-to-frame conversion, GEI's extraction by applying to preprocess, and ROI identification, feature extraction, fusion, and classification of data.	The model-based approach is dependent on the data and may fail if the RIO is not correct.
Arshad et al. [20]	2020	Experimental	The method obtained 99.70%, accuracy on CASIA-A, 93.30% accuracy on CASIA-B, 92.20% accuracy	Features using AlexNet and VGG19, feature fusion, entropy, and skewness-based feature	The feature extraction process is complex and there may be a loss of features during

			on CASIA-C, and 99.80% accuracy on AVAMVG gait	optimization, machine-learning classification	the feature selection
Mehmood et al. [21]	2022	Experimental	The HGR method is tested using six CASIA-B angles and obtained an accuracy of 95.80% on the 00 angle, 96.0% on the 18 angle, 95.90% on the 36 angle, 96.20% on the 54 angle, 95.60% on 72 angle, and 95.50% on 90 angle.	Frames acquisition, feature extraction, selection, serial fusion, and classification.	The method is accurate and robust but may be dependent on data quality and also computationally intensive due to the feature selection process
Saleem et al. [22]	2021	Experimental	The method is evaluated on CASIA-B dataset and obtained an average accuracy of 89.0%	Preprocessing, feature extraction, feature optimization, fusion, and classification	The method is less flexible as compared to multi-stream techniques
Zhu l. [23]	2023	Experimental	An average accuracy of 89.80% using OUMVLP and	Gait feature extraction, body shape feature extraction,	The performance is degraded on clothing variation

			92.13% using CASIA-B		
Bialal et al. [24]	2024	Experimental	Accuracy of 96.40% on CASIA-B, CASIA-C on 67.30, and 54.21% on Gait3D	Spatial and Temporal features, Dynamic weights computing , features transformation classification	The method didn't work well for all datasets
Hasan et al. [25]	2023	Experimental Analysis	Maximum 97.17% accuracy on CASIA-B	Training and testing of different CNN models on gait data	The model testing is done on limited data
Khan et al. [26]	2023	Experimental	Accuracy of 92.04% on CASIA-B and 94.97% using CASIA-C	Preprocessing, feature extraction, fusion, optimization, classification.	The model is computationally intensive due to optimization.

Proposed Methodology

In this work, a new HGR method is designed based on two phases. In Phase 1, the data is prepared for the proposed CNN model. Initially, the video data is converted into frames for further processing. After that, the data is processed by applying resizing, data augmentation (rotation, flipping, and Affine transformation), and normalization. After data preparation, an attention-based CNN model is designed that is comprised of three convolution blocks, flatten layer, dense fully connect layer, ReLU layer, Multi-head attention layer, and output or classification layer. The convolution block is further based on three layers such as Conv2D, ReLU, and max pooling. The architecture of the model is also shown in Figure 1.

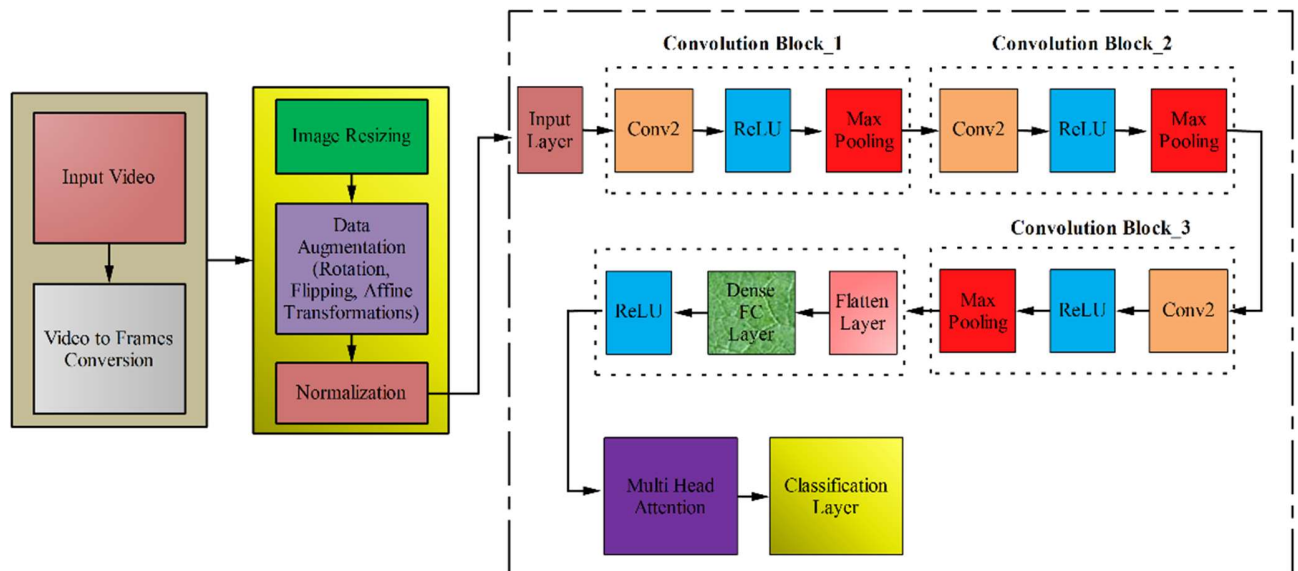
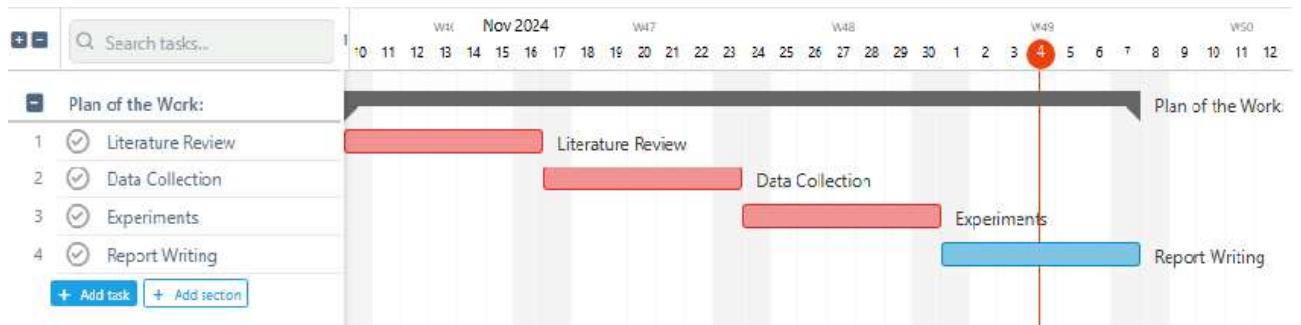


Figure 1: Architecture of Proposed Human Gait Recognition Method

Expected Results

The proposed method will be evaluated using some of the statistical measure such as training accuracy and testing accuracy, training loss, and testing loss. Furthermore, the results will be verified using training curves and confusion matrices. The method will be evaluated on different HGR datasets. The expected outcomes are to achieve an accuracy of more than 90% for different datasets.

Plan of the Work: Gantt Chart



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