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Human Gait Recognition Using Dwarf Mongoose Optimisation in the GAN Model

Ganesh Karthik Muppagowni

Koneru Lakshmaiah Education Foundation, Guntur 522502,India
K saikumar, Department of ECE, Koneru Lakshmaiah Education Foundation, India-522302,

saikumarkayam4@ieee.org

ABSTRACTs

Automated video surveillance systems (AVSs) have recently become vital for ensuring public safety, particularly at events with huge audiences like sporting events. Machine (ML) and deep learning (DL) open the way for computers to think like humans even further by including training and learning components, which artificial intelligence (AI) already provides. In order to evaluate and make sense of surveillance data acquired by fixed or mobile cameras mounted indoors or outdoors, DL algorithms require datalabelling and high-performance processors. Recent advances in generative adversarial networks (GANs) for image synthesis and creation in VSSs have made it a hot topic in the field of study to establish if a given input is typical or atypical. Therefore, this researchpresents a better GAN network to recognise human gaits and to distinguish between human actions that are normal and pathological in VSSs. To achieve this goal, we first combine global and local features to enhance learning in crucial local regions that include multiple key points. Two, we use metric learning to pull out shared and unique characteristics. After features have been retrieved, they are used as input by the classification module in order to identify GAN-generated pictures. DMO is used in this study to perform hyper-parameter optimization (HPO) in GAN, which provides significant metaheuristic balance between the survey and misuse phases.

Keywords:

video surveillance system, generative adversarial networks, human gait recognition, dwarf mongoose optimization, hyper- parameter optimization

1. INTRODUCTION

The computer vision community has become more interested in human gait detection from video in recent years,despite the task's reputation for being difficult and fraught with problems. Gait recognition is seen as a possible next- generation method [1], whereas other biometric technologies like facial recognition and fingerprinting are seen as current- generation techniques. Gait recognition has numerous advantages over other biometrics, including the fact that it does not require the subject's active participation or physical touch, and that the target data does not need to be extremely high-resolution or extremely close up to be effective. It is alsohard to hide one's stride. Criminals often hide their identities by using disguises that render facial recognition systems useless. Gait recognition is the only practical and efficient means of identification in such cases [2]. As a result, gait recognition is extremely sensitive to both the functional structure of the human body and the dynamics of human walking motion. In the past decade, HGR has emerged as a vision. Gait recognition has various uses in industry, including biometrics [3-4], which is why it is widely used in fields like surveillance and healthcare.

2. RELATED WORKS

Using video sequences, [5] presented a completely IACO method for HGR. There are primarily four stages to the suggested structure. The initial process included standardizing the database within the context of a moving image. Second, the characteristics of the dataset are used to inform the selection and refinement of one of two pre-trained replicas, ResNet101 and InceptionV3. The two adapted models were then trained by transfer learning, and features were retrieved. The retrieved characteristics were optimised with the help of the

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IACO algorithm. The best characteristics were chosen using IACO and then fed into a Cubic Support Vector Machine for classification. Multiclass analysis is usedby the cubic support vector machine. The accuracy was 95.2%,93.92%, and 98.2% across the board, respectively, when testedon the CASIAB dataset from 0, 18, and 180 degrees. The suggested method has also been compared to other approachesand found to be superior in terms of accuracy and computing time.

The solution described [6-8] efficiently dealswith real-time issues such as changing viewing angles and different gaits. The proposed novel framework consists of thefollowing steps: (a) capturing video in real-time; (b) extractingfeatures. The most cutting-edge machine learning classifiers are then used to categorise the characteristics with the greatestdegree of discriminatory power. Both the CASIA B dataset and a real-time recorded dataset were used to fuel the simulation process. Specifically, the accuracy is between 95.26 and 96.60 percent on several datasets. The findings demonstrate the superiority of our suggested framework over numerous established methods.

The Vision Transformer (ViT) is used for gait detection in Gait-ViT [9-11], which incorporates an attention mechanism. When implementing the suggested Gait-ViT, we first averaged a series of photos taken during the gait cycle toproduce the gait energy image. Next, flattening and patch embedding are used to convert the picture patches into sequences. In order to recover the patch positions, position embedding is performed on the sequence of patches alongsidepatch embedding. After receiving the vector sequence, the Transformer encoder was used to generate the final gait representation. When determining a sequence's categorization,the initial item was fed into a multi-layer perceptron for label prediction. The Vision Transformer model's superior performance over state-of-the-art approaches is demonstratedby the suggested method's results.

3. PROPOSED SYSTEM

Dataset

In this study, we used the CASIA A gait dataset, the CASIAB gait dataset, and the CASIA C gait dataset, all of whichare accessible for public use. Figure 1 displays the sample frames for each dataset. Here is a quick summary of several connected data sets:

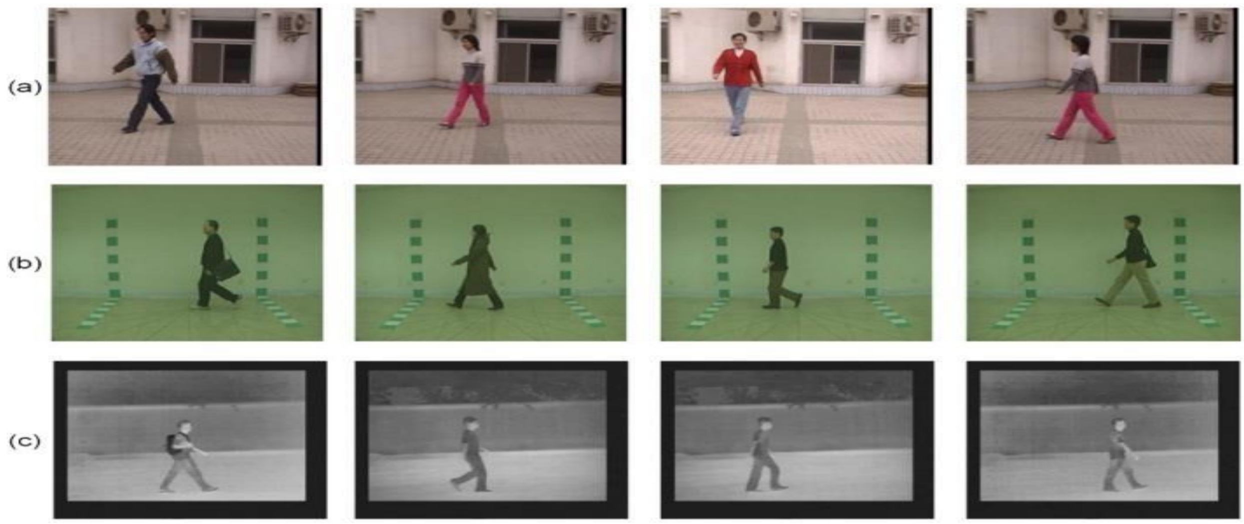


Figure 1. Frames representative of the gait recognitiondatasets that were chosen

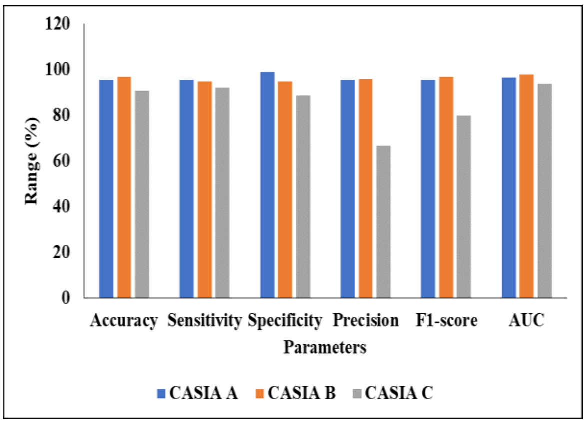
CASIA Field recordings from two consecutive days were used to create a gait dataset. Twenty participants walked through three different camera angles—lateral (0°), oblique (45°), and frontal (90°) —to create this dataset. With an average gait sequence duration of around 90 frames collectedat 25 fps and a resolution of 352x240, the dataset has a total of240 gait sequences. A total of 168 video sequences were usedin this study, some for training and some for assessment.

The CASIA B gait dataset is frequently employed as a database for multi-view gait identification. A total of 124 participants (93 men and 31 women) were videotaped while walking around an indoor arena from 11

various angles utilising USB cameras. Each of the 18 possible directions of view is ordered as follows: 0 degrees, 18 degrees, 36 degrees,54 degrees, 72 degrees, 90 degrees, 108 degrees, 126 degrees,
144 degrees, 162 degrees, and 180 degrees Six video sequences of the same person wearing a coat (WC) and two video sequences of the same person carrying a bag (CB) werecaptured to serve as gait sequences for multi-view. The framesize of the movies was 320 x 240, and the recording speed was25 frames per second. That means there are a total of 13,640 video sequences in the dataset, or 1011124. Only videos with a 90-degree field of view were evaluated for this post, for a grand total of 1240 clips. The 70:30 validation method was used, as in the CASIA A dataset.

$Precision+Sensitivity$

Area Under Curve (AUC) and Receiver Operating Characteristics (ROC) curves were created to quantitatively estimate the performance of the proposed GAN-DMO model. Tables 1 and 2 compare the proposed GAN model with and without optimization (DMO) on three separate datasets.



4. RESULTS AND DISCUSSION

In this part, we show how our proposed system has been tested with many data sets and evaluated with various metrics.In order to do this, we used a 70:30 split for training and testingon three publicly available datasets. After data partitioning, a pre-trained model was loaded, and activation was determinedusing cross entropy. The DMO algorithm decided on a learning rate of 0.001 and an initial mini batch size of 64. Thisprocedure was built in Matconvnet, a deep learning toolkit in MATLAB2018a. The sensitivity, precision rate, false- negative rate, false-positive rate, area under the curve (AUC),F1-score, and accuracy were used to evaluate the system. The total amount of time needed by the suggested system to do a categorization was also determined.

Table 2. Analysis of GAN model with DMO

Metric	CASIA B	CASIA C	CASIA A
Precision	99.848	75.00	98.557
F1-score	99.872	85.525	98.457
Accuracy	99.78	93.75	98.482
Sensitivity	99.864	99.632	98.523
Specificity	99.969	92.426	99.579
AUC	99.85	95.05	99.78

When the GAN model is tested with DMO, it achievedbetter performance on three different datasets such as A, B and
C. In the CASIA A dataset, the GAN-DMO model achieved nearly 98% to 99% of accuracy, sensitivity, specificity, precision, F1-score and AUC. In the analysis of CASIA C dataset, the proposed GAN-DMO model

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achieved 93% of accuracy, 99% of sensitivity, 92% of specificity, 75% ofprecision, 85.52% of F1-score and 95% of AUC. In the CASIAB dataset, the proposed model achieved 99% on all metrics such as accuracy, precision, sensitivity, specificity, F1-score and AUC. Figure 7 presents the graphical analysis of proposedGAN-DMO for all dataset.

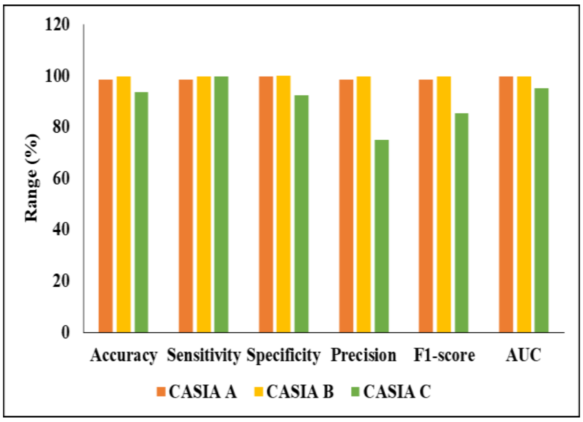

Figure 7. Analysis of GAN-DMO model for three datasets

4.1 Comparative analysis of proposed model

Table 3 presents the techniques in terms of all datasets. Theexisting techniques such as IACO on CASIA B, ResNet
[19] on CASIA B, ViT on CASIA-B, VGG-16 on CASIA-B, ELM on CASIA-B are considered, but the proposed GAN-DMO model uses three datasets. Therefore, the techniques from are implemented with these datasets and results are averaged.

Table 3. Comparative analysis of GAN-DMO with varioustechniques

didn't focus on tuning the parameters for high classification accuracy. Likewise, the analysis of CASIA B dataset, the existing techniques achieved nearly 87% to 94% and 82% to 89% of accuracy on CASIA C, where proposed model achieved 99% and 93% of accuracy on CASIA-C dataset. Figure 8 provides the graphical representation of proposed model with existing techniques.

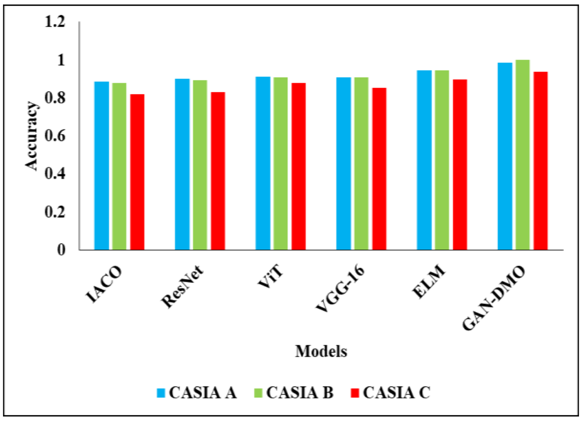

Figure 8. Analysis of accuracy on three datasets

5. CONCLUSION

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Our suggested general method combines global and local characteristics with metric learning based on the training loss of gait prediction to enhance the generalisation potential of existing GAN-generated gait image recognition systems. The experimental findings show that the suggested approach outperforms several pre-existing algorithms and provides an acceptable generalisation capacity, with average accuracy values exceeding 0.99 across all three testing datasets. Here are some of the more important ones: By combining global andlocal features extracted by the residual attention network, a) the learning on crucial local areas is reinforced, and b) the metric learning is applied to obtain common features in the same type of gait images and discriminative features betweennatural and GAN-generated gait in the feature learning phase.There is little doubt that the suggested method greatly benefitsfrom HPO optimization since its performance is greatly enhanced. Possible future actions are listed here.

- The optimum fusion method can be chosen depending on the accuracy of the methods used.
- In addition, the OU-MVLP, OU-LP-BAG, and TUM-GAID datasets will be taken into account throughout the experimentation phase.
- Increase your recognition precision by using a two- pronged strategy that combines techniques like optical flow with raw picture analysis.
- Get in-depth information by utilising cutting-edg deep models, such as Efficient Net, for featur extraction.

Techniques	CASIA A	CASIA B	CASIA C
IACO	0.8863	0.8775	0.8207
ResNet	0.8997	0.8925	0.8297
ViT	0.9111	0.9098	0.8775
VGG-16	0.9088	0.9095	0.8525
ELM	0.9437	0.9449	0.8965
GAN-DMO	0.9848	0.9987	0.9377

In the CASIA-A dataset, the existing techniques such as IACO, ResNet achieved 88% to 89%, VGG and ViT achieved 90% to 91%, ELM achieved 94% and proposed model achieved 98.48%. The reason for better performance is that theGAN's HPO is optimized by DMO, where existing techniques

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