QALAAI ZANISTSCIENTIFIC JOURNAL
A Scientific Quarterly Refereed Journal Issued by Lebanese French University – Erbil, Kurdistan, Iraq
Vol. (10), No (1), Spring 2025
ISSN 2518-6566 (Online) - ISSN 2518-6558 (Print)

Deep Learning-based Surveillance System to Provide Secure Gait Signatures

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ARTICLE INFO

Article History:
Received: 19/9/2023
Accepted:12/11/2023
Published: Spring2025

Keywords:
Deep learning, surveillance system, gait signatures, convolution neural network, biometric.

Doi:
10.25212/lfu.qzj.10.1.39

ABSTRACT

Recently, deep learning models have played a great role in various fields such as computer vision, speech recognition, and image recognition due to their ability to extract complex features from large data sets and learn automatically. Today, providing security has become one of the basic things to do to protect people and departments, so the need for a monitoring system has become necessary to achieve that safety in order to reduce security risks and breaches. Gait is the way a person walks while moving, and the movement of each individual is unique. Therefore, it can be used in biometrics to identify the person by using gait recognition technology for security purposes (healthcare, airports, crimes, etc.), which is distinguished by the fact that it does not require the cooperation of the individual. However, there are challenges represented by variations in viewpoint, clothing, carrying conditions, and so on. To address this issue and to increase the accuracy of

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identification, we investigate gait recognition using deep learning in this research and develop an innovative method based on convolutional long short-term memory (Conv-LSTM) and two other methods (Conv-AlexNet) and (Convl-ResNet150) to identify and recognize human walking. We implemented our approach based on two datasets: the CASIA B dataset and the local dataset. According to our experimental results, the results of the experiment show that the suggested approach achieved an excellent recognition rate of 95% when applied to the CASIA B dataset and 100% when applied to the local dataset.

1.Introduction

Gait is one of the unified human characteristics, such as the fingerprint, speech, face (Adjabi et al., 2020), and iris (Nguyen et al., 2017). Gait recognition methodologies have recently become a source of interest for researchers because they could identify a person from a long distance without the need for direct cooperation from an individual through a surveillance camera or video. There is another feature that distinguishes gait recognition. It is to identify the person even if the image has low resolution (Rida et al., 2019). This is why it can be adopted in many areas of health, sports, security, and surveillance. In fact, in addition to the challenges in recognizing gait, such as changing the shape of the body while walking or lighting and climatic changes, there are other difficulties and challenges, which are represented in clothing, carrying a bag, or changing the angle of the camera (Liu et al., 2022). There are two types of approaches depending on the human body: appearance-based and model-based. To identify the person, it is necessary to create such reliable systems based on their biometric behavior, which includes their physical movements and appearance (clothes and carrying bags) (Rida, 2019).

As mentioned above, in order to contain the problem of the difficulty of recognizing people in changing situations and from different viewing angles, appearance-based

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methods have been adopted that use the original gait sequence and extract the discriminative gait features. Deep learning techniques that have greatly enhanced the field of gait recognition, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (Hochreiter, n.d.), have been successful in extracting meaningful features from gait data and improving the accuracy of gait recognition systems. (X. Wang & Yan, n.d.) used the Long Short-Term Memory (LSTM) (Sepas-Moghaddam & Etemad, 2021), a popular RNN architecture capable of learning long-term dependencies for cross-view human gait recognition based on frame-by-frame GEIs. The ability of LSTM networks to capture long-term dependencies in the data makes them well-suited for analyzing temporal patterns and variations in gait sequences.

In this paper, three approaches were proposed (CNN-LSTM), (AlexNet-LSTM), and (ResNet-LSTM), respectively, to provide a better outcome for extracting features from sequences (frames) captured from a video to recognize people. The following is a list of proposed approach contributions:

- create a local dataset that involved 26 people.
- Feature extraction and classification based on silhouette images.
- A distinct gait representation, a sequence (cycle) of images, will increase the robustness of the person's gait recognition.
- Propose a unique model that combines CNN and LSTM.
- Finally, the dataset was trained with three deep convolutional networks combined with LSTM (CNN, AlexNet, and ResNet152).

Following is a breakdown of the remaining sections of the paper. Section 2 will cover review related work on gait recognition. In Section 3, a novel gait recognition approach, Conv-LSTM, will be introduced to perform gait classification and recognition and provide details on the new gait feature representation sequence (cycle) of the images. In Section 4, in order to test the suggested algorithms, in this

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study, experiments are completed using the CASIA B dataset and the local dataset. Finally, Section 5 will discuss this paper's conclusion and its future work.

2. Related work

The deep-learning methodology has recently produced state-of-the-art results in computer vision areas of study. Convolutional neural networks (CNNs) were first introduced by Castro et al. (2016) with the purpose of extracting different gait features utilizing optical flow as their input data. They got motivation from the deep learning architectures for action recognition that are built on video. They used the spatial-temporal stream of CNN proposed by Simonyan and Zisserman (n.d., 2014) to solve the gait recognition problem. That CNN architecture is the standard approach used by most researchers. For extracting the gait features, Feng et al. (2016) suggested another deep learning technique named "Long Short-Term Memory." They suggested using a body joint heat map using the post-estimation method instead of a binary silhouette, which could be affected by covariate factors. In contrast to Gait Energy Image, which has a tendency to lose temporal information while averaging the binary silhouette sequences, they claimed that their proposed solution may preserve dynamic information. (Shiraga et al., 2016) presented the eight-layered CNN architecture known as GEInet, which uses GEI as the input. Convolution, pooling, and normalization triplet layers were implemented.

(Wolf et al., 2016) A novel gait recognition technique based on multiple-temporal-scale 3D CNN is proposed in this research. The MT3D can extract information on gait sequence silhouettes more effectively by combining spatial-temporal data on both short and large temporal scales at the sequence level. (Gadaleta & Rossi, 2016) IDNet (IDentification Network) proposes a new system that uses gyroscope (inertial) signals to capture motion data from smartphones to authenticate mobile users, which combines deep convolutional neural networks (CNN) and support vector machines (SVM).

(Alotaibi & Mahmood, 2017) With a huge training dataset at its disposal, deep CNN has the benefit of being able to extract discriminative features and 408 superior classifications. ReLU is the activation function that is utilized, and Softmax is the classification function. For the purpose of gait recognition, 3D local convolutional neural networks enable the extraction of local 3D volumes of body components in a sequence with adjustable spatial and temporal scales, positions, and lengths. Multiple convolutional and ReLU layers make up the feature extraction module.

(Zou et al., 2018) This study looked at gait recognition on smartphones in the real world. A hybrid approach that combines the DCNN and DRNN (CNN+LSTM) was presented for reliable representation of the inertial gait feature. To directly learn the disentangled appearance, canonical, and pose features from walking videos, they propose a novel CNN-based model called GaitNet. (Tong et al., 2018) Using a spatial-temporal deep neural network (STDNN), which combines TFN and SFN, this research presents a novel approach to the problem of multi-view gait identification. The two-stream network is intended to separate, respectively, the temporal and spatial characteristics of gait sequences. (Zhang et al., 2019) They also propose a new gait database (FVG), with a focus on more difficult frontal views, and use a multi-layer LSTM structure to further leverage temporal information to generate a gait representation for each video sequence. In Hashem et al. (2020), it has been used to transfer learning based on a pre-trained convolutional neural network. Instead of using more conventional representations, such as binary silhouette computing and hand-crafted engineering features, it can extract deep feature vectors and identify people directly. (Li et al., 2020) used a skinned multi-person linear (SMPL) model for human modeling and a trained human mesh recovery (HMR) network to estimate its parameters in a proposed end-to-end model-based gait recognition solution. examined how well shape and pose features performed in various recognition tasks. (Sepas-Moghaddam & Etemad, 2020a) They suggest a network that initially gains the ability to separate frame-level convolutional features from gait convolutional energy maps (GCEM).

In order to leverage the relationships between learned partial spatiotemporal representations, it also employs a recurrent neural network to learn from the split bins of the GCEM. They utilize an attention technique to preferentially concentrate on significant, recurrently learned partial representations. In this study (Inui et al., 2020), CNN utilized for gait recognition is further enhanced by employing batch normalization, and GEI with noise removal is generated by using Mask R-CNN. By conducting tests on two different gaits, one without a bag and one with a bag, the efficacy of this strategy was verified. (Sepas-Moghaddam & Etemad, 2020) Using the relationships between various partial representations, spatially and temporally, propose an attentive recurrent model to learn from gait convolutional energy maps.

(X. Wang et al., 2020) In order to fully utilize local information and remove the stringent limitation of gait cycle segmentation, a well-designed gait representation, known as triple gait silhouettes (TTGS), has been given in this study. Then, a unique gait identification technique based on MCNN has been proposed. It makes use of CNN's potent capacity to extract the key aspects of human gait while also adhering to the new gait representation. (Chao et al., 2021) It introduced a novel approach known as a GaitSet that views gait as a deep set. The suggested GaitSet method collects both temporal and spatial information.

(Peng et al., 2021) It suggests a novel multi-scale gait graph (MSGG) network that automatically and hierarchically extracts the gait patterns from the raw skeleton data. They created the straightforward yet powerful Bimodal Fusion (Bi-Fusion) network, which combines with silhouette representations and completely uses the natural discriminating in skeletons to learn rich features for gait identification. (Teepe et al., 2021) In their innovative interpretation of gait as a series of skeletal graphs, they present GaitGraph, which takes into account the 2D skeleton's inherent graph structure and uses a human pose estimator to extract the gait information. (Amin et al., 2021) To categorize the video frames of human gait, a new model called convolutional bidirectional long short-term memory (Conv-BiLSTM) is presented. The ResNet-18 convolutional neural network (CNN) used in this model to create features

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is fed as an input to the LSTM model, which produces more distinct temporal information. With expected scores, the YOLOv2-squeezeNet model is intended to recognize and localize human gaits.

(L. Wang et al., 2022) They described a novel two-branch neural network in this research that consists of a CNN-based branch that extracts gait features from silhouettes and a GCN-based branch that extracts gait features from skeletons. For effective and efficient gait feature representation, they also created an attention module and an easy yet powerful fully linked graph convolution operator.

In contrast to the previous research, proposed method of gait recognition includes the utilization of long short-term memory (LSTM) with each deep learning model (CNN, AlexNet, and ResNet152), which is a novel type of recurrent neural network (RNN) with significant benefits for storing sequential data. The primary reason that LSTM is preferred over other deep learning models is because human gait is time-series-based and each step is impacted by its previous state.

3. Proposed Methodology

The proposed model comprises two primary stages: robust feature extraction and classification, which are complex tasks for recognizing human gaits. In the first stage, construct the convolutional neural network (CNN) model, designed to extract deep features from the localized images, with regular representations (such as video sequences or images) serving as input. The second stage involves employing a convolutional long-short-term memory (LSTM) network for the classification of various human gait types.

The structure of the proposed method for gait recognition consists of the following steps:

- Data collection: capturing video.
- Frame extraction: the video is transformed into a frame.
- Generate a silhouetted image: Remove the background of the image.

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- Preprocessing and resizing the image: the silhouette image is resized and preprocessed.
- Model training: the three models (CNN-LSTM, AlexNet-LSTM, and ResNet152-LSTM) are trained using a preprocessed dataset.
- Performance of classification: performance assessment is conducted using the ROC curve measurement.

To clarify aforementioned steps, illustrative Fig. 1.

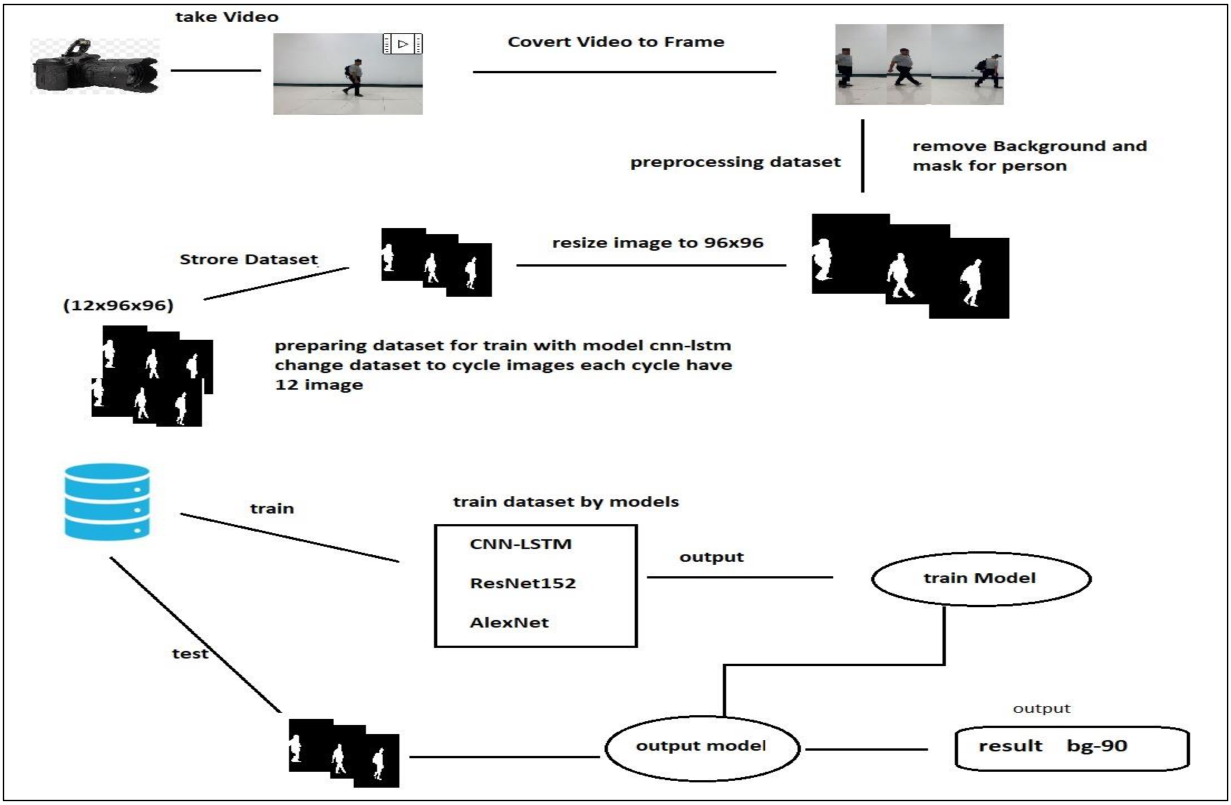

Figure (1): proposed gait recognition model.

The steps of proposed model were briefly explained as follow:

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3.1 Data collection and preparation

As mentioned above, this paper evaluated the proposed model into two datasets to solve the problems related to the scope of implementation, so the local dataset is used, which consists of 26 subjects, and the CASIA B dataset, which consists of 124 subjects (S. Yu et al., 2006). To collect the dataset, two recording sessions are conducted in the location that had been set up in advance with two cameras—one on the front and the other on the side—because they required videos from three different views (0°, 90°, and 180° degrees) as well as under three different conditions: carrying a bag, wearing a coat, and normal. In one of our country's malls, 26 people are subjected to the above-mentioned conditions. Once the videos were needed for the proposal, an online tool was used to convert them into frames. From there, a background removal algorithm was used to turn those frames into silhouettes. At this point, remove any noise that has formed around the person and use the Paint application to clean the data, image by image. Then, after preprocessing the dataset and resizing the image to 96x96, the proposed method relied on inserting a sequence of images by cycling the dataset, so that each cycle contains 12 images; in other words, twelve images that entered the system each time instead of entering one image, which made the data entry system in this method faster than others. At the end of these processes, the cleaned and normalized data was returned after being established. As shown in Fig. 2, explain the steps taken to prepare the dataset that was collected and work on it.

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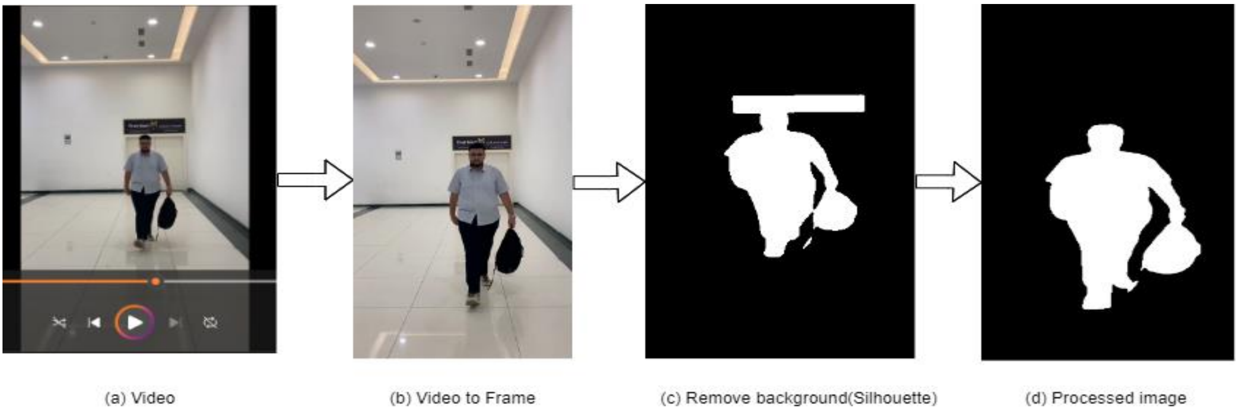

Figure (2): Dataset preparation steps.

3.2 CNN-LSTM Model

Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are combined in the CNN-LSTM neural network design to analyze sequential data, such as time series or image sequences. This architecture is frequently employed in jobs where it is necessary to extract both spatial and temporal information from data. For each time step or frame of the input data (for example, frames of a video or snapshots of an image sequence), the CNN layers of the CNN-LSTM architecture are commonly employed as a feature extractor to extract spatial characteristics. The LSTM layers get these extracted features, after which they model the temporal dependencies between them.

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The architecture of the proposed method (Conv-LSTM) for the recognition of human gait consists of three major phases: feature extraction, classification, and recognition. Based on a deep convolution neural network (CNN) combined with long short-term memory (LSTM) for extracting features from the cycle of the image as input to the designed CNN architecture in this study, which consists of three convolution layers with an activation function (ReLue) (Agarap, 2018), three max-pooling layers, and a fully connected layer. For the classification phase, the LSTM layer is used and the activation function (ReLue) in the dense layer. Then the approach evaluated on two datasets: the large dataset (CASIA B), which contains 124 subjects, and the local dataset, which contains 26 subjects. The last phase is the output of these layers. In the following Fig. 3, illustrate the layers of the design CNN model, which is structured for gait recognition, indicating the three steps: feature extraction, classification, and recognition.

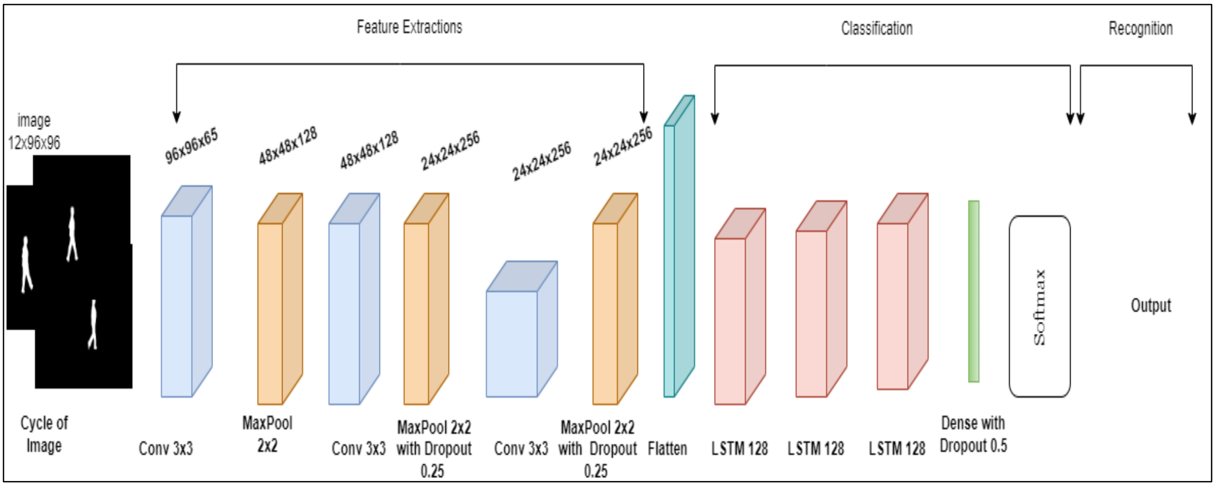

Figure (3): proposed architectural design CNN-LSTM.

In the proposed model CNN-LSTM, in the classification section, one of the simplest activation functions that is utilized in artificial neural networks, especially convolutional neural networks (CNNs), is ReLue (rectified linear unit) in each convolution layer (Ramachandran et al., 2017). defined as the positive part of its argument, as indicated in the following equation:

$$max(0, x) = \begin{cases} x & if \ \ x > 0, \\ o & otherwise \end{cases} \tag{1}$$

The previous stages allow us to extract the gait signatures for a given input, and the last phase involves classifying those signatures to determine the subject identification. Then use the well-known activation function softmax (Banerjee et al., 2020) at the last layer described in this equation.

$$softmax(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}} \tag{2}$$

Where x_i is an element of the gait signature. The softmax function is frequently employed as a neural network's final activation function to normalize the output to a probability distribution over the expected output class.

3.3 AlexNet-LSTM Model

AlexNet is a deep convolutional neural network architecture that has made significant contributions to the development of computer vision, especially in the context of image classification problems. It was created by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton and won the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [(Banerjee et al., 2020)], which was a known advance for deep learning. The development of deeper and more complex convolutional neural network architectures, such as VGG, ResNet, and Inception, was made possible by AlexNet's success, which illustrated the potential of deep learning in computer vision. Object identification, image generation, and image classification are only a few of the computer vision applications for which these architectures have now become essential tools.

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The eight layers of AlexNet were divided into the following groups: the first five were convolutional layers, some of them were followed by max-pooling layers, and the final three were fully connected layers. Two copies of the network are created, each running on a single GPU (with the exception of the last layer). It utilized the non-saturating ReLU activation function, which demonstrated enhanced training efficiency compared to tanh and sigmoid.

In order to obtain an efficient method for extracting features from silhouette images, take advantage of one of the deep neural learning models represented by AlexNet. Due to the efficiency, it provides in this field, combined it with the long-short-term (LSTM) method to obtain a distinctive classification for gait recognition.

3.4 ResNet152-LSTM Model

Residual Network: This architecture introduced the idea of residual blocks to address the vanishing or exploding gradient issue. They apply a method known as skip connections in this network. By skipping some levels in between, the skip connection links the activations of one layer to those of other layers. This creates a block of residue. These building blocks are stacked to form ResNets (Wightman et al., 2021).

A deep convolutional neural network design is known as ResNet-152, or Residual Network with 152 Layers. It is known for its exceptional depth and is a member of the ResNet family of neural networks, especially ResNetv2. In order to solve the vanishing gradient issue that frequently affects very deep neural networks, ResNet-152 was developed (H. Yu et al., 2022).

As a feature extractor, ResNet-152 is useful for jobs involving gait recognition. Only the convolutional layers of ResNet-152 should be retained; remove the final classification layers (global average pooling and fully connected layers). The output of the convolutional layers can be used to represent the gait sequences' features. After that, integrate it with an LSTM for classification instead of the last layer in ResNet, a fully connected layer, and a softmax activation layer added to the last layer to achieve the best results for gait detection.

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Details of the implementation: utilized an optimizer named Adam with a low learning rate of 0.001. The network was trained using a 100-epoch model with 32 batch sizes. On an NVIDIA GeForce GTX 1070 8GB GPU, the experiment was conducted using the Python Keras library with the TensorFlow backend.

3.5 metric measurements

a. Receiver Operating Characteristic (ROC)

The evaluation of performance is a crucial component in machine learning. Therefore, to compute the accuracy of the proposal architecture design, depending on the AUC (Area Under the Curve)-ROC (Receiver Operating Characteristics) curve is necessary to evaluate or represent the performance of the multi-class classification (Gonçalves et al., 2014). It is one of the most crucial evaluation criteria for evaluating the effectiveness of any classification model. TPR is plotted against FPR on the ROC curve, with FPR on the x-axis and TPR on the y-axis.

In order to evaluate the performance of a gait recognition system, receiver operating characteristic (ROC) curves are frequently employed in gait recognition, particularly for binary classification applications. With regard to various classification thresholds, ROC curves enable you to visualize and quantify the trade-off between the true positive rate and the false positive rate.

The essential elements of a ROC curve are as follows:

1. TPR (True Positive Rate): It is a measure of how many positive samples the model classified correctly as positive. The equation of the TPR is formulated as follows:

$$TPR = \frac{TP}{FN+TP} \qquad (3)$$

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2. FPR (False Negative Rate): It is a measure of how many negative samples the model classified incorrectly as positive. It is calculated according to the following equation:

$$FPR \quad = \frac{FP}{TN+FP} \qquad (4)$$

You can make well-informed choices about threshold selection and system design with the use of the ROC curve and AUC-ROC, providing an in-depth understanding of the advantages and disadvantages of gait recognition system performance.

b. Precision (Positive Predicted Value)

Precision is defined as the number of true positives divided by the sum of true and false positives. Precision expresses the proportion of data correctly predicted as positive. Using it as a metric, you can define the percent of the predicted class inside the data you classified as that class. In other words, precision helps you measure how often you correctly predicted that a data point belongs to the class your model assigned it to. The equation for it is:

$$Precision = \frac{TP}{TP+FP} \qquad (5)$$

(TP)means True Positive, (FP) False Negative.

c. Recall (Sensitivity, True Positive Rate)

The recall can be calculated by dividing the total number of false negatives and true positives by the sum of the two. It provides the ability to identify every significant occurrence within a dataset. The recall of your model indicates how well it predicts positive cases. It represents the percentage of true positive instances that were accurately detected. The recall equation is:

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (6)$$

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TP indicated to True Positive, when FN refers to False negative.

d. F1 Score

A machine learning evaluation metric called the F1 score combines recall and precision scores. is one of the most dependable methods for evaluating a classification model's performance. By definition, it is the weighted average of recall and precision, as given by the following equation:

$$F1 = 2\ [(Recall * Precision) / (Recall + Precision)] \quad (7)$$

Achieving an equal balance between precision and recall is ensured by the F1 score. The F1 score will be low whenever any of those two variables is low. Since a high F1 score indicates that both precision and recall are achieved, it is an excellent indication of a well-performing model.

4. Results and Discussions

To evaluate the effectiveness of the suggested architecture, used two different datasets. It was mentioned that the data that the researchers conducted experiments on, the details of the work and how to prepare that data so that it is ready to work on it, and the results that were obtained when applying it to the models that were proposed in this work.

4.1 Local dataset

In order to implement the proposal method in different contexts, a local dataset is created to determine the ability of the method to extract features and classifications in this area. The local datasets that are collected consist of (26 person) different variations with various conditions. There are three viewing angles that make a big difference and are considered challenges to the efficiency of the model, so we are focused on these angles that are represented by (0°, 90°, and 180°) for each person. Additionally, consider three different conditions: normally walking, wearing a coat, and carrying or handling a bag. Two groups were created from the data: one for testing and one for training. We chose 20 individuals for testing and 6 for training. To

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enhance the accuracy of identification of people in gait recognition systems, we conducted experiments on three systems (CNN-LSTM, ALexNet-LSTM, and ResNet-LSTM) and compared them with each other to find out the best performance provided by these systems for identifying a person through his walking way. Table 1 explains the performance of each model and illustrates the result from three view angles with three conditions to find out in which case the model presents the perfect performance and which model has a weakness in that case.

Table (1): local dataset accuracy results for the three-condition walking with a bag (BG), walking with a coat (CL)and walking normally (NM) at each model.

Accuracy					
0°-90-180°					
		0°	90°	180°	**Mean**
BG	**CNN-LSTM**	0.90	0.98	1.00	96.0%
	AlexNet-LSTM	1.00	1.00	1.00	100.0%
	ResNet152-LSTM	0.89	0.98	0.94	93.7%
CL	**CNN-LSTM**	0.82	1.00	1.00	94.0%
	AlexNet-LSTM	1.00	1.00	1.00	100.0%
	ResNet 152-LSTM	0.82	0.99	0.96	92.3%
NM	**CNN-LSTM**	0.91	0.98	1.00	96.3%
	AlexNet-LSTM	1.00	1.00	1.00	100.0%
	ResNet 152-LSTM	0.82	1.00	0.96	92.7%

In Table 2, the averages for each model were calculated separately for each of the three conditions. Through the experiments that were conducted using local data and testing them on the three models, all of them showed ideal results, especially the AlexNet-LSTM, which showed distinctive results in identifying the person's gait. In

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addition, the proposed design had good results. Therefore, in the case of a small area, we can rely on the two methods to identify people by their walking patterns.

Table (2): overall local dataset results for each model.

Models	Mean
CNN-LSTM	95%
AlexNet-LSTM	**100%**
ResNet 152-LSTM	93%

For classification issues at various threshold settings, the AUC-ROC curve provides a performance indicator. The degree or measure of separability is represented by AUC, and ROC is a probability curve. It indicates how well the model can distinguish between classes. An excellent model has an AUC close to 1, indicating that it has a high level of separability. An AUC close to 0, which indicates the worst measure of separability, indicates a poor model. Because of the unified characteristics of this unit of measurement, it was utilized in this study to evaluate the effectiveness of the models on which researchers conducted the experiments and to compare them against one another to identify the most effective model to depend on for identifying a person's gait. After performing the experiment, having learned that the AlexNet-LSTM model performed efficiently using the local dataset compared with two other models, CNN-LSTM and ResNet152-LSTM, which presented 0.96 in AlexNet-LSTM while other models, CNN-LSTM and ResNet152-LSTM, presented 0.95 and 0.93, respectively. As shown in Fig. 4,

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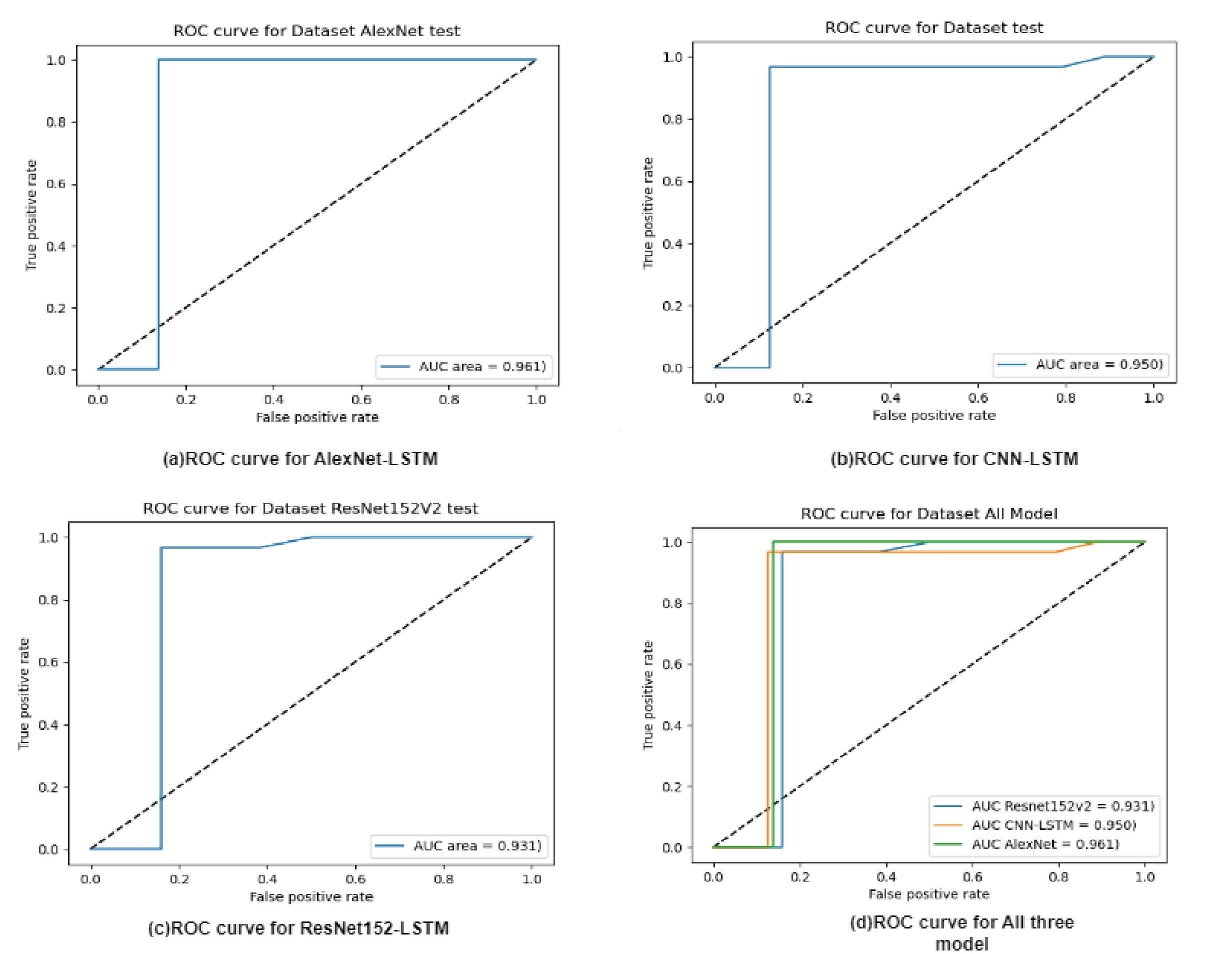

(a)ROC curve for AlexNet-LSTM

(b)ROC curve for CNN-LSTM

(c)ROC curve for ResNet152-LSTM

(d)ROC curve for All three model

Figure (4): local dataset Roc curve for each model.

In a machine learning system, there are metrics (precision, recall, and f1-score) that help you understand the quality of your system. Because of the importance of these standards, we have used them in our proposal. Among the results that emerged when applying these standards to the system proposed in this study is that it achieved ideal results when applied to local data, as shown in Table 3.

Table (3): Classification performance of proposed method on Local Dataset.

Local Dataset				
Model	**precision**	**recall**	**f1-score**	**Accuracy**
CNN-LSTM	95.7%	95.4%	95.4%	95.4%
AlexNet-LSTM	100%	100%	100%	100%
ResNet152-LSTM	93.0%	92.9%	92.8%	92.9%

4.2 CASIA B dataset

In order to have the ability to generalize the proposed approach using a large dataset, A well-known and frequently used dataset in the study of gait recognition is the CASIA-B dataset. It is part of the larger gait database maintained by the Chinese Academy of Sciences Institute of Automation (CASIA) and was created especially for research on gait recognition (S. Yu et al., 2006). It was developed in January 2005 and is a large Multiview gait database. The gait data was collected from 11 viewpoints (0°, 18°, 36°, 54°, 72°, 90°, 108°, 126°, 144°, 162°, 180°) involving 124 individuals with three normal conditions: wearing a coat and carrying a bag. Two groups were created from the data: one for testing and one for training. We chose 24 individuals for testing and 100 for training. The image shown in Fig. 5 shows the sample of the CASIA B dataset with an explanation of all the views that consist of 11 view angles with the three conditions, which consist of normally walking, coat wearing, and carrying a bag.

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A Scientific Quarterly Refereed Journal Issued by Lebanese French University – Erbil, Kurdistan, Iraq
Vol. (10), No (1), Spring 2025
ISSN 2518-6566 (Online) - ISSN 2518-6558 (Print)

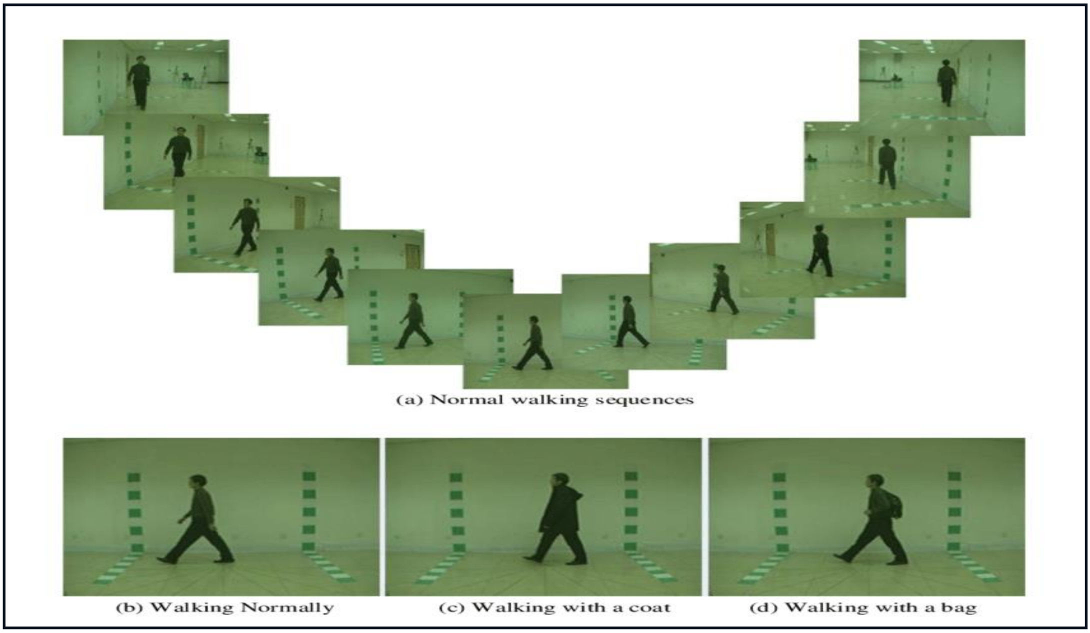

Figure (5): The sample of CASIA B dataset.

To evaluate the model proposed in this paper, we performed the experiment on the most popular and widely used data in the field of gait recognition. To determine the efficiency of the proposal, we implemented it on three deep learning models and then compared the results, as shown in Table 4, to show us that the model that was designed outperformed the other two methods. Thus, this proposal proved its efficiency in identifying people.

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A Scientific Quarterly Refereed Journal Issued by Lebanese French University – Erbil, Kurdistan, Iraq
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Table (4): CASIA B dataset accuracy results for the three-condition walking with a bag (BG), walking with a coat (CL)and walking normally (NM) at each model.

							Accuracy						
							0°-180°						
		0°	18°	36°	54°	72°	90°	108°	126°	144°	162°	180°	**Mean**
BG	**CNN-LSTM**	0.91	0.99	0.99	0.92	1	1	0.98	1	0.99	0.94	0.96	**97.1%**
	AlexNet-LSTM	0.72	1	1	0.85	0.99	1	0.8	0.99	1	0.84	0.83	**91.1%**
	ResNet 152-LSTM	0.67	0.97	1	0.66	0.97	0.93	0.63	0.97	0.89	0.53	0.81	**82.1%**
CL	**CNN-LSTM**	1	0.98	0.97	0.99	0.99	0.98	0.96	0.97	1	1	1	**98.5%**
	AlexNet-LSTM	0.95	1	0.99	1	0.99	0.99	0.89	0.85	0.97	1	0.98	**96.5%**
	ResNet 152-LSTM	0.85	0.94	0.96	0.95	0.98	0.97	0.74	0.79	0.93	0.94	0.95	**90.9%**
NM	**CNN-LSTM**	0.99	1	1	1	0.98	1	1	1	1	1	0.98	**99.5%**
	AlexNet-LSTM	1	1	0.99	0.99	0.93	0.97	0.99	0.99	1	0.99	0.97	**98.4%**
	ResNet 152-LSTM	0.96	0.99	0.97	0.79	0.77	0.83	0.95	0.99	0.96	0.99	0.91	**91.9%**

By calculating the outcomes that appeared in the three scenarios, we determined the averages for each model independently and displayed them in Table 5. recognized that all three of the models produced excellent results in the experiments run utilizing the CASIA B dataset and testing them on the three models. However, the proposed design model, CNN-LSTM, stands out for its ability to detect a person's gait. Which introduces 98.4%, while other methods, AlexNet-LSTM and ResNet152-LSTM, introduce 95.3% and 88.3%, respectively.

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Table (5): overall CASIA B dataset results for each model.

Models	Mean
CNN-LSTM	**98.4%**
AlexNet-LSTM	95.3%
ResNet 152-LSTM	88.3%

To evaluate the performance of proposal method on CASIA B dataset, utilized the most popular accuracy measurements AUC-ROC curve to determine the effectiveness of method to classification. After doing experiment, discovered that the AlexNet-LSTM model performed effectively using the CASIA B dataset when compared to two other models, CNN-LSTM and ResNet152-LSTM. AlexNet-LSTM showed 0.97, while CNN-LSTM and ResNet152-LSTM presented 0.96 and 0.85, respectively. As displayed in Fig. 6. observe the ROC curve of AlexNet-LSTM method's capability for classification in CASIA B dataset

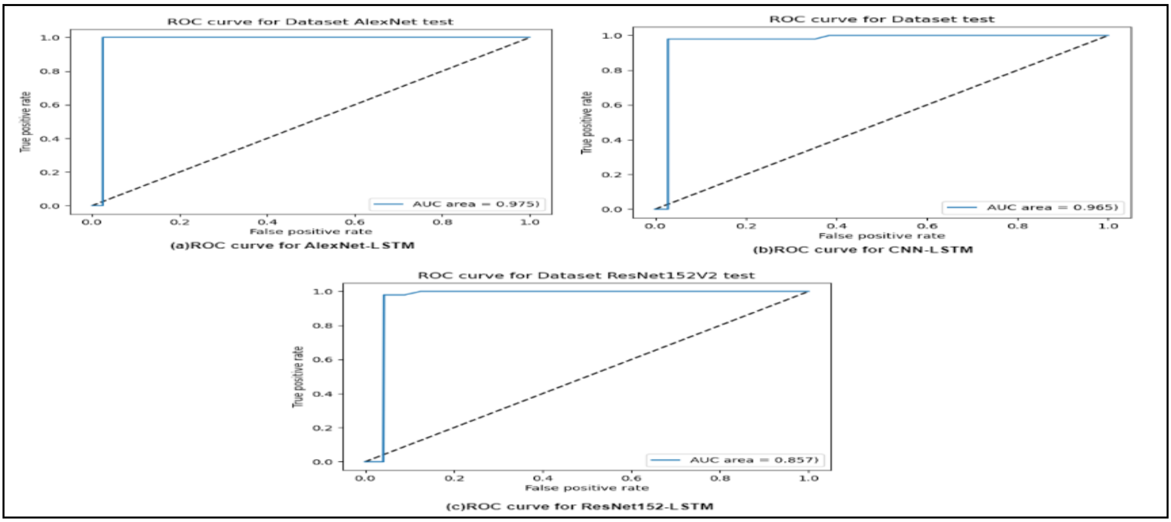

Figure (6): CASIA B dataset Roc curve for each model.

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To overcome the problem of extracting features and classification by designing a novel approach for inputting data into the feature extraction phase using a sequence of images in each class, each class has a set of sequences of images that increase the efficiency of the system. After training in the local dataset, get 100% in AlexNet-LSTM, 95% in CNN-LSTM, and 93% in ResNet-LSTM frequently. Also, get 98.4% in CNN-LSTM when experimenting with the CASIA B dataset. Thus, it appears to us. The specialized architecture introduced in this proposal produces efficient performance when experimented with on two different datasets to demonstrate the efficiency and capability of implementing two small and large datasets for recognition. So, we verify the model's performance on additional datasets or in other settings before developing a gait recognition system for real applications to ensure its robustness.
In the fields of machine learning and pattern recognition, metrics like recall, precision, and the F1 score are often utilized. The efficacy of a gait recognition system is evaluated using these measures. Your system's ability to recognize individuals based on their gait patterns may be objectively measured using these metrics. Table 6 demonstrates the results of the metrics on the CASIA B dataset.

Table (6): Classification performance of proposed method on CASIA B dataset.

CASIA B Dataset				
Models	**precision**	**Recall**	**f1-score**	**accuracy**
CNN-LSTM	98.4%	98.4%	98.4%	98.4%
AlexNet-LSTM	95.6%	95.1%	95.0%	95.3%
ResNet152-LSTM	89.2%	89.2%	87.8%	88.3%

In order to determine the efficiency of the proposed method, we conducted a comparison with other studies that used the CASIA B dataset. Table 7 shows the average obtained by other studies in addition to the study proposed in this article.

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Table (7): The comparison results proposed method with other studies on CASIA B dataset.

Model	Accuracy (Cross View, AVG)	NM	CL	BG
GaitSet(Chao et al., 2018)	84.2	95	87.2	70.4
GaitPart(Fan et al., n.d.)	88.8	96.2	91.5	78.7
gaitGraph(Teepe et al., 2021)	76.3	87.7	74.8	66.3
GaitMixer(Pinyoanuntapong et al., 2022)	88.3	94.9	85.6	84.5
GaitRef(Zhu et al., 2023)	94	98.1	95.9	88
CNN-LSTM	98.4	99.5	98.5	97.1
AlexNet-LSTM	95.3%	98.4	96.5	91.1
ResNet152-LSTM	88.3%	91.9	90.9	82.1

After completing experiments on the models that worked in this study, we conducted a comparison with the latest studies in this field, which showed us the efficiency of the proposed method compared to others.

5. Conclusion and future work

The design of classifiers and feature representation are the most difficult gait recognition challenges. In this study, a novel gait recognition system was introduced that fully utilizes deep learning technology. The suggested method based on entering data from a series of images into the proposed models increased the efficiency of the proposal and designed a model that benefited from the ability of deep learning methods (LSTM) to display the perfect result for representing video and sequence images. This is due to the properties it has for storing data. implemented the proposal into two different datasets: the local dataset and the popular dataset in the gait recognition field, the CASIA B dataset.

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In this paper, the studies were conducted with a local dataset in three different conditions (normal, clothes, bag) and three various viewpoints (0°, 90°, and 180°). The suggested strategy was successful in achieving the promising result of 100% with AlexNet-LSTM. Other models also performed effectively, with 95% in CNN-LSTM and 93% in ResNet-LSTM independently. This is if implemented on a limited scale. To know the scalability of the proposed method, we experimented with a large popular dataset known in gait recognition (CASIA B) with three conditions (normal, clothes, bag) and Multiview's angle (0°, 18°, 36°, 54°, 72°, 90°, 108°, 126°, 144°, 162°, and 180°). It achieved an effective result. The experiment results showed the effectiveness of the proposal at 98.4% in CNN-LSTM; other models got an effective result of 95.3% in AlexNet-LSTM and 88.3% in ResNet-LSTM.

This work is different from the other works in that hybrid techniques have been used in gait recognition. The combined LSTM with three models (CNN, AlexNet, and ResNet152) have been used. Through the experiments conducted, it was found that the proposed method provided good results in both areas (small dataset and large dataset). So, it can be reliable to identify a person by his walking way. In future work, it is intended to implement the suggestion method in real time when the tool is applied in real-life applications.

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سیستەمی چاودێری لەسەر بنەمای فێربوونی قووڵ بۆ دابینکردنی واژۆی ڕۆیشتنی پارێزراو

پوختە:

لەم دواییانەدا مۆدێلی فێربوونی قووڵ ڕۆڵێکی گەورەی هەبوو لە بوارە جیاوازەکانی وەک بینینی کۆمپیوتەر، ناسینەوەی قسەکردن، و ناسینەوەی وێنە بەهۆی توانای دەرهێنانی تایبەتمەندی ئاڵۆز لە داتا گەورەکان و فێربوون بە شێوەیەکی ئۆتۆماتیکی. ئەمڕۆ دابینکردنی ئاسایش بۆتە یەکێک لە شتە سەرەتاییەکان بۆ پاراستنی خەڵک و دەستەکان، بۆیە پێویستی بە سیستەمی چاودێری بۆ بەدیهێنانی ئەو سەلامەتییە بۆتە پێویست بۆ ئەوەی مەترسی و پێشێلکارییە ئەمنییەکان کەم بکرێتەوە. ڕۆیشتن بریتییە لە شێوازی ڕۆیشتنی مرۆڤ لەکاتی جوڵەدا، جوڵەی هەر تاکێکیش تایبەتە، هەر بۆیە دەتوانرێت لە بایۆمەتریدا بەکاربهێنرێت بۆ ناسینەوەی کەسەکە بە بەکارهێنانی تەکنەلۆژیای ناسینەوەی ڕۆیشتن، بۆ مەبەستی ئەمنی (چاودێری تەندروستی، فڕۆکەخانە، و تاوان و هتد.) کە بەو ڕاستییە جیا دەکرێتەوە کە پێویستی بە هاوکاری تاک نییە. بەڵام تەحەددا هەیە کە بە گۆڕانکاری لە دیدگا، جل و بەرگ، بارودۆخی هەڵگرتن و هتد نوێنەرایەتی دەکرێت. بۆ چارەسەرکردنی ئەم پرسە و زیادکردنی وردی ناسینەوە، ئێمە لێکۆڵینەوە لە ناسینەوەی ڕۆیشتن دەکەین بە بەکارهێنانی فێربوونی قووڵ لەم لێکۆڵینەوەیەدا و پەرەپێدانی شێوازێکی داهێنەرانە لەسەر بنەمای بیرەوەری کورتخایەنی پێچاوپێچ (Conv-LSTM) و دوو شێوازی دیکە (Conv-AlexNet) و... (Convl-ResNet150) بۆ دەستنیشانکردن و ناسینەوەی ڕۆیشتنی مرۆڤ. ئێمە ڕێبازەکەمان لەسەر بنەمای دوو کۆمەڵە داتا

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A Scientific Quarterly Refereed Journal Issued by Lebanese French University – Erbil, Kurdistan, Iraq
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ISSN 2518-6566 (Online) - ISSN 2518-6558 (Print)

جێبەجێ کرد، کۆمەڵە داتاکانی CASIA B و کۆمەڵە داتاکانی ناوخۆیی. بەپێی ئەنجامە تاقیکارییەکانمان، ئەنجامەکانی تاقیکردنەوەکە نیشان دەدەن کە ڕێگەی پێشنیارکراوی ڕێژەیەکی ناسینەوەی نایابی بەدەستهێناوە لە 95% (Conv-ALexNet) کاتێک بەکارهێنرا بۆ کۆمەڵە داتاکانی CASIA B , 100% کاتێک بەکارهێنرا بۆ کۆمەڵە داتا ناوخۆییەکان.

نظام مراقبة قائم على التعلم العميق لتوفير توقيعات آمنة للمشية

الملخص:

في الآونة الأخيرة، كان لنماذج التعلم العميق دور كبير في مجالات مختلفة مثل رؤية الكمبيوتر والتعرف على الكلام والتعرف على الصور نظرًا لقدرتها على استخراج الميزات المعقدة من البيانات الكبيرة والتعلم تلقائيًا. اليوم أصبح توفير الأمن من الأشياء الأساسية لحماية الأشخاص والإدارات، لذلك أصبحت الحاجة إلى نظام مراقبة ضروري لتحقيق تلك السلامة من أجل تقليل المخاطر والانتهاكات الأمنية. المشية هي الطريقة التي يمشي بها الشخص أثناء تحركه، وحركة كل فرد فريدة من نوعها، وبالتالي يمكن استخدامها في القياسات الحيوية للتعرف على الشخص باستخدام تقنية التعرف على المشية، لأغراض أمنية (الرعاية الصحية، المطار، الجرائم، إلخ).) والتي تتميز بأنها لا تتطلب تعاون الفرد. ومع ذلك، هناك تحديات تتمثل في الاختلافات في وجهات النظر، والملابس، وظروف الحمل، وما إلى ذلك. لمعالجة هذه المشكلة وزيادة دقة التحديد، نقوم بالتحقيق في التعرف على المشية باستخدام التعلم العميق في هذا البحث وتطوير طريقة مبتكرة تعتمد على الذاكرة التلافيفية طويلة المدى (Conv-LSTM) وطريقتين أخريين (Conv-AlexNet) و (Convl-ResNet150) للتعرف والتعرف على المشي البشري. لقد قمنا بتنفيذ نهجنا استنادًا إلى مجموعتي بيانات، مجموعة بيانات CASIA B ومجموعة البيانات المحلية. وفقًا لنتائجنا التجريبية، أظهرت نتائج التجربة أن النهج المقترح حقق معدل تعرف ممتاز في (Conv-ALexNet) بنسبة 95% عند تطبيقه على مجموعة بيانات CASIA B , 100% عند تطبيقه على مجموعة البيانات المحلية.