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Accurate metaheuristic deep convolutional structure for a robust human gait recognition

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ABSTRACT

Gait recognition has become a developing technology in various security, industrial, medical, and military applications. This paper proposed a deep convolutional neural network (CNN) model to authenticate humans via their walking style. The proposed model has been applied to two commonly used standardized datasets, Chinese Academy of Sciences (CASIA) and Osaka University-Institute of Scientific and Industrial Research (OU-ISIR). After the silhouette images have been isolated from the gait image datasets, their features have been extracted using the proposed deep CNN and the traditional ones, including AlexNet, Inception (GoogleNet), VGGNet, ResNet50, and Xception. The best features were selected using genetic, grey wolf optimizer (GWO), particle swarm optimizer (PSO), and chi-square algorithms. Finally, recognize the selected features using the proposed deep neural network (DNN). Several performance evaluation parameters have been estimated to evaluate the model's quality, including accuracy, specificity, sensitivity, false negative rate (FNR), and training time. Experiments have demonstrated that the suggested framework with a genetic feature selector outperforms previous selectors and recent research, scoring accuracy values of 99.46% and 99.09% for evaluating the CASIA and OU-ISIR datasets, respectively, in low time (19 seconds for training).

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1. INTRODUCTION

Human gait refers to the variations in posture of the entire body, particularly the legs, during walking. Gait recognition and its applications have attracted much attention in the previous decade. Compared to other biological features like deoxyribonucleic acid (DNA), face, fingerprint, iris, and so on, gait has several advantages, which are represented in, it is non-invasive, identifies humans from long distances, does not require subject cooperation, and is resistant to low-resolution images. Moreover, it is difficult to conceal because it is based on gait features of entire-body posture changes while walking; it is hard to hide with gloves and masks such as fingerprints and face [1]. The advantages of the gait authentication technique have led to its wide variety of applications, including banks, hospitals, airports, trade centers, and military bases [2].

Gait identification has several benefits, but certain negative aspects are brought on by changes in clothes or carrying objects, which affect recognition accuracy [3]. Due to this, a number of recent studies have focused on enhancing gait detection traits by model-based and appearance-based techniques using deep learning. In this paper, after the pedestrian frames have been segmented from the background, enhanced, and normalized. Its features have been extracted using the proposed convolutional neural network (CNN) and other pre-trained models, then selected the best of them by genetic, particle swarm optimizer (PSO), grey wolf optimizer (GWO), and chi-square models. Finally, recognize these features using the proposed deep neural network (DNN) model. The main contribution of the proposed methodology can be listed as follows: i) isolating pedestrians from the data gait video frames, improving and normalizing them; ii) proposing the well-designed CNN structure for extracting the gait features from Chinese Academy of Sciences (CASIA) and Osaka University-Institute of Scientific and Industrial Research (OU-ISIR) datasets; iii) selecting the significant features using genetic, PSO, GWO, and Chi-square models; iii) proposing a DNN for identifying the gait features accurately; and iv) comparing the gait recognition performance metrics with the recent studies and the other pre-trained models. The remaining article has the following structure: the methodology for the proposed model is described in section 2, the proposed CNN model and the feature selector models are explained in section 3, the main results of the study are presented in section 4, and the study's conclusions and recommendations are discussed in section 5.

Wen and Wang [1] have proposed a gait authentication model by extracting a gait energy image from video frames and dimensionality reduction by sparse linear subspace. Then, classify them by support vector machine model, which uses Gaussian radial basis function (RBF) kernels to attain cross-view gait identification. Finally, the performance of the proposed gait recognition system is demonstrated using CASIA and OU-ISIR datasets. Their experimental results scored 90.5% and 91.3% of accuracy values on CASIA-B and OU-ISIR datasets, respectively. George *et al.* [4] presented a color-mapped contour gait image as a gait characteristic for tackling cofactor variations and the identification of gait across perspectives. Moreover, they compared and chose the best edge detection methods for gait blueprint generation on the CASIA-B dataset and the OULP database. Their experimental results significantly improve gait recognition for different views.

Premalatha and Chandramani [5] proposed a gait authentication technique to overcome the gait covariate factors. Their model extracted the gait features from silhouette images using a histogram of oriented gradients (HOG) algorithm and then recognized them by a K-nearest neighbor (K-NN) technique. The evaluation result scored a high identification rate when applied to the CASIA B gait database, ranging from 95.5% to 98.7% of accuracy value. Sokolova and Konushin [6] have presented a pose-based CNN model for gait authentication. Firstly, they estimated the optical flow among gait frames to extract the motion information. They then proposed a DNN model for computing pose-based gait descriptors. Finally, the experimental experiments show that their study outperforms state-of-the-art studies.

Parashar *et al.* [7] used a pose-based gait recognition algorithm to attempt people wearing an overcoat, carrying things, or other factors. It intends to use CNN to estimate human movement. They used a multilayer recurrent neural network (RNN) to recognize gait datasets from the pose images. Moreover, they presented a graphical user interface (GUI) for gait detection to be accurate, easy, and quick application. The experimental result offered an accuracy ranging from 60.88% to 95.23%. Chen *et al.* [8] proposed a gait identification framework called gait aggregation multi-feature representation (GaitAMR) for obtaining the most selective subject features. The GaitAMR extracts global and local body movement descriptors by a complete and partial temporal accumulation technique, besides effectively collecting feature representations from many domains. Experimental results on the most common gait datasets prove that GaitAMR enhances gait recognition and outperforms the other current studies.

In order to collect information about human locomotion, Dong *et al.* [9] proposed a recognition framework based on the feature fusion of human gait frames and phases. Support vector machines (SVM), backpropagation (Bp) neural networks, AlexNet, and LeNet5 algorithms are just a few examples of the deep learning models and machines that have been utilized to recognize and assess the fused characteristics. The proposed framework's efficacy was demonstrated by the proposed model's accuracy of 97.7% for gait phase recognition. In order to recognize gait phases during human movement, Zhang *et al.* [10] created a model called SBLSTM that integrates DNN, bidirectional long short-term memory (BiLSTM), and sparse autoencoder (SAE) models. The four phases of the gait cycle heel strike, foot flat, heel off, and swing phase can be distinguished using this model. The BiLSTM learns the temporal patterns and periodic changes in the gait image after the SAE extracts the gait data. The gait stages are identified, and DNN obtains the output classification results. The presented model demonstrates that the SBLSTM algorithm is successful at recognizing gaits, and its performance results outperform those of other algorithms, supporting this claim.

Altilio *et al.* [11] applied various machine learning classification methods on the gait dataset to classify patient motions from gait frames automatically by probabilistic neural network (PNN) technique. The proposed model achieved an accuracy rating of 91% for home-based and cost-effective rehabilitation techniques. In research [12], the human gait Frames of the CASIA (B) database have been classified using a

SVM and a HOG models. First, they extract silhouette images, then create gait energy images (GEIs) to use as input for the classifier models. The evaluation results achieve an accuracy value of 87.9% in wearing a coat and a mean value of 83.33% for all classes.

2. METHOD

The main procedures of the proposed gait recognition technique have been depicted in Figure 1, which contains five main steps: data gathering and preprocessing, feature extraction, feature selection, and image label recognition. After the dataset had been collected and preprocessed, it is features were extracted using the proposed CNN architecture and several pre-trained models, including, AlexNet, GoogleNet, Vgg, ResNet50, and Xception. Then, the best among them were selected using PSO, GWO, Chi-square, and the genetic model. Finally, recognize them by the fine-tuned DNN. The following subsections will thoroughly demonstrate the approach of the suggested framework using the CASIA and OU-ISIR gait datasets.

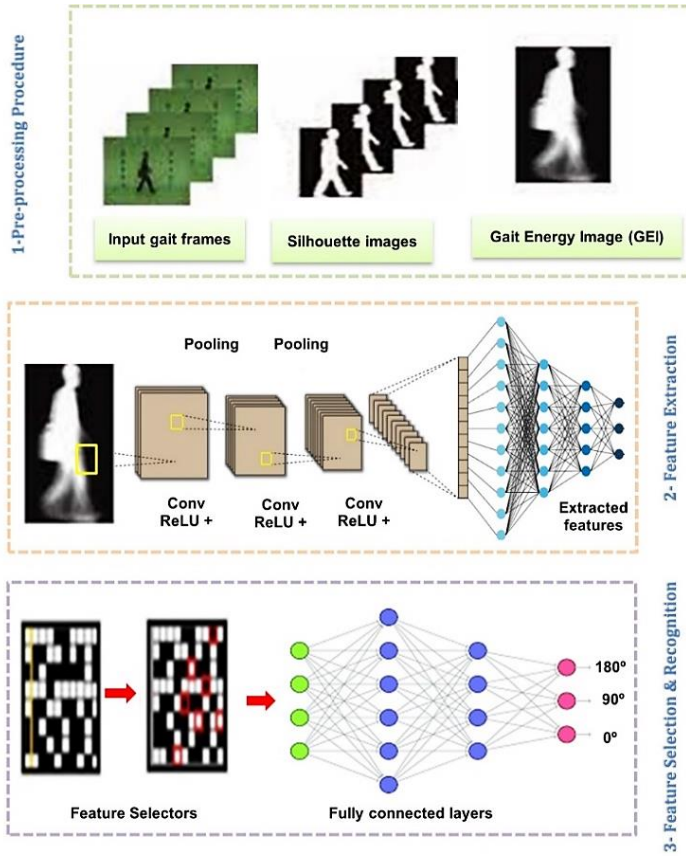


Figure 1. The suggested gait authentication model framework

2.1. Gait dataset

Several datasets have been created for gait authentication research, such as CASIA and OU-ISIR. The Institute of Automation Chinese Academy has established the CASIA dataset, which includes the four datasets A, B, C, and D. Over 20K frames in the CASIA gait dataset [13] vary in pace, view angle, and garment changes. The Institute of Scientific and Industrial Research developed the OU-ISIR gait dataset [14], which contains 63,846 people ages 2 to 90 who walked along a path captured by the camera at 30 frames per second. The sample of gait datasets from CASIA and OU-ISIR is shown in Figures 2(a) to 2(d).

2.2. Pre-processing criteria

The preprocessing steps of this study are shown in Figure 3 and are mentioned below. The main aim of the preprocessing approaches is to increase image quality, minimize distortion, and reduce disturbance in order to identify the images with clearly discernible silhouettes from the backdrop. The proposed procedures of gait image preprocessing pass through the following steps:

Step 1: The gait frames were reduced to 140×140 to reduce the computing time and then converted to gray images.
Step 2: Subtract each frame from its background to obtain silhouette images.
Step 3: Contrast silhouette images using the histogram equalization model [15].
Step 4: Binarize result frames by the Otsu threshold [16] technique, then apply some morphological operations such as dilating and filling to remove contaminants from the isolated binary successive frames using a disk structure element (SE) of radius one.
Step 5: Normalize all binary images [17] and merge one cycle from frames to obtain GEIs for each individual.
Step 6: Split the result images into three groups: training (70%), validation (15%), and testing (15%).

(a) (b) (c)

(d)

Figure 2. The sample of dataset (a) CASIA-A with view angle 0º, (b) CASIA-A with view angle 45º, (c) CASIA-A with view angle 90º, and (d) OU-ISIR with different ages

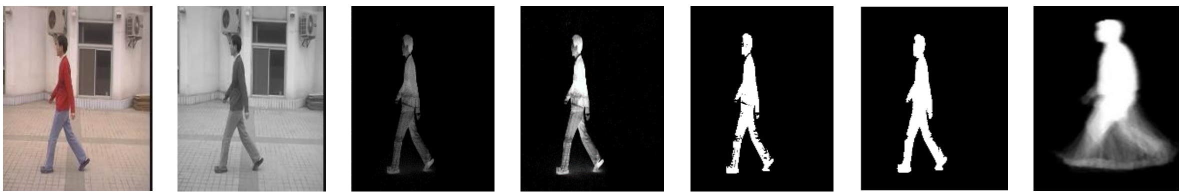


Figure 3. The preprocessing steps of the proposed model

2.3. Feature extraction and selection criteria

After the gait images have been isolated, enhanced, and normalized, their features have been extracted using the proposed CNN model called deep gait network (DGNet). Moreover, the other features have been extracted using the standard pre-trained models, including AlexNet, GoogleNet, VGGNet, ResNet50, and Xception. These models contain layers comprising linear and nonlinear processes learned in a joint modality. Convolution, pooling, and fully connected layers are the most prevalent layers in any CNN; the convolution layer extracts the features, the pooling layer downsamples the feature map, and the fully connected layer flattens the result downsample feature map. Six convolutional layers and three max pool layers constitute the DGNet. Each layer is stacked after two convolutional layers with mask sizes 2×2. Each convolution layer has 32, 64, and 128 filters with a 3×3 filter size, one stride, and a rectified linear unit (ReLU) activation function, respectively. As illustrated in Figure 4, the output features were flattened using a fully connected layer, a dense layer with a depth of 512, and a dropout layer to prevent overfitting. The most salient features among the extracted ones from the proposed and pre-trained models have been selected by PSO, GWO, Chi-square, and genetic models, which have the following characteristics,

2.3.1. GWO

A popular type of meta-heuristic algorithm that examines the gray wolves’ motions while pursuing prey, which contains four kinds of wolves called: Alpha (α), Beta (β), Delta (δ), and Omega (ω). The GWO algorithm's optimal solutions are Alpha (G_α), Beta (G_β), and Delta (G_δ), where Alpha is the best, and the remaining two are the second and third best. Generally, the GWO prediction process is divided into three stages: surrounding, hunting, and attacking. When the grey wolves sense the presence of prey, they round it using the (1) to (4).

$$\vec{E} = \left|\vec{d}.\vec{M}_p(t) - \vec{M}(t)\right| \tag{1}$$

$$\vec{M}(t+1) = \vec{M}_p(t) - \vec{B}.\vec{D} \tag{2}$$

where $\vec{B}$ and $\vec{d}$ are the coefficient vectors, $\vec{M}_p$ is the prey's position vector, and $\overrightarrow{M}$ refers to a wolf's position vector. The vectors $\vec{B}$ and $\vec{d}$ are computed by (3) and (4) [18]:

$$\vec{B} = 2\vec{b}.\vec{r}_1 - \vec{b} \tag{3}$$

$$\vec{d} = 2.\vec{r}_2 \tag{4}$$

where $\vec{b}$ and its features are linearly value from 2 to 0 throughout the course, and r_1 and r_2 are chosen random values ∈ [0, 1].

2.3.2. PSO

In 1995, Kennedy and Eberhart created the PSO technique according to swarm intelligence (SI), which finds the problem's optimal solution. It imitates the social behavior of groups of live organisms, such as fish schools and bird colonies, to find food. It starts by randomly scattering all the group members, then updates their paths based on the nearest spot to the food. Similarly, PSO [19] begins with several solutions, each with a unique velocity and position, then is updated later based on interactions with other swarm members until it reaches the optimal solution. Mathematically, the speed updated by (5) and position from (6) [20],

$$v_{ij}(t+1) = v_{ij}(t) + r_1 * \left(Pbest_{ij} - X_{ij}(t)\right) + r_2 * \left(Gbest_j - X_{ij}(t)\right) \tag{5}$$

$$X_{ij}(t+1) = X_{ij}(t) + v_{ij}(t+1) \tag{6}$$

where v_{ij} and X_{ij} are the initial speeds and positions for the i^{th} particle and the j^{th} dimension, respectively, and r_1 and r_2 are randomly chosen values between 0 and 1. P_{best} stands for the individual agent's best solution, while G_{best} stands for the best solution received from the best agent globally [21].

2.3.3. Chi-square algorithm

A feature selection technique uses a numerical test to evaluate divergence from the expected distribution without considering any association between the occurrence of the feature and the class [22]. Additionally, it draws out the characteristics that each class values the most from the population.

2.3.4. Genetic algorithm

It is a meta-heuristic algorithm that optimizes issues and provides valuable solutions. Furthermore, it is sensible and can identify the best solution by changing the evolution of population chromosomes [23]. It contains four techniques, inheritance, mutation, crossover, and selection using fitness.

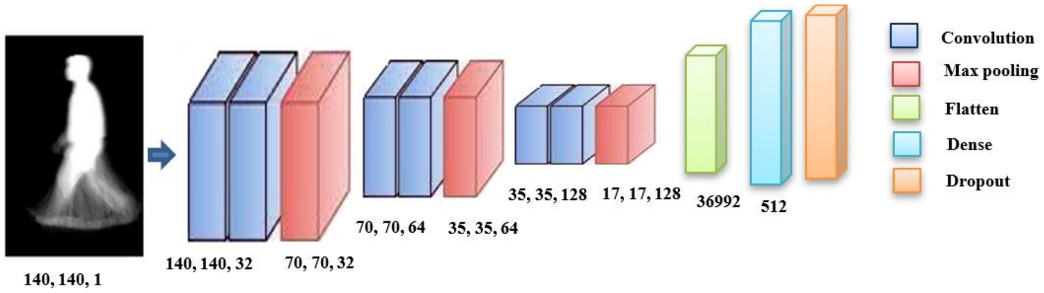


Figure 4. The structure of the proposed CNN model DGNet

2.4. Image recognition

Finally, the gait images have been recognized using the proposed DNN, which contains input, two hidden, and output layers. The input layer contains the selected features, the two hidden layers have 512 and 124 dense, respectively, and the output layer has the image label. The training process of any DNN passes through two phases: the feed forward (FF) phase and the back propagation (BP) phase. Each neuron in the FF phase has been unsupervised training using the training part of data, and the other inputs have been used as the output for the last neuron.

In the backpropagation phase, the back propagation (BP) neural network parameters have been utilized to compute the error value [24]. The suggested framework of the proposed work is illustrated in algorithm 1. Moreover, the proposed strategy complexity analysis is presented in Table 1 based on algorithm. Using feature population number symbolled by n and iterations number Mt.

Algorithm 1. The proposed methodology

```
Input: RGB gait dataset and background images.
Output: Identified gait Images
Start procedure
Import Model libraries
Read RGB gait dataset (G) and background images (Bg).
Preprocess image (resizing, gray scale image, contrast)
Binarize I then apply filtering process with some morphological operation (dilating and
filling holes)
Get the Isolated Gait dataset (ROI).
Normalize all isolated images (I).
Split images (I) to 70% train, 15% test, and 15% valid.
        - Training Set: train_X;
        - Label of Training Data: train_ y, M=Model;
Training and testing Algorithms
        for M=[AlexNet, VGG, GoogleNet, ResNet50, Xception]
                   Extract gait features Xi (population)
                for N=[PSO, GWO, Chi-square, Genetic]
                          Evaluate fitness Fn for each Xi
                     Find the best features X*
                     Train DNN network layers using Xi features.
                     Summary the model
                     Compile Model
                                   where {loss=Li /Opt=yi/Metrics=Acc.}
                                       Fit Model
                                   Where {epochs=30/Batch size=32/Verb.=2}
                          Evaluate the model
                          Plot accuracy (Acc.)/Loss curves
                          Plot Conf. Matrix
                          Calculate precision/recall/F1-score
                          Apply statistical analysis ANOVA/Wilcoxon Test
                          Store the Model
                  end
           end
End procedure
```

Table 1. The proposed model computational complexity

No.	Operation	Complexity
1	Reading silhouettes images	$O(1)$
2	Initializing population features	$O(1)$
3	Evaluating fitness function F_n	$O(n)$
4	Getting best features $\overrightarrow{X*}$	$O(n)$
5	Updating selector parameters	$O(M_t \times n)$
6	Evaluating agents' fitness function using PSO, GWO, Chi-square, Genetic	$O(M_t \times n)$
7	Evaluating the best selector	$O(M_t \times n)$
8	Updating parameters	$O(M_t)$
9	Producing the best fitness	$O(1)$
10	Evaluating the model	$O(1)$

3. PERFORMANCE METRICS

There are several performance metrics evaluated from the proposed model confusion matrix parameters, including true positive value (TP), true negative value (TN), false positive value (FP), and false-negative value (FN). These metrics, such as accuracy, sensitivity, specificity, F-score, training time, and intersection over union (IoU), verify the model's robustness in both the training and testing phase. The mentioned metrics have been computed from the (7) to (11) [25],

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \times 100 \quad (7)$$

$$\text{TPR} = \frac{\text{TP}}{\text{TP+FN}} \times 100 \quad (8)$$

$$\text{TNR} = \frac{\text{TN}}{\text{TN+Fp}} \times 100 \quad (9)$$

$$\text{F} - \text{score} = \frac{\text{2TP}}{\text{2TP+FP+FN}} \times 100 \quad (10)$$

$$\text{IoU} = \frac{\text{TP}}{\text{TP+FP+FN}} \times 100 \quad (11)$$

4. RESULTS AND DISCUSSION

The proposed DNN has been compiled and fitted based on the number of tuning parameters, such as batch normalization with size 64, the learning rate value with step size 0.01, and the momentum factor 0.5, which enhance the accuracy value and the training speed. Furthermore, Ata *et al.* [26] was utilized as the optimizer, which used a more powerful stochastic optimization approach to consume memory than others, with low computational power and the sparse categorical cross-entropy as a loss function for gathering all used datasets, which have multiple outputs. Table 2 refers to the selected tuning hyper-parameters in our proposed study, implemented with the Tensor Flow framework, an open-source deep learning library by Kaggle. All proposed experiments have been evaluated using a personal computer (PC) with the following characteristics: Microsoft Windows 10 operating system, processor 7-core @4.0 GHz, RAM size 12 GB, and GPU NVidia Tesla 16 GB.

Table 2. The tuning hyper-parameter

Variable	Power (kW)
Batch num	64
Learning Rate	1×10^{-2}
Epochs	30
Optimizer	Adam
Momentum Factor	0.5
Loss Function	Sparse categorical

4.1. CASIA dataset analysis

From the optimal hyperparameters in Table 2, the proposed structural technique was estimated by the CASIA gait dataset, which includes various view angle degrees for a class label. Performance metrics results have been extracted from the confusion matrix for different mentioned experiments that proved the proposed CNN with genetic feature selectors scored the best values among the other pre-trained models. The parameters of the feature selectors models are tabulated in Table 3, and the sample of the confusion matrix for DGNet with different feature selectors is shown in Figures 5(a) to 5(d).

Table 3. The main parameters of feature selectors models

Model	Parameter (s)	Value (s)
General	Number of Iterations	20
	Search domain	[0,1]
PSO	Inertia weight, W	0.9
	Acceleration factors C1, C2	[2,2]
	K-neighbors	5
GWO	Number of agents	3
	a	2 to 0
	r	[0,1]
GENETIC	Mutation ratio	0.1
	Crossover	0.9
	Selection Mechanism	Roulette wheel

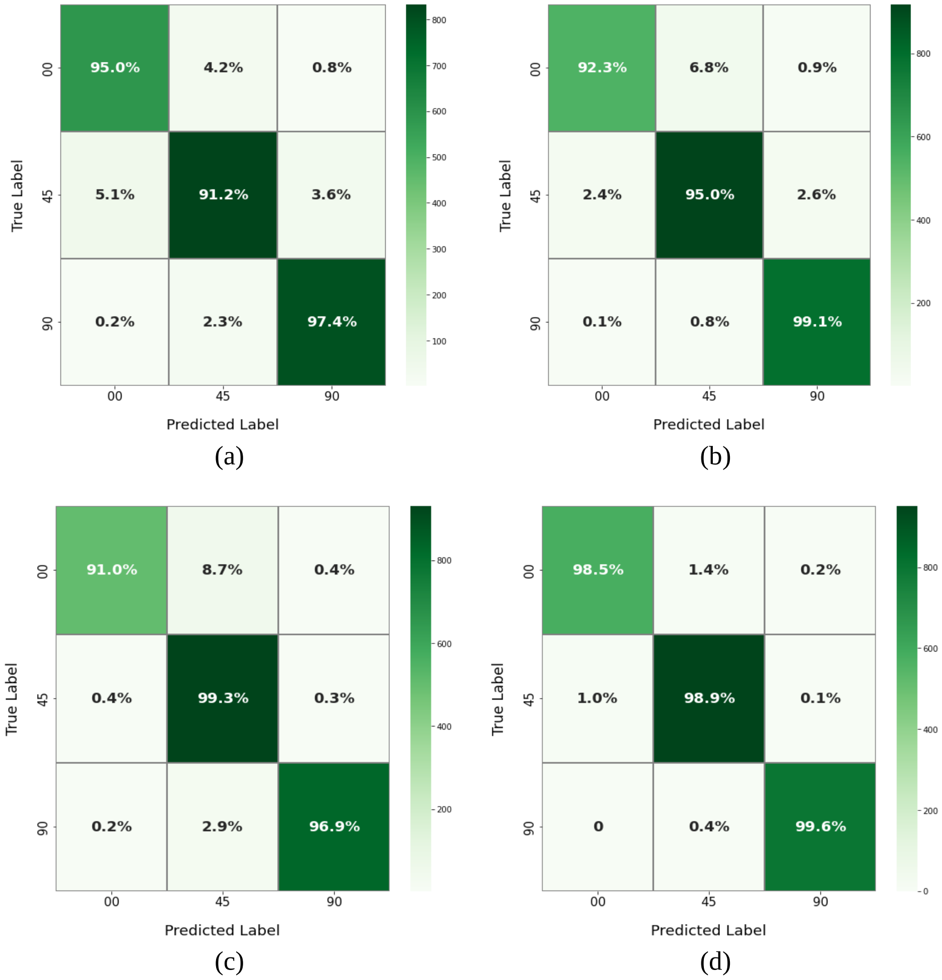


Figure 5. The confusion matrix of DGNet with genetic feature selector (a) PSO, (b) GWO, (c) chi-square, and (d) genetic algorithm

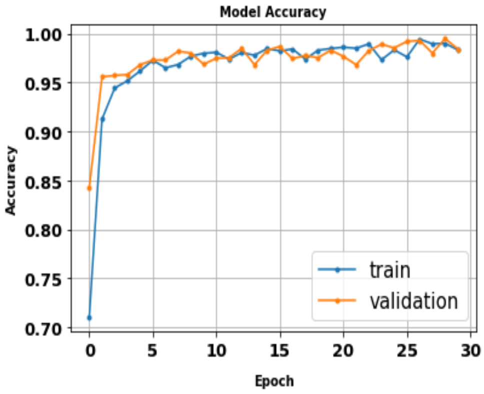
The performance metrics of the DGNet with different feature selectors have been tabulated in Table 4, which scored an accuracy value of 99.46% using genetic feature selectors in 20 seconds only. Figures 6(a) and 6(b) shows the accuracy and loss curves of DGNet with the genetic selector model based on 12 runs and 20 iterations (maximum iterations) for the n feature from the DGNet model (population size). Moreover, Table 5 presents the different feature selector test results using a one-way ANOVA test [27]. In contrast, Table 6 discusses the different applied feature selectors model comparison results using the Wilcoxon Signed-Rank test. From the table results, the p-value scored less than 0.05, demonstrating the significant difference between the feature selector results [28].

Table 4. Performance metrics of the DGNet with different feature selectors for CASIA gait dataset

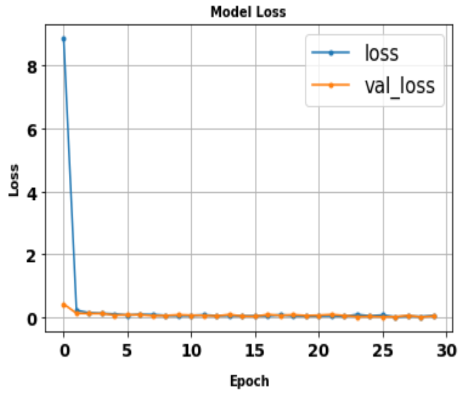
Model	Accuracy (%)	SENS (%)	IOU (%)	SPEC (%)	FNR (%)	FPR (%)	TIME
PSO	96.2	94.38	89.36	97.19	5.61	2.8	20.4s
GWO	97.2	95.7	91.84	97.8	4.25	2.12	23.5s
Chi-square	97.6	96.4	93.1	98.21	3.57	1.78	16s
Genetic	99.46	99.02	98.06	99.5	0.97	0.48	19.7s

4.2. OU-ISIR dataset analysis

Moreover, the DGNet and pre-trained models have been tested using the OU-ISIR gait dataset according to the same optimal tunning parameters with different feature selectors. The performance metrics of the DGNet with different feature selectors have been tabulated in Table 7. The mentioned results proved that the proposed model with the Genetic feature selector scored the best in low training time.



(a)



(b)

Figure 6. The DGNet with Genetic feature selector (a) accuracy and (b) loss curve

Table 5. ANOVA test for different feature selection algorithms on DGNet

	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	0.008824	3	0.002941	F (3, 44) =13.31	P<0.0001
Residual (within columns)	0.009725	44	0.0002210	_	_
Total	0.01855	47	_	_	_

Table 6. Wilcoxon test on DGNet for various feature selection techniques

	PSO	GWO	Chi-Square	Genetic
Theoretical median	0	0	0	0
Actual median	0.96	0.9725	0.971	0.99
Number of values	12	12	12	12
Wilcoxon signed rank test				
Sum of signed ranks (W)	78	78	78	78
Sum of positive ranks	78	78	78	78
Sum of negative ranks	0	0	0	0
P value (two tailed)	0.0005	0.0005	0.0005	0.0005
Exact or estimate?	Exact	Exact	Exact	Exact
P value summary	***	***	***	***
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes
How big is the discrepancy?				
Discrepancy	0.96	0.9725	0.971	0.99

Table 7. Performance metrics of the DGNet with different feature selectors for OU-ISIR gait dataset

Model	Accuracy (%)	SENS (%)	IOU (%)	SPEC (%)	FNR (%)	FPR (%)	TIME
PSO	97.8	90.3	82.3	98.7	9.65	1.206	9 m 5 s
GWO	98.1	94.02	88.7	99.2	5.9	0.74	15 m 22 s
Chi-square	97.9	90.5	82.7	98.8	9.4	1.17	4 m 10 s
Genetic	99.09	95.9	92.2	99.4	4.05	0.506	6 m 24 s

4.3. Comparative study

The DGNet and pre-trained models have been tested using the same optimum tuning hyper parameters listed in Table 8. Moreover, the proposed technique has been compared with the recent state-of-art studies and tabulated in Table 9, which approved that the proposed technique outperforms the current studies despite its deep structure and using many models. Still, it enhanced the accuracy value by 1.46% than [4], 0.67% than [5], 4.24% than [10], and 8.07% than [1].

Table 8. Accuracy values of the pre-trained models with different feature selectors

Model	DGNet	AlexNet	GoogleNet	VGGNet	ResNet50	Xception
PSO	97.8	94.3	96.2	98.1	98.08	93.2
GWO	98.1	93.5	94.9	97.3	97.4	96.2
Chi-square	97.9	94.3	96.9	97.6	96.8	94.5
Genetic	99.09	97.9	97.8	98.5	98.1	98.6

Table 9. Comparator study with the current studies

Reference	Year	Accuracy
George *et al.* [4]	2020	98%
Premalatha and Chandramani [5]	2020	98.79%
Wen and Wang [1]	2021	91.39%
Zhang *et al.* [10]	2022	95.22%
Han *et al.* [3]	2022	87.5%
Dong *et al.* [9]	2023	97.7%
Ours	2023	99.46%

5. CONCLUSION

This paper proposes a methodology for gait authentication successive frames with a well-designed approach. Firstly, the gait frames have been extracted, enhanced, and normalized. Secondly, the gait features have been extracted using the proposed CNN model called DGNet and other pre-trained models. Then the best was selected using genetic, PSO, chi-square, and GWO models. Finally, the proposed DNN model identifies the gait images using the selected features. According to performance metrics results, the DGNet with the Genetic feature selector outperforms the other pre-trained models and the current studies, which scored 99.46% and 99.09% in recognition accuracy for CASIA and OU-ISIR datasets, respectively. The proposed structure will likely be tested on various gait datasets in the future to verify its robustness, and several models, such as RNN, graph CNN, and generative adversarial network (GAN), will likely be used.

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