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Human Gait Recognition using an Enhanced Convolutional Neural Network

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Abstract

Gait is a kind of behavioral biometric feature, which is defined as the way a person walks. Unlike other biometrics like face and iris which are limited by the distance. Soft biometric are features that can be extracted remotely and do not require human interaction. The force of gait, is that it does not require cooperative subjects and it is recognizable from low-resolution surveillance videos. This paper presents a proposed framework for gait recognition by building the required dataset. This work include two steps. First, nine gait attributes are extracted using MediaPipe and second, recognition is done using an Enhanced Convolutional Neural Network (ECNN). The proposed model achieved an accuracy of 89.583%. Although the accuracy is not high, yet the gait recognition is very important, especially in a remote viewing environment.

Keywords: Gait recognition, Soft Biometrics, MediaPipe, Enhanced Convolutional Neural Networks

التعرف على مشية الإنسان باستخدام شبكة عصبية تلافيفية محسنة

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الخلاصة

المشية هي نوع من السمات البيومترية السلوكية، والتي يتم تعريفها على أنها الطريقة التي يمشي بها الشخص. على عكس القياسات الحيوية الأخرى مثل الوجه والقزحية التي تكون محدودة بالمسافة. القياسات الحيوية الناعمة هي ميزات يمكن استخراجها عن بعد ولا تتطلب تفاعلًا بشريًا. تكمن قوة المشية في أنها لا تتطلب أشخاصًا متعاونين ويمكن التعرف عليها من

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خلال مقاطع فيديو المراقبة منخفضة الدقة. تقدم هذه الورقة إطارًا مقترحًا للتعرف على المشية من خلال بناء مجموعة البيانات المطلوبة. يتضمن هذا العمل خطوتين. أولاً، يتم استخراج تسع سمات مشية باستخدام MediaPipe وثانيًا، يتم التعرف باستخدام الشبكة العصبية التلافيفية المحسنة (ECNN). حقق النموذج المقترح دقة بلغت 89.583%. على الرغم من أن الدقة ليست عالية، إلا أن التعرف على المشية مهم جدًا، خاصة في بيئة المشاهدة عن بعد

كلمات مفتاحية: التعرف على المشية ، القياسات الحيوية اللينة ، MediaPipe ، الشبكات العصبية التلافيفية المحسنة

Introduction

Gait is a walking behavior of human body that is used to distinctively recognize individuals at a distance from a camera even in less illuminating and dense environmental areas [1]. The way a person walks can be described as human gait, or more formal, the motion pattern of the limbs during movement [2]. Gait recognition utilizes physical characteristics and movement posture of a pedestrian [3]. Human Gait Recognition is being utilized for security purposes at banks, airports and embassies [4]. The gait recognition process has an ability of identifying a person from remotely, at variance other biometric applications, for example, iris, face and fingerprint [5]. The most of gait recognition algorithms demand to extract the human profile in order to determine the spatiotemporal features of a walking person [6].

There are two approaches of human gait recognition process: model-based and model-free [7]. The model-based ways extract attributes by modeling human body structure and motion patterns of various body parts [8], while Model-free approach which analyze the movement of the walking subject and then distinct attributes are extracted from the motion [9]. Model-based features are utilized to path the human body parts and movement [10]. In this work will used Model-based features.

Soft biometrics are physical and behavioral characteristics used to describe, verify, and identify human subjects [11]. Soft biometrics provides several benefits over other forms of identification at remotely as they can be obtained from low resolution and low frame rate videos [12]. This paper will use soft biometric features from gait method of persons. The features that used in this work (angle elbow, angle hip, length hip, angle mid hip, angle ankle, length ankle, distains ankle1, distains ankle2, distains mid pinky).

Related Works

Sahak et al. [13] they presented method of human recognition based on oblique and frontal gait using features extracted from Kinect, orthogonal least square (OLS) is used for feature selection and multi-layer perceptron for classification. Then the optimized Multi-Layer Perceptron (MLP) with two feature sets is used for the recognition of gait and estimated its effectiveness by using neural network classifier that provides better classification results. Nithyakani et al. [14] they offer forward a method that trains the neural network architecture using gait energy images (GEI) to utilize Deep Convolutional Neural Networks (DCNN) to extract a person's gait attributes. They used the TUM-GAID dataset to construct this experiment, and the technique produced "average recognition rates" of 94.7%. Chao et al. [15] they suggested GaitSet, an all-encompassing deep learning model. First, frame-level characteristics are individually extracted from each silhouette using a CNN. Second, to combine frame-level features into a single set-level feature, a process known as Set -pooling is performed. To get the final representation, the set-level feature is mapped into a more discriminative space using a structure known as horizontal pyramid mapping. Sharif et al. [16] in this research a novel method for recognizing human gaits is proposed, using precise segmentation and multi-level feature extraction. Four main steps are performed: enhancement of movement area in frame by the implementation of linear transformation with HSI color space, Region of Interest (ROI) detection, shape and geometric features extraction and parallel fusion and finally support vector machine (SVM) was employed to perform the classification. Wang et al. [17] they demonstrated a brand-new gait classifier that completely applies deep learning (DL) technology and puts forward a convolutional long short-term memory (Conv-LSTM)-based approach. The network comprises three convolutional and pooling layers, a fully connected layer, three LSTM layers and a softmax layer. Elharrouss, et al. [18] they demonstrated a technique for re-identifying people using their stride. This method relies on viewing angle estimate of the gait energy images (GEIs) of the input probe pictures to recognize gait images. Using the CNN classifier, we can determine the subject's gait from the estimated angle. Nie, Xuan& Li, Hongmei [19] they proposed method for human recognition by computer vision methods to identify people based on walking way. This paper offer approach based on pose features to try gait recognition of people with an overcoat, carrying something, or other covariates. It focus to estimate human motion using Convolutional Neural Networks. This method achieved accuracy from 60.88% to 95.23%.

Material and methods

Dataset

The authors locally constructed the dataset for this work. This dataset contains a video of various people that was recorded in real-time as they passed in next to the camera. Figure 1 shows the environment of building the dataset that used where the camera was placed “130 cm” above the ground and (450 cm) away from the subject.

Figure 1: Environment of Building Dataset

Thirty-three persons are participated as samples for building this dataset. One video is taken for each person. Table (1) shows information of the dataset.

Table (1) Information of Dataset

No.	Dataset Details	Number
1	Number of sample (person)	33
2	Frame Rate	1frame per sec.
3	Camera type	Nikon d7200
4	File Format	MP4

The proposed Gait Recognition Model

The proposed human gait recognition model includes three main steps: features extraction, pre-processing features, and gait recognition. Figure 2 shows the general block diagram of the proposed system in this paper.

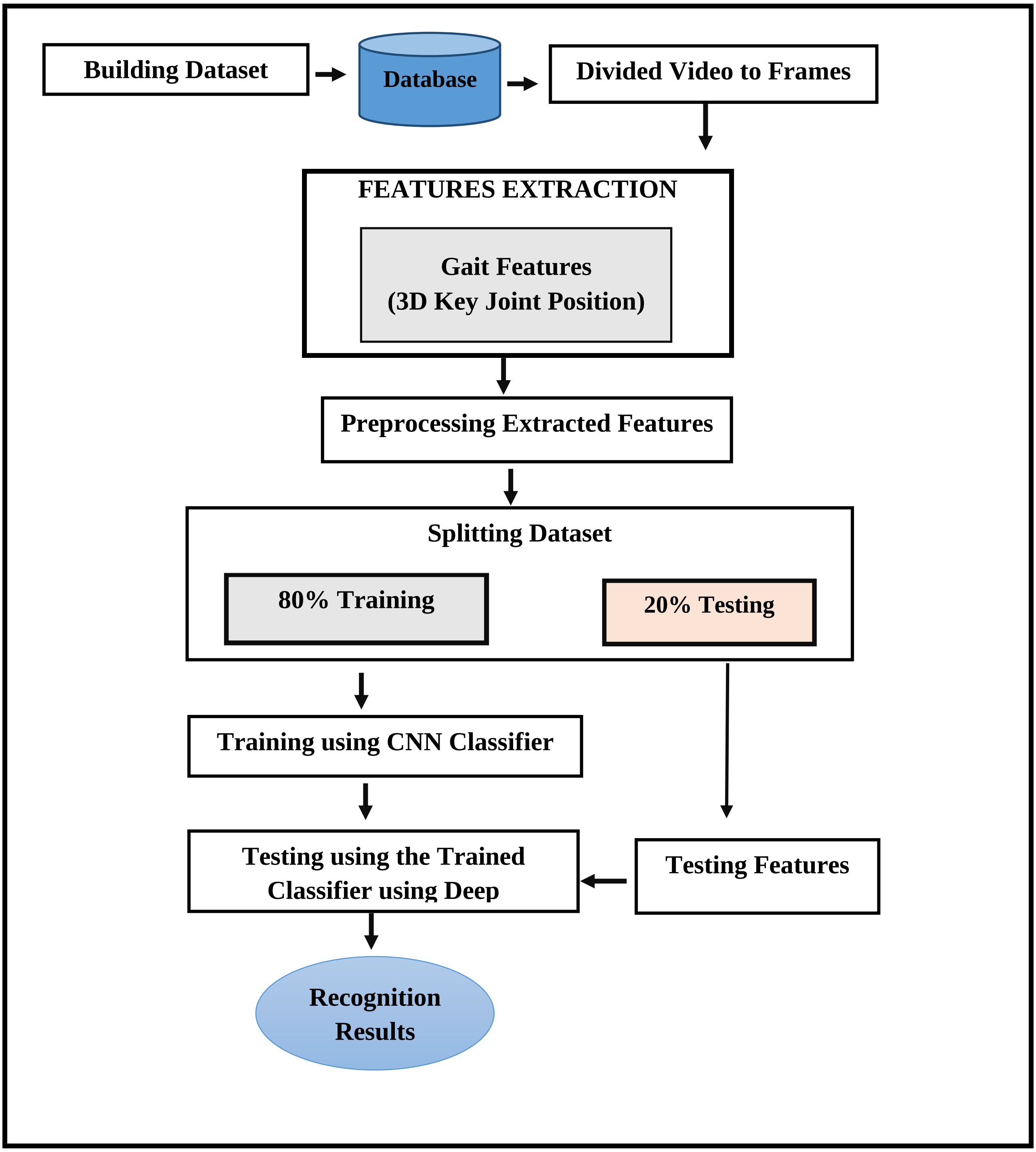


Figure 2: General Block Diagram

1. Feature Extraction:

In this step, the Media Pipe model is used in this paper to find the 3D key joint positions for each frame of the side video. The position estimate component of the proposed model anticipates the locations of all (32) key joint positions for each individual. A gait analysis is carried out after the subject has been identified using the estimation of “3D pose positions”. Figure 3 illustrates the crucial joint positions (angle elbow, angle hip, length hip, angle mid hip, angle ankle, length ankle, distains ankle1, distains ankle2 and distains mid pinky) that are necessary for this work.

Number	Names of key joint positions
0	angle elbow
1	angle hip
2	length hip
3	angle mid hip
4	angle ankle
5	length ankle
6	distains ankle1
7	distains ankle2
[illegible]	[illegible]

Figure 3: Names of the Key Joint Position

2. Pre-processing Features:

The inputs of this step are the features that were extracted from the 3d key join points. The pre-processing step consists of two sub-steps which are cleaning data using Exploratory Data Analysis (EDA) and balance data using Synthetic Minority Oversampling (SMOTE) technique. Cleaning Data involves analyzing and removing the outliers from the dataset. Exploratory data analysis is a method of sifting through large amounts of information to find outliers. The EDA handles outliers in the data using algorithm (1).

Where, the column is dataset, Min: smallest value in the dataset, Max: maximum value in the dataset, Q1: The median of the first half and Q3: The median of the second half.

Algorithms (1) Removing Outliers
Input: Data Set **Output:** Cleaned Dataset
Begin **Step 1:** For each column in a dataset: a. Retrieve the lower range and upper range values from the column. b. Sort the items of the column in ascending order. c. Calculate the quantiles for the column: - Q1 = column.quantile(0.25) - Q3 = column.quantile(0.75) d. Determine the lower range and upper range values based on the interquartile range (IQR): - IQR = Q3 - Q1 - lower range = Q1 - (1.5 * IQR) - upper range = Q3 + (1.5 * IQR) e. Update the data in the column with the new range values. **Step 2:** For each value in the column: a. If the value is less than the lower range: - Set the new value as the lower range value. b. Update the value in the column. c. If the value is greater than the upper range: - Set the new value as the upper range value. d. Update the value in the column. **End**

In this step, SMOTE over-sampling technique is used on the dataset. The SMOTE technique is clarified in algorithm (2). By adding the synthetic samples to the minority class data, the issue of class imbalance is effectively addressed. The inclusion of these synthetic instances help bridge the gap between the minority and majority classes, resulting in a more balanced representation of all classes in the dataset.

Algorithm (2) SMOTE Algorithm

Input: dataset**,** Smote Percentage call (N)**,** Number of nearest neighbors (k)

Output: Balanced training dataset

Begin

Step1: for each minorities data in the dataset, do

{ get data and name class **}**

Step2: for each row [X] in the data minorities Class, do

{ a. Find the k nearest neighbors of the row

b. per= N/100

c.while Per ≠ 0 do

{ Select one of k nearest neighbors, call Y

Select a random number R ∈[0,1]

Y=X+R(Y-X)

append Y to New Sample

Per= Per -1

}}

Step 3: add a new sample to data minorities Class call Synthetic data

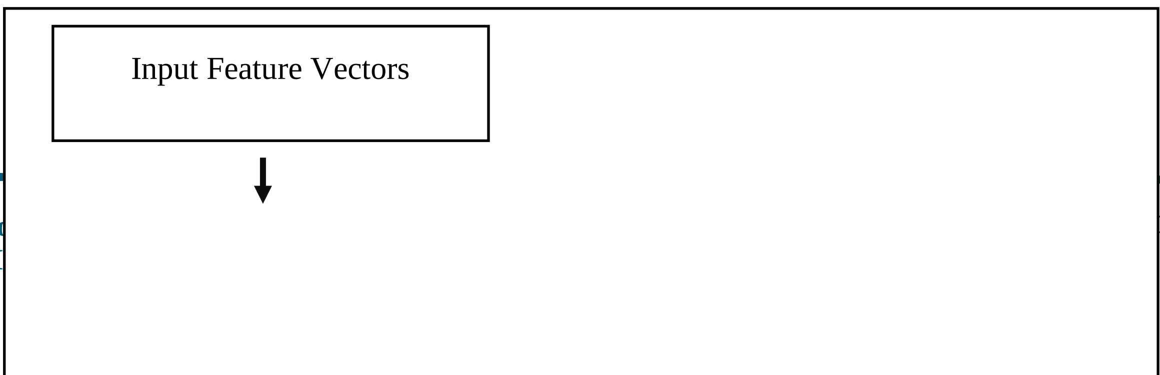
Step 4: return Synthetic data

End

3. Human Gait Recognition:

Recognition of a person is based on the pattern of the gait obtained in the preceding steps. Every gait images are converted to a gait codes or patterns to be used in recognition algorithms. Features have been utilized as input in the proposed enhancement CNN (ECCN) algorithm.

The CNN is enhancement through the use of the CNN one dimension four times and the global average pooling one dimension. As shown in Figure 4 the suggested design comprises of 4 convolution layers, Global Average Pooling layers, a soft max function, and 2 dense layers.



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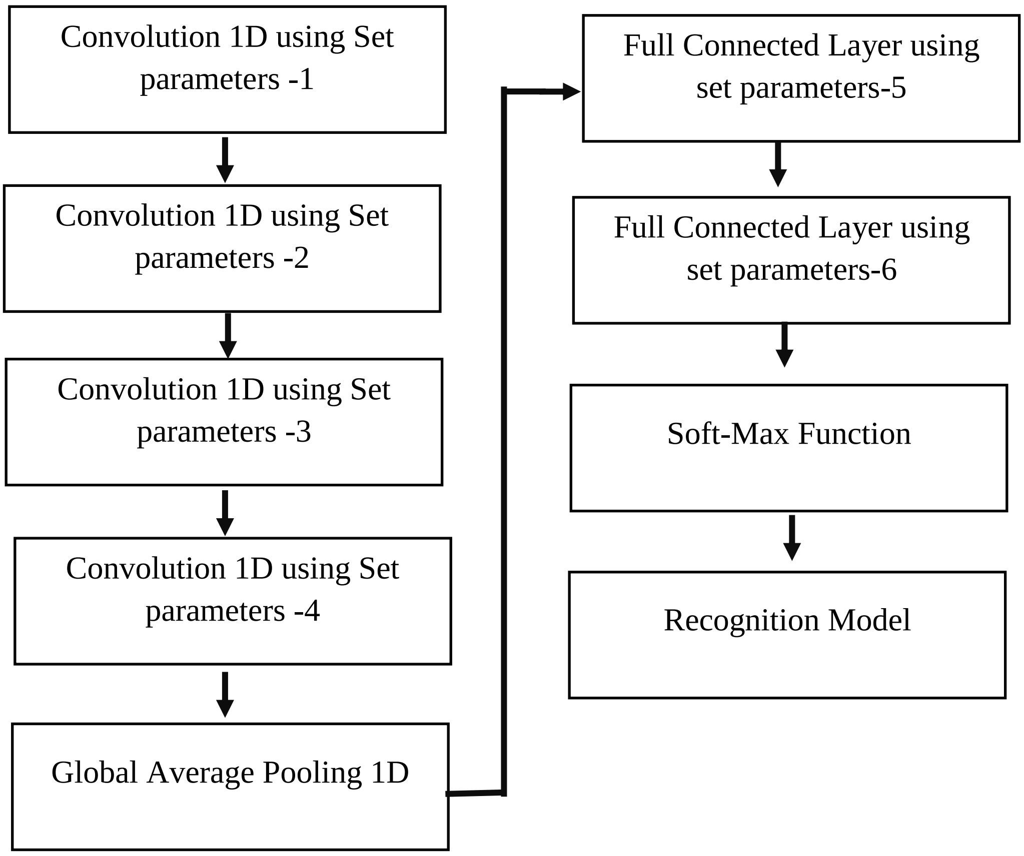

Figure 4: The Block Diagram of the Proposed ECNN

The details of the ECNN algorithm is clarified in figure 5.

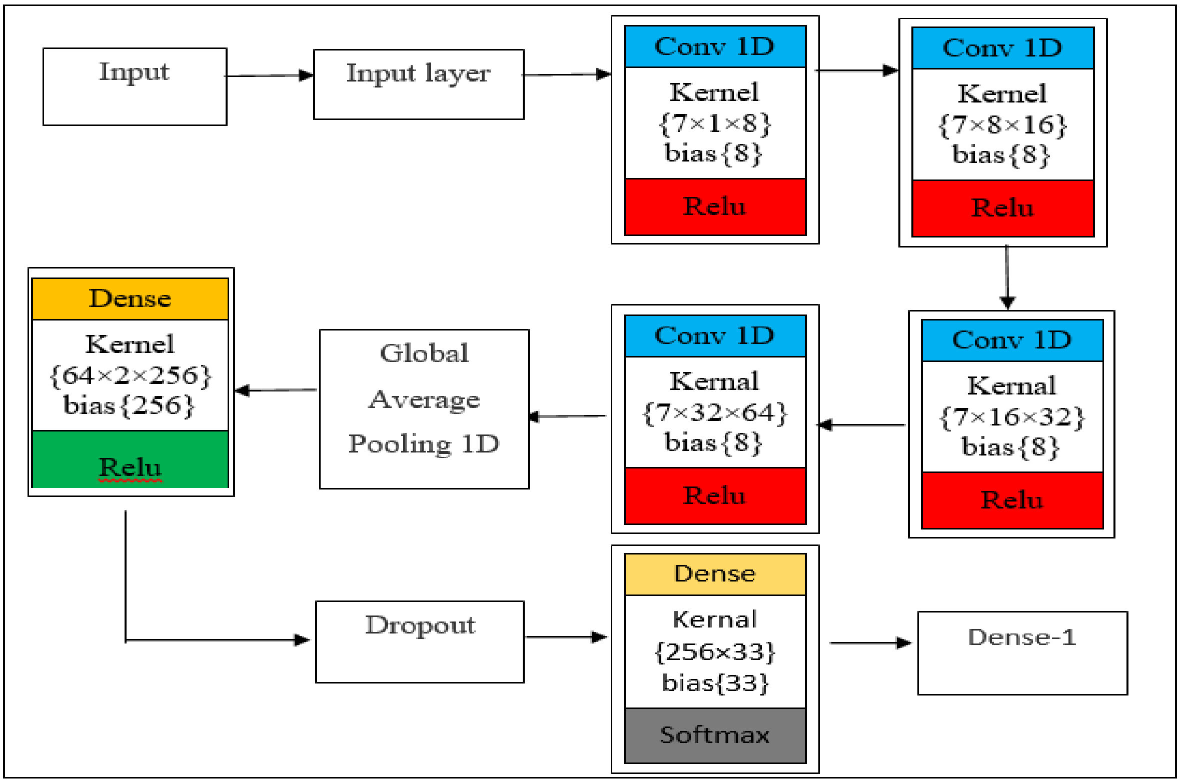

Figure 5: The Summary of the Proposed ECNN

The main steps of ECNN algorithm are summarized in an Algorithm (3).

Algorithm(3) The Proposed ECNN Algorithm
Input: Features Output: mode
Begin Step1:Initialize the model as a sequential model. model = Sequential () Step2:Add a 1D convolutional layer to the model with 8 filters, a kernel size of 7, ReLU activation, padding, and an input shape of (x.shape[1], 1) Step3:Add another 1D convolutional layer to the model with 16 filters, a kernel size of 7, ReLU activation, and padding. Step4:Add a third 1D convolutional layer to the model with 32 filters , a kernel size of 7, ReLU activation, and padding. Step5:Add a fourth 1D convolutional layer to the model with 64 filters , a kernel size of 7, ReLU activation, and padding. Step6:Add a global average pooling layer to the model Step7: Add a fully connected (dense) layer to the model with 256 units, and “ReLU” activation Step8:Add a dropout layer to the model with a dropout rate of 0.5 Step9:Add a final dense layer to the model with a number of units equal to the length of the num_class variable, and softmax activation End

Results

In this study, the enhancement convolutional neural network (ECNN) algorithm is employed as the chosen classification method. The proposed (ECNN) is evaluated on a locally collected gait dataset.

The dataset is carefully split into two distinct categories: a training set comprising 80% of the data and a testing set containing the remaining 20%.This separation ensures that the classification method can be effectively applied to recognize individuals.

Figure 6 clarifies the accuracy for both training (80%) and testing (20%) of the gait recognition. While, figure 7 the loss for both training and testing of Gait Recognition.

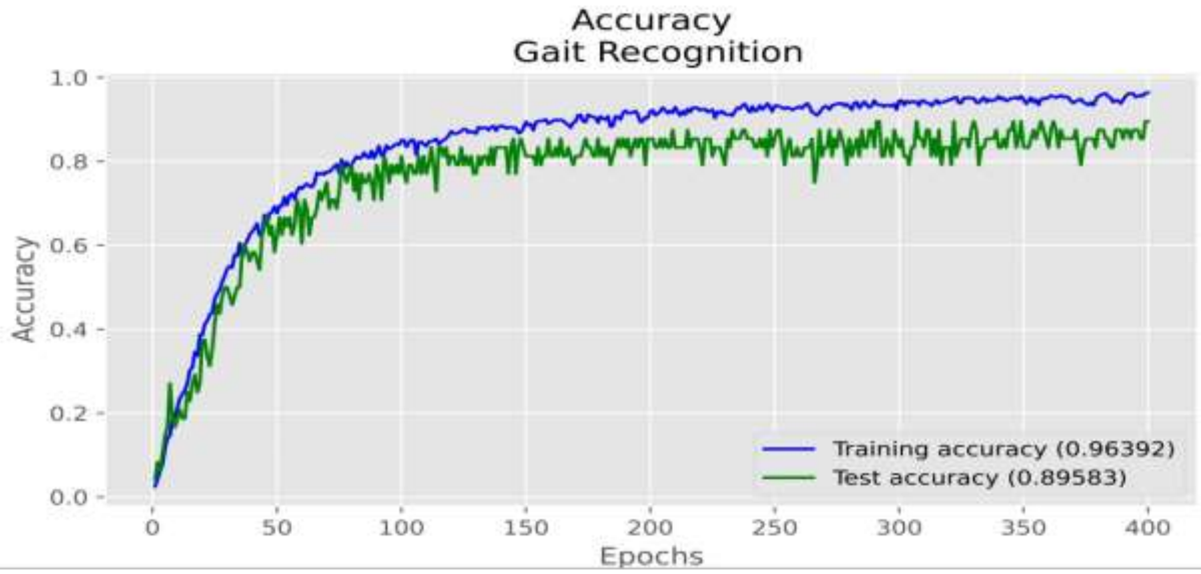

Figure 6: Accuracy for both training and testing of the Gait Recognition

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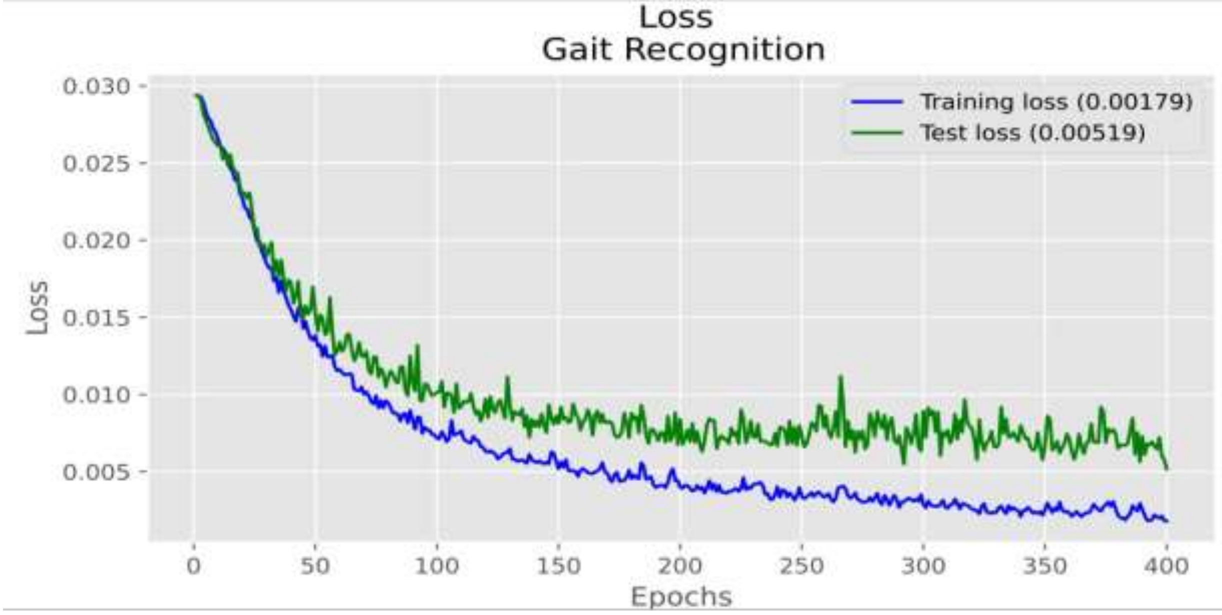

Figure 7: Loss for both training and testing of the Gait Recognition

The training accuracy value is about (0.96392) and the testing accuracy is about (0.89583) with (400) Epoch as in figure 5. The training loss value is about (0.00179) and the Testing loss is about (0.00519) with 400 Epoch as in figure 6.

Table 2 illustrate the performance results achieved by the proposed ECNN classification algorithm to recognize 32 individuals.

Table 2: Performance values of the Proposed ECNN

Data	Summary Performance Proposed ECNN Classification Algorithm based on Error Metrics:			
	accuracy	Precision	Recall	F1-score
Training	0.96392	0.931109	0.926497	0.92646
Testing	0.89583	0.854167	0.833333	0.829524

Comparison with Previous Works

This section shows a comparison between proposed classification system of gait recognition and related methods, as illustrated in Table (3).

Table 3: Comparison between the Proposed System and Related Methods

Ref.	Classification Approach	Classification algorithm	Dataset Name or type of biometric	Accuracy value
Sahak, et al. [13]	Deep Learning	Multi-Layer perceptron (MLP)	New dataset	90.6%.
Nithyakani, et. al., [14]	Deep learning	Deep Convolutional Neural Network (DCNN)	TUM- GAID dataset	94.7%
Chao, et al. [15]	Deep learning	proposed a GaitSet algorithm	CASIA-B gait dataset	95.0%
			OU-MVLP gait dataset	87.1%
Sharif, et al. [16]	Machine learning	Multi-class support vector machine (MSVM)	1.CASIA-A dataset	98.6%
			2.CASIA-B dataset	93.5%
			3.CASIA-C dataset	97.3%
Wang, et al. [17]	Deep learning	convolutional Long Short-Term Memory (Conv-LSTM)	OU-ISIR dataset	99%
Elharrouss, et al. [18]	Deep learning	Convolutional Neural Network (CNN)	CASIA-(B) dataset	99%
			OU-ISIR and OU-MVLP dataset	98%
Nie, Xuan, et al. [19]	Machine learning	Convolutional Neural Network (CNN)	New dataset	95.23%
Our proposed system	Deep learning	ECNN	New dataset	0.89%

Conclusion

A new method for human gait recognition using soft biometric features is presented. Data was collected locally, features were extracted using MediaPipe, and then classified using an improved convolutional neural network algorithm. Although the accuracy of human recognition through his\her gait achieved by this work is (89.583%) and it is not high, yet the gait recognition is very important, especially in a remote viewing environment, as well as in a low-accuracy viewing environment, and dark environments. Therefore, the performance of the proposed model using the CNN is considered a good work, and can be relayed on.

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