Computational Intelligence Approach for Biometric Gait Identification

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Abstract

Gait recognition has gained significant attention in recent years due to its potential applications in various fields, including surveillance, security, and healthcare. Biometric gait identification, which involves recognizing individuals based on their walking patterns, is a challenging task due to the inherent variations in gait caused by factors such as clothing, footwear, and walking speed. In this paper, we propose a computational intelligence approach for biometric gait identification. Specifically, we integrate an intelligent convolutional model to identify human gaits based on the inertial sensory data captured from the body movement during the human walk. Extensive experiments on two datasets demonstrated that the efficiency of the proposed approach outperforms the existing methods. Our approach has the potential to be used in real-world applications such as surveillance systems and healthcare monitoring, where accurate and efficient identification of individuals based on their gait is crucial.

Keywords: computational intelligence; applied deep learning; gait recognition; surveillance; security

1. Introduction

Gait recognition is a biometric technology that has received considerable attention in recent years. It involves recognizing individuals based on their walking patterns, which can be captured using video or other sensor-based systems. Gait recognition has potential applications in a variety of fields, including security and surveillance, healthcare, and sports [1]. One of the main advantages of gait recognition over other biometric technologies such as face and fingerprint recognition is that it can be performed at a distance without requiring any physical contact, making it highly suitable for applications where privacy and convenience are important [2].

However, gait recognition is a challenging task due to the inherent variations in gait caused by factors such as clothing, footwear, and walking speed. These variations can make it difficult to accurately identify individuals based on their walking patterns [3]. To overcome these challenges, researchers have proposed various approaches based on machine learning, computer vision, and signal processing techniques. These approaches typically involve extracting features from gait data and using them to train classifiers that can recognize individuals based on their gait patterns [4].

Machine learning (ML) has played a crucial role in advancing the field of gait identification by enabling the automatic extraction of discriminative features from gait data and the development of accurate and efficient recognition models [5]. ML-based approaches can handle the complex and high-dimensional nature of gait data and learn patterns and relationships that are difficult for humans to perceive. However, there are also several downsides to the use of ML for gait identification. One major challenge is the need for large amounts of annotated data to train and evaluate the models effectively. Another challenge is the sensitivity of the models to variations in the data, such as changes in clothing, footwear, and walking speed, which can affect the accuracy and robustness of the identification results [6]. Additionally, the interpretability of the models is often limited, making it difficult to understand the underlying factors that contribute to the identification performance. Nonetheless, with the continued development of new ML algorithms

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and techniques, it is expected that these challenges will be addressed, and the use of ML for gait identification will become even more effective and widespread [7-8].

In this paper, we propose a computational intelligence approach for biometric gait identification. Specifically, we present an applied convolutional network to extract features from gait data and classify individuals based on their walking patterns. The proposed approach is evaluated on a publicly available dataset and compared with existing state-of-the-art methods.

1. Related Work

In this section, we review the related work in the field of gait identification, focusing on the approaches that have been proposed based on machine learning and computational intelligence. The work [9] proposed a novel approach for cross-view gait recognition by treating gait features as a set rather than a sequence. They proposed a feature extraction method that captures discriminative information from different views of the gait using a 3D convolutional neural network. They then applied a set-based matching method that compares sets of features from different views to recognize individuals. The proposed approach achieved state-of-the-art performance on several benchmark datasets for cross-view gait recognition. In [10], the authors discussed the various types of biometric modalities such as fingerprint, face, iris, and voice recognition, and provide an in-depth analysis of each modality. They also studied the advantages and limitations of biometric technologies and their potential applications in various fields such as security, healthcare, and finance. They also highlighted the importance of accuracy, reliability, and privacy in biometric systems and discuss the ethical and legal issues associated with their use. The work [11] developed a novel approach for human gait recognition based on leg and arm movements. They developed a model-based approach that captures the kinematic and dynamic features of gait using a combination of leg and arm movements. They used a Bayesian framework to estimate the parameters of the model and extract discriminative features from the gait data. The proposed approach was evaluated on a dataset of 20 subjects and compared with several state-of-the-art methods. In [12], the authors provided a comprehensive survey of the use of computational intelligence techniques in biometric applications. They studied the various biometric modalities such as face, fingerprint, iris, and gait recognition, and provide an overview of the different computational intelligence techniques used in each modality. They also explored the advantages and limitations of these techniques and their potential applications in various fields such as security, healthcare, and finance. Liu et al [13] proposed an approach for gait recognition based on the outermost contour of the human body. The authors develop a method that extracts the outermost contour of the human body from gait sequences using a background subtraction technique. They then applied a feature extraction method that captures the shape and texture information of the outermost contour using a combination of Gabor filters and Zernike moments. The work [14] provided a comprehensive that explored the various approaches and techniques used in gait recognition, including machine learning, computer vision, and signal processing methods. They also reviewed the different types of gait data, such as 2D and 3D gait data, and the various challenges and limitations associated with gait recognition, such as variations in gait due to changes in clothing and walking speed. The authors provided a detailed analysis of the existing literature on gait recognition and highlight the strengths and weaknesses of the different approaches. In [15], the authors proposed an approach for person identification based on anthropometric and gait data captured by the Kinect sensor. They developed a method that extracts the anthropometric and gait features of individuals using the Kinect sensor and applies machine learning techniques to identify individuals based on these features.

2. Methodology

In this section, we provide a detailed description of the experimental setup, data preprocessing steps, and the proposed algorithm for our study. Then, we present the proposed algorithm, including the architecture and parameters of the model, the loss function, and the optimization algorithm. We also provide a detailed explanation of the evaluation metrics used to assess the performance of the model and the experimental setup used to validate the results. This section serves as a comprehensive guide to the methods and techniques used in the study, providing the reader with a clear understanding of the experimental design and the validity of the results.

In the preprocessing phase of our approach, we have data collected from different sensors that may have different scales and offsets. Therefore, we apply Z-score normalization to standardize the data before being fed into the model. Given that the inertial gait data may contain missing values due to sensor failure or other reasons. Missing data is

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imputed using mean imputation to avoid bias in the analysis. Then, an outlier detection technique is used to identify and remove outliers from the data [16-18].

The proposed model is a Convolutional Neural Network (CNN) for classification tasks on time-series data. The input to the network is a 3D tensor of shape $(n_{timesteps}, n_{features})$ where $n_{timesteps}$is the length of the time series and $n_{features}$ is the number of features at each time step. The model architecture consists of several layers of Conv1D (1D convolutional) and MaxPooling1D layers, followed by a flattened layer, and two fully connected layers with a softmax activation function in the output layer. The first layer of the model is a convolutional layer with 64 filters and a kernel size of 5, which applies a sliding window of size 5 over the input tensor and convolves it with 64 filters. The activation function used in the convolutional layer is ReLU (Rectified Linear Unit), which sets negative values to zero and leaves positive values unchanged [18].

The second layer is also a convolutional layer with 64 filters and a kernel size of 5, followed by a MaxPooling1D layer with a pool size of 2, which reduces the size of the output tensor by a factor of 2. The third layer is another convolutional layer with 32 filters and a kernel size of 5, followed by another MaxPooling1D layer with a pool size of 2. The fourth layer is a convolutional layer with 64 filters and a kernel size of 5, followed by a Dropout layer with a rate of 0.1, which randomly drops out 10% of the connections between the previous layer and this layer to prevent overfitting. The Dropout layer is followed by another MaxPooling1D layer with a pool size of 2.

The fifth layer is a flattened layer that flattens the output tensor from the previous layer into a 1-dimensional vector. The sixth layer is a fully connected layer with 100 neurons and a $ReLU$ activation function. The seventh and final layer is another fully connected layer with a $SoftMax$ activation function that produces the classification output. The number of neurons in the output layer is equal to the number of classes in the classification problem.

The Adam optimizer is used to update the parameters of the model according to the categorical cross-entropy loss function, whereby the accuracy metric is used to evaluate the performance of the model during training. Figure 1 displays a summary of the layers in the model, including the input and output shape of each layer and the number of trainable parameters in the model.

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3. Experimental Analysis

Layer (type)	Output Shape	Param #
conv1d_12 (Conv1D)	(None, 124, 64)	1984
conv1d_13 (Conv1D)	(None, 120, 64)	20544
max_pooling1d_3 (MaxPooling1	(None, 60, 64)	0
conv1d_14 (Conv1D)	(None, 56, 32)	10272
max_pooling1d_4 (MaxPooling1	(None, 28, 32)	0
conv1d_15 (Conv1D)	(None, 24, 64)	10304
dropout_3 (Dropout)	(None, 24, 64)	0
max_pooling1d_5 (MaxPooling1	(None, 12, 64)	0
flatten_3 (Flatten)	(None, 768)	0
dense_6 (Dense)	(None, 100)	76900
dense_7 (Dense)	(None, 20)	2020

Figure 1: summary of the parameters of the proposed model at each layer.

Two common inertial gait datasets are adopted to empirically validate our concepts [19]. The first dataset used in this study was obtained from 118 individuals. The collected gait data were annotated into steps using the stepwise segmentation technique. To improve the performance of gait recognition, gait instances were collected by partitioning the gait curvature into two constant strides, based on previous research demonstrating that two-step data yielded better results. Additionally, to standardize the length of the instances, one instance was interpolated into a static distance of 128 using the Linear Interpolation function. To increase the size of the data, a single-step overlay was added between each pair of adjacent instances for all subjects. Consequently, 36,844 gait instances were collected, with 33,104 instances being used for training and the remaining 3,740 instances for testing. The second dataset used in this study was obtained from 20 individuals. As the dataset for each subject in this study contained significantly more data than Dataset #1, no overlap was added between the instances. In total, 49,275 instances were collected, with 44,339 instances being used for training and the remaining 4,936 instances for testing purposes.

Experimental comparative analysis is performed in this study against other machine learning algorithms as a crucial step in evaluating the performance of our gait classification model. By comparing our model's performance against other state-of-the-art algorithms, we can determine whether our model is competitive in terms of accuracy, speed, and scalability. There are several machine learning algorithms commonly used for classification tasks, such as Support

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vector machine, Random Forest, MLP, and Decision tree. Each algorithm has its strengths and weaknesses, depending on the specific characteristics of the dataset and the classification problem. To conduct a comparative analysis, we would typically train and test our gait classification model using the same dataset and evaluation metrics as the other algorithms. We would then compare the performance of our model against the other algorithms, using metrics such as accuracy, F1-score, and AUC-ROC. Table 1 and Table 2 show the numerical results of experimental comparisons for Table 1 and Table 2, respectively. As shown, the models show higher performance across different metrics, which is demonstrating the competitive advantage of the proposed approach.

Table 1: The numerical comparison between the proposed approach and the state-of-the-art on dataset 1.

Methods	Accuracy	F1-score	AUC
Support vector machine	92.46	89.07	94.10
Random Forest	93.07	89.28	95.66
MLP	91.81	90.51	94.41
Decision tree	94.21	91.89	97.30
Proposed	95.23	92.01	98.53

Table 2: The numerical comparison between the proposed approach and the state-of-the-art on dataset 2.

Methods	Accuracy	F1-score	AUC
Support vector machine	92.44	91.89	93.64
Random Forest	92.56	93.17	96.71
MLP	93.55	89.87	95.45
Decision tree	93.03	90.57	96.31
Proposed	94.13	93.22	97.81

Learning curve analysis is conducted here to evaluate the performance of our applied model by measuring its accuracy or loss function on a training and validation set as a function of the number of training examples. Figure 2 is plotting the learning curves as a graph with the number of training examples on the x-axis and the accuracy or loss function on the y-axis (the plot is for datasets 2). It could be noted that the plot shows the ability of the model to generalize to new data and it's also free from overfitting or underfitting during the training. More, figure 3 shows ROC (Receiver Operating Characteristic) analysis is a widely used technique for evaluating the performance of our model by

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providing a graphical representation of the trade-off between the true positive rate (TPR) and the false positive rate

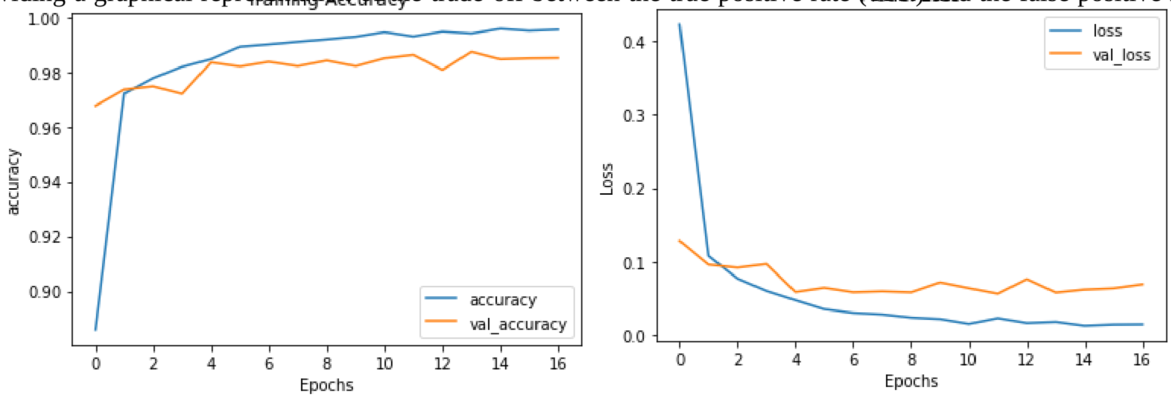

Figure 3: learning curves for the applied computational intelligence approach on dataset 2.

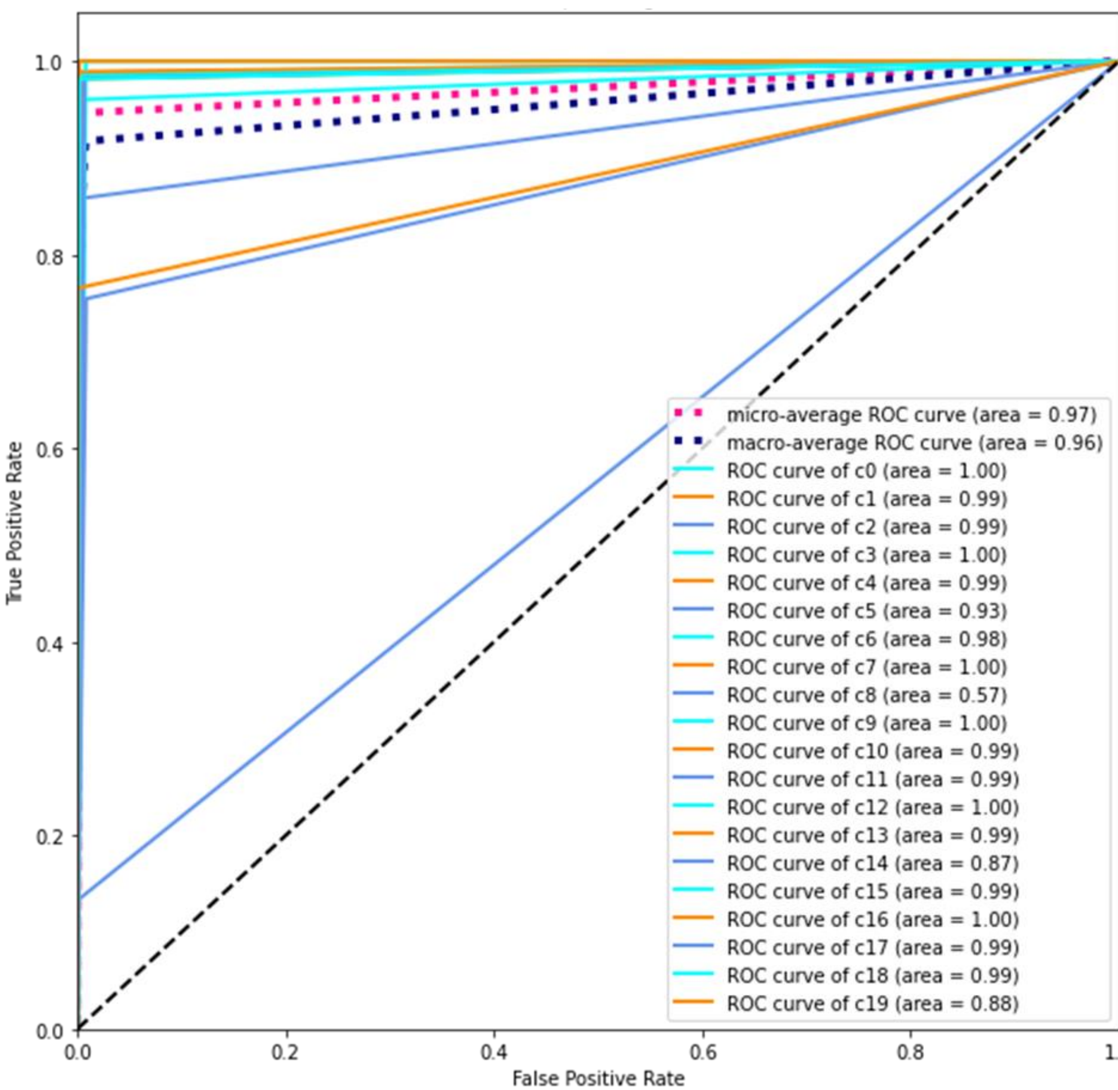

Figure 3: RoC curves for the applied computational intelligence approach on dataset 2.

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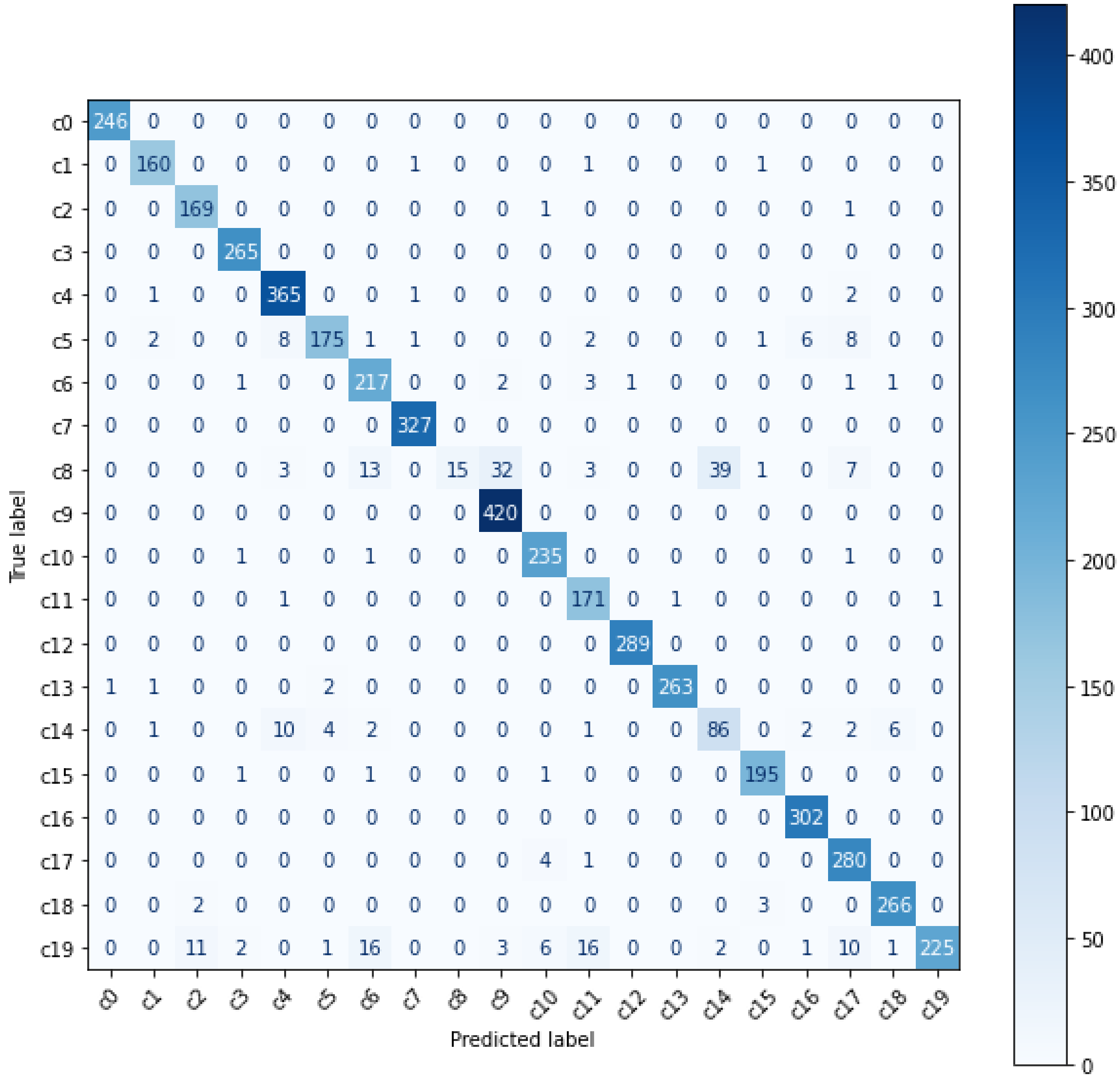

Figure 4: confusion matrix of the applied computational intelligence approach on dataset 2.

(FPR) of a classifier, as the discrimination threshold is varied. In our case, the TPR represents the proportion of correctly classified pathological gait instances (sensitivity), while the FPR represents the proportion of healthy gait instances that are incorrectly classified as pathological (1-specificity). Notably, the proposed model exhibits high discriminative power between different individual gaits. Figure 4 displays the confusion matrix as a valuable tool for evaluating the performance of our gait classification model, providing a detailed breakdown of its strengths and weaknesses and allowing for targeted improvements to the model's architecture and parameters.

4. Concluding Remarks

This study presents an intelligent computational intelligence approach for identifying human individuals based on inertial gait data. Our approach exploits the representational power of convolutional networks to extract inherent gait patterns from three-dimensional sensory data. Exhaustive experiments show that the proposed approach is efficient and competitive in performance over the literature studies. The findings demonstrated the promise of the proposed approach to be used in improving the security of human-authorization systems in both indoor and outdoor environments.

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