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Gait Silhouette Enhancement with Modified CLAHE and Precise Gait Recognition Using a Lightweight Convolutional Neural Network

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Abstract: Gait recognition is a behavioural biometric that can recognize an individual from a distance based on their walking pattern. Gait recognition techniques are persistently evolving for security purposes, as new advances in person recognition, range from traditional machine learning to deep learning. Various circumstances, such as lighting conditions, wearing garments, carrying a bag, and walking surfaces, can affect gait recognition performance. Furthermore, gait recognition from different points of view is a big challenge. A new framework, GRLNet: Light-weight Convolution Neural Network for Gait Recognition is proposed to identify the individual in various lighting conditions, clothing, etc. GRLNet is a portable architecture with a reduced memory size. Depth-wise and point-wise separable convolution is used to reduce the floating–point operations (FLOPs) and several parameters. A novel Hamming Correlated Gait Cycle Detection and Modified Contrast Limited Adaptive Histogram Equalization (MCLAHE) for gait silhouette image is proposed to enhance the gait energy image. Experiments on the popular public benchmark CASIA-B dataset was done to evaluate the efficiency of our proposed framework and our approach outperformed state-of-the-art solutions with covariates of carrying bag and wearing different clothes.

Keywords: *Deep Learning, Gait recognition, Human Gait cycle detection, Silhouette enhancement technique.*

1. Introduction

Biometrics is the science of recognizing and authenticating an individual based on some observable trait of their physical or behavioural characteristics. Because gait biometric methods can recognize an individual at a distance and distinct from other biometrics like fingerprints, iris, ears, and palms. Further, gait traits [1] are not easy to disguise and can be easily identified even in a low-resolution image. Popular applications of gait recognition include subject identification, gender and age prediction, rehabilitation, behaviour analysis, disease diagnosis and rehabilitation.

Human gait cycles are made up of swing and stance phases [2] which are distinctive due to the variety of joint motions and simultaneous actions it entails. Model-based and appearance-based gait identification approaches dominate the earliest studies in this field. Researchers have concentrated more on the latter group with numerous silhouette-based features, frequency-domain features, chrono-gait pictures, and Gabor GEIs, as well as motion-based features due to the good recognition rate with low resolution images [3]. CASIA-B, USF, OU-ISIR, HuGaID, etc. are only a few of the well-known publicly available datasets for human gait cycle recognition[18]. Moghaddam et al. [4] completed a survey on human gait identification algorithms based on walking styles exploring several publicly available datasets, test procedures, state-of-the-art solutions, future directions, and problems. To recognize cross-view gaits, Z. Zheng et al[6] suggested the Multi-view Gait Generative Adversarial Network (MvGGAN) to improve the recognition performance of CASIA B and OuMVLP datasets.

Researchers have recently utilised deep learning algorithms such as convolutional neural network[5][6][7][8]][10][13], capsule network[9] and BiLSTM[15] to enhance software that recognise person with gait. Wang et al [11] introduces a new Middle-fusion TCNN and Last-fusion TCNN, to use the inherent feature expression capability of CNN and the temporal peculiarities of human gait. A deep neural network and a fuzzy entropy-controlled skewness (FEcS) technique are used to provide an integrated framework for HGR[12]. Khan et al [14] implemented a fully automated deep learning and improved ant colony optimization (IACO) framework to increase the efficiency in different view angle. Xiaoguang Liu et al[16] have proposed lightweight double-channel depth-wise separable convolutional neural network to reduce the complexity of the deep learning model which recognize person with gait features extracted from wearable devices.

The difficulty of the computation is still another crucial factor in addition to accuracy. Real-world activities frequently aim to achieve the highest level of accuracy

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within a constrained computing budget, as determined by the target platform (for example, hardware) and application situations (e.g., auto driving requires low latency). This drived several projects, like Xception, MobileNet, MobileNet V2, ShuffleNet, and CondenseNet, to create lightweight architecture and achieve better speed-accuracy tradeoffs. These works rely primarily on group convolution and depth-wise convolution. The number of float-point operations, or FLOPs, is a common way to measure how hard a computation is. In this research work, the challenging intra subject variation factors[17] such as view angle, clothing and carrying objects are focused on to improve gait recognition with better accuracy when compared with state of art technique using CASIA B dataset[19].

The main contributions made by the proposed research work are listed below.

(i) A novel silhouette image enhancement using Modified Limited Adaptive Histogram Equalization (MCLAHE) to overcome the loss of standard image enhancement techniques.

(ii) Hamming Distance correlated Gait Cycle detection algorithm is proposed to increase the gait recognition performance.

(iii) Lightweight convolution neural network for gait recognition is proposed to reduce the number of parameters with portal architecture.

2. Method Overview

The general appearance-based gait recognition method involves video capture, frame separation, background subtraction, silhouette extraction, feature extraction, and recognition. The proposed approach enhances the silhouette image using modified contrast limited adaptive histogram equalization. The Gait cycle is detected from the enhanced silhouette image with the Hamming distance correlated approach. Gait energy Image (GEI) is generated from the images which form a gait cycle and feeds into the proposed Lightweight convolutional neural network for human recognition as shown in fig. 1.

2.1. MCLAHE Enhancement of Silhouette Images

Contrast Limited Adaptive Histogram Equalization(CLAHE) improves the contrast and reduces the amplification of noise in the given image[20]. CLAHE performance is determined by the clip limit and the number of tile parameters. Clip limit interpolates with the neighboring pixel in the selected kernel. Amplification of noise is controlled by clip limit whereas the value of several tiles is taken automatically. Though CLAHE enhances the image quality, improper selection of clip limit and number of tiles leads to information loss. To overcome this issue, Modified CLAHE is proposed in which bilateral filtering is incorporated to retain the fine edges of the gait silhouette image. Modified CLAHE enhancement techniques improve the quality of the gait silhouette image with the desired clip limit.

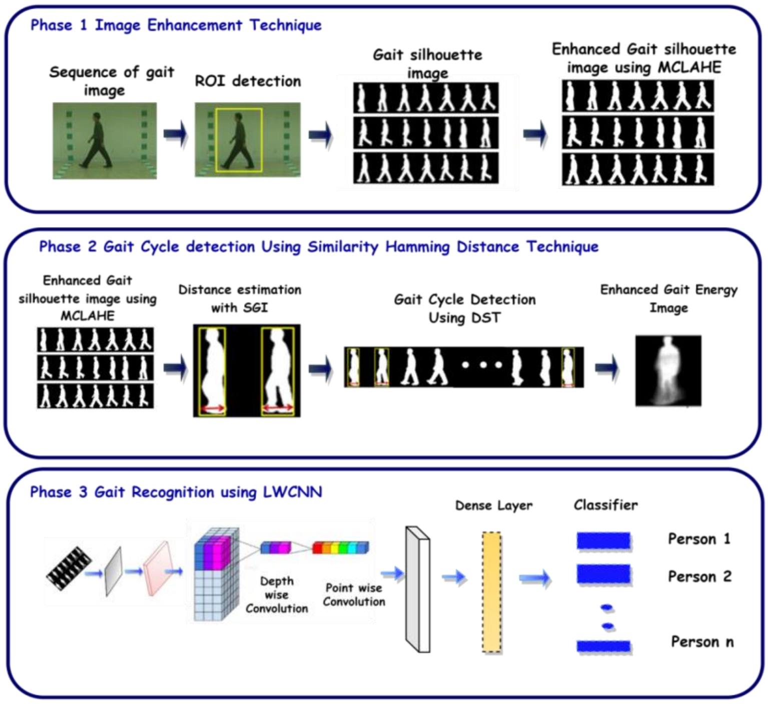


Fig. 1. The proposed architecture GRLNet with three phases 1. Image enhancement technique with MCLAHE (Modified Contrast Limited Histogram Equalization). 2. Gait cycle detection using Manhattan Distance Technique. 3. Gait Recognition using the proposed lightweight convolutional neural network.

2.2. Hamming Correlated Gait Cycle Detection

The Gait cycle detection phase plays an important role in the gait energy image generation. A complete gait cycle detection is quite difficult in real-time. Sugandhi et al has derived the overlap based approach to detect the gait cycle[21]. In this work, Hamming correlated gait cycle detection algorithm is proposed to find the complete gait cycle accurately in a live stream with the reduced parameter. The proposed technique uses perceptual hashing and hamming distance. The perceptual hashing algorithm scales the original image to a gray-level image with a size of 8 x 8. For every 64 pixels, hashing calculation is carried on.

Perceptual hashing : Given two images Img1 and Img2, their associated perceptual hashes *h1 = H(Img1) and h2 = H(Img2)*, a similarity metric *Dist(h1,h2)'* shows that Img1 and Img2 are similar or not with slight content-preserving changes. In order to detect similar images using perceptual hashing methods, the hashes obtained from the images are compared using a similarity metric. The minimum number of bit flips necessary to change one hash into another is known as the Hamming Distance (HD) [22]. The Hamming Distance between two hash strings Ph1 and Ph2 proves the similarity. Equations (1),(2) and (3) gives the formula to calculate the hamming distance of two hash string derived from two gait sequence as shown in Table 1.

$$Ph_1 = \{ Ph_1(0), Ph_1(1), \ldots, Ph_1(n-1) \} \quad (1)$$

$$Ph_2 = \{ Ph_2(0), Ph_2(1), \ldots Ph_2(n-1) \} \quad (2)$$

$$HD(Ph1, Ph2) = \sum_{i=0}^{n-1} Ph_1(i) XOR\ Ph_2(i) \quad (3)$$

Hamming distance between two similar images has a very small value. The threshold level is used to determine the similarity. If *HD<Threshold* level, two images are similar, else not similar.

2.3. Gait energy image

The Enhanced silhouette image's gait sequence, *S(x,y)*, which constitutes a complete gait cycle, is processed to create the gray-level gait energy image, *E*. The coordinate of the 2D image is represented by the values of *x* and *y*. *N* stands for the number of gait frames determined by the hamming correlated gait cycle detection approach, and the gait energy image (GEI) is shown as stated in (4).

$$E(x,y) = \frac{1}{N} \sum_{i=1}^{N} S_i(x,y) \quad (4)$$

Consequently, the gait energy image effectively encapsulates the dynamic alterations in silhouette shapes within each enhanced gait frame. Several advantages of utilizing the Gait Energy image over binary silhouettes include: 1) Decreased storage requirements and 2) Accelerated computational processes with a reduced likelihood of introducing noise.

3. Proposed Depth Separable Based Light-Weighted Convolution Network

The proposed Lightweight convolutional neural network leverages depth-wise convolution [27] to reduce computational costs. As the number of multiplications increases, so does the computational cost of the model. The dimensions of the input image are represented as Di x Di x

Table 1. Calculation of Hamming distance correlation for detecting gait cycle

Frame Number	Perceptual hash value	Hamming Distance (FRAME 1, FRAME n)	Status (Threshold value = 7)
1	38383c3c7c783c7c	-	Added to gait cycle1
2	ff181c1c3c3c3c3c	12	Added to gait cycle 1
3	183c1c1c3c3c7e7e	10	Added to gait cycle 1
4	181c1c1c3c3e7e7e	12	Added to gait cycle 1
5	3838383c3c3cee76	10	Added to gait cycle 1
6	38381c3c3c3c7ee6	10	Added to gait cycle 1
7	383838387c3c7e76	8	Added to gait cycle 1
8	30383878787c7e76	10	Added to gait cycle 1
9	30383838787c7e7e	8	Added to gait cycle 1
10	38383838783e7e76	10	Added to gait cycle 1
11	383c3c3c3c3c3e3c	6	Added to gait cycle 1
12	1d0d0f0f1d1f0f0f	32	Next gait cycle 2

N, with "C" denoting the number of channels, "*Di*" representing the height and width of the input image, and "*KxK*" indicating the size of the convolution kernel. After the convolution operation, the resulting feature map has dimensions of "*Do* x *Do* x *N*." This output from the convolution serves as input for a point-wise convolution with a 1x1 kernel[29]. To create the final output feature map of size "*Df* x *Df* x *S*" point-wise convolutions are applied.

The total number of multiplications is determined by adding those required for Depthwise and Pointwise convolutions:

Total Multiplications

= Multiplications for Depthwise + Multiplications for Pointwise

= (Do2 x K2 x N) + (Do2 x N x S)

= Do2 x N x (K2 + S)

Depthwise Convolution / Standard Convolution

= (Do2 x N x (K2 + S)) / (Do2 x K2 x N x S)

= (1 / Do2) + (1 / K2)

Thus, the utilization of depthwise convolution results in reductions in both computational cost and the number of parameters compared to standard convolution.

The suggested lightweight convolutional neural network's network topology with 8 layers utilize the special properties of convolving kernels for each input channel and merging the results of output channels, a separable convolutional layer has been included as shown in Fig. 1. The typical convolution receives the pre-processed enhanced gait energy image. The input image is down sampled and its dimensions are reduced with the assistance of the pooling layer, yielding several feature maps. This model makes use of a max pooling filter with a non-overlapping function [26]. With the help of weights, the convolutional layer performs convolution across the width and length of the input image across the chosen regions of the image and delivers the output to the following layer. The recognition features are then extracted using four depth separable convolution layers. After every depth-separable convolution, max pooling and ReLU activation are used. The Softmax function and cross-Entropy Loss are used to calculate categorical cross-entropy.

Normalization, max pooling, dropout, and *L1* and *L2* regularization techniques are strategically employed to counteract overfitting. A batch normalization layer is incorporated into every convolutional layer within this model to mitigate overfitting while simultaneously enhancing training efficiency [23]. To combat overfitting and curtail parameter proliferation in subsequent layers, the convolution layer is paired with a max pooling layer [24]. Dropout layers are applied to all convolution layers as well [25]. In this context, the Adam optimizer (Adaptive Moment Estimation) is harnessed, and it dynamically calculates the learning rate for each training epoch. Adam's application facilitates faster convergence, more efficient learning, and guards against learning rate decay when compared to alternative adaptive learning rate algorithms. The model's training leverages the parameters outlined in Table 2.

Table 2. Parameter of the proposed Model

Parameter	**Value**
Number of Epochs	100
Batch Size	32
Initial Learning rate	0.001
Shuffling	Every epoch
Optimizer	Adam
Learning decay rate	0.00001
Processor	GPU

The provided table outlines the crucial parameters governing the training of the proposed model. First, the number of epochs determines how many complete passes the model makes through the training dataset; here, it's set at 100 epochs. Batch size signifies the number of data samples processed together in each training iteration, with a batch size of 32 in this case. The initial learning rate sets the starting point for controlling parameter adjustments during training, initialized at 0.001. Shuffling reveals whether the dataset is randomly reorganized before each epoch, a practice employed here. The Optimizer, Learning Decay Rate, and Processor respectively dictate the optimization algorithm (Adam), the learning rate's reduction rate (0.00001 per epoch), and the hardware used (GPU for enhanced computational speed). These parameters collectively define the training process, significantly influencing the neural network's performance and outcomes.

4. Experimental Results and Discussions

In the process of subjecting the proposed model to a comprehensive experimental evaluation, a meticulous and systematic approach is adopted to compare it with a diverse set of alternative models. Each of these models is subjected to the same rigorous training regimen, encompassing 100 epochs of training, a fixed batch size of 32, and the consistent use of the Adam optimizer. This unwavering adherence to uniform training parameters not only guarantees a level playing field but also establishes the foundation for a fair and consistent benchmarking process. Through this methodical evaluation, the performance of the proposed model can be rigorously assessed in relation to its peer models, enabling a robust and insightful comparison.

1. Original - Convolutional neural network (CNN) with silhouette gait image
2. GEI + CNN - Convolutional neural network (CNN) with Gait Energy Image (GEI)
3. GEI + LWCNN - Lightweight Convolutional neural network (LWCNN) with Gait Energy Image (GEI)
4. EGEI+ CNN - Convolutional neural network (CNN) with Enhanced Gait Energy Image (EGEI)
5. EGEI+ LWCNN - Lightweight Convolutional neural network (LWCNN) with Enhanced Gait Energy Image (EGEI)
6. MCLAHE+EGEI+CNN- Convolutional neural network (CNN) with Hamming distance correlated Enhanced Gait Energy Image (EGEI) and Modified Contrast Limited Adaptive Histogram Equalization (MCLAHE)
7. GRLNet: MCLAHE+EGEI+LWCNN - Lightweight Convolutional neural network (LWCNN) with Hamming distance correlated Enhanced Gait Energy Image (EGEI) and Modified Contrast Limited Adaptive Histogram Equalization (MCLAHE)

The evaluation results showcase the accuracy and loss metrics of three distinct models: the Light Weight Convolutional Neural Network (LWCNN) paired with Gait Energy Image (GEI), LWCNN with GEI, and the novel Light Weight Convolutional Neural Network (LWCNN) integrated with Hamming distance correlated Enhanced Gait Energy Image (EGEI) and Modified Contrast Limited Adaptive Histogram Equalization (MCLAHE). Impressively, these models demonstrated accuracy rates of 94.82%, 95.34%, and 97.65%, respectively, as graphically depicted in Fig. 2. Notably, the proposed GRLNet model outperformed its counterparts, boasting the highest accuracy across various invariants such as normal walking, carrying a bag, and wearing different attire. Notably, it becomes evident that with the increase in the number of epochs, all models exhibit a consistent upward trend in accuracy. However, the proposed GRLNet model, equipped with the fusion of MCLAHE, EGEI, and LWCNN, consistently outshines the others, achieving the highest accuracy scores. Moreover, when considering the training metrics, the GRLNet model, trained on the CASIA B dataset, emerges as the frontrunner with an impressive training accuracy of 97.65% and an exceedingly low training loss of 0.02%. These results collectively underline the superior performance of the proposed GRLNet model in the context of gait recognition, affirming its prowess across various scenarios and cementing its status as the standout choice among the evaluated models.

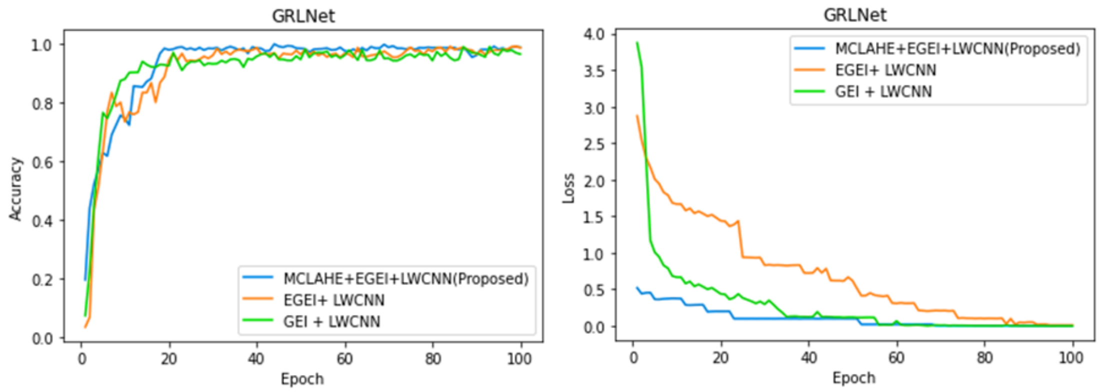
The table 3 provides a comprehensive overview of the performance metrics for various experimented models in the context of gait recognition. The Accuracy (%) metric showcases the percentage of correctly recognized gait patterns by each model, with higher values indicating superior overall performance. Precision measures the ratio of true positive predictions to all positive predictions, assessing the accuracy of gait pattern identifications. "Recall" quantifies the proportion of true positive predictions among all actual positive instances, reflecting a model's ability to capture relevant gait patterns. The F1 Score combines precision and recall, yielding a single value that considers false positives and false negatives for a holistic performance assessment. Lastly, the AUC (Area Under the Curve) represents a model's capability to distinguish between positive and negative instances in a receiver operating characteristic (ROC) curve, with higher AUC values indicating better discrimination ability. In this context, model 7(MCLAHE+ EGEI + LWCNN), stands out as it achieves the highest accuracy, precision, recall, F1 score, and AUC, signifying its superiority in gait recognition among the experimented models.

Figure 3 highlights the covariate factors that pose challenges in gait recognition, specifically, variations in carrying objects, clothing, and view angles. It serves as a visual representation of the recognition rates associated with these covariates. Notably, the gait images captured under normal conditions (NM) exhibit the highest recognition rate, reaching an impressive 98%. This signifies that the gait recognition system excels when individuals walk without carrying objects or wearing different attire. Even in scenarios involving carrying bags (BG) or wearing different clothes (CL), the system's performance remains robust, with recognition rates standing at 97%. This data underscores the system's ability to handle diverse conditions and demonstrates its adaptability in real-world scenarios, where variations in clothing or carrying objects are common, while still maintaining a remarkably high level of accuracy.

A comprehensive analysis of gait recognition accuracy across a spectrum of view angles, carrying bag and wearing different clothes focusing on the performance of different recognition methods using normal gait images is given in Table 4.

4.1. Normal Condition with different view angle

The gait recognition accuracy with normal gait image captured in various angles such as 0◦, 18◦, 36◦, 54◦, 72◦, 90◦, 108◦, 126◦, 144◦, 162◦ and 180◦ is shown in Table 4. Normal gait image (NM01 – NM04) is taken as the gallery dataset against the probe set (NM05 – NM06). The proposed model GRLNet (MCLAHE+EGEI+LWCNN) outperforms the other models and increased the recognition rate with view angle 0◦, 18◦,90◦, 108◦, 126◦, 144◦ and 180◦ with mean accuracy of 98%.



Accuracy Loss

Fig. 2. Accuracy and Loss of the Proposed Model on the Training Dataset.

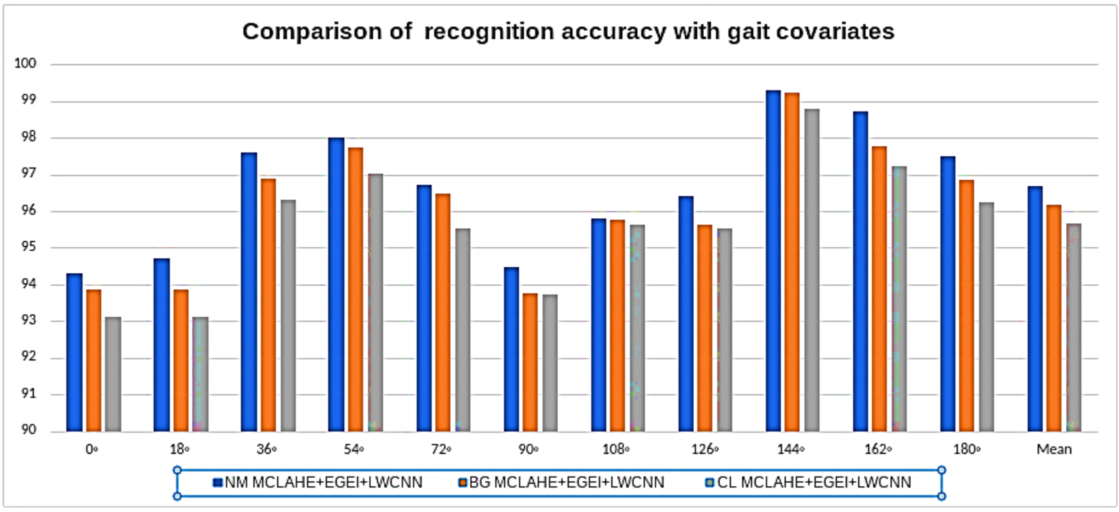


Fig. 3 Comparative analysis of Gait recognition with covariates such as Normal (NM), carrying Bag(BG) and wearing different clothes(CL).

Table 3. Performance metrics of Gait recognition with Experimented models

	Model	Accuracy (%)	Precision	Recall	F1 Score	AUC
1.	Original	94.23	0.91	0.95	0.92	0.94
2.	GEI + CNN	94.61	0.89	0.93	0.91	0.93
3.	GEI + LWCNN	94.82	0.93	0.94	0.89	0.93
4.	EGEI+ CNN	94.76	0.88	0.89	0.90	0.94
5.	EGEI+ LWCNN	95.34	**0.94**	0.95	0.93	0.95
6.	MCLAHE+EGEI+CNN	95.67	0.91	0.93	0.94	0.96
7.	**MCLAHE+EGEI+LWCNN**	**97.95**	0.93	**0.97**	**0.96**	**0.97**

Table 5. Performance metrics of Gait recognition with Experimented models

Models	Accuracy (%)	Parameters (In million)	Training Time (Seconds)	Testing Speed (Seconds)	Floating Point Operations (e + 02 G)
CNN [29]	94.5	10	8640.412	32.8	8
Vgg19- CNN[30]	93.6	28	6516.674	42.6	12
Xception	96.8	15	7918.765	16.5	5
Mobilenet	95.3	8	2918.765	12.3	3
Proposed GRLNet	**97.95**	**2**	**1103.94**	**8.4**	**1.5**

4. **Table 4.** Gait Recognition accuracy with different view angle, normal gait image, carrying bag and wearing different clothes y e

Probe	Method	0◦	18◦	36◦	54◦	72◦	90◦	108◦	126◦	144◦	162◦	180◦	Mean
Normal	1. Original	91.3	94.7	96.1	97.8	94.2	92.8	94.9	95.6	96.2	96.2	91.6	95
	2. GEI + CNN	91.6	94.8	97.2	97.8	94.5	93.8	93.1	93.5	95.7	97.2	93.1	95
	3. GEI + LWCNN	91.8	95.1	97.3	97.4	92.8	94.1	93.6	94.6	97.1	96.2	93.5	95
	4. EGEI+ CNN	91.8	95.2	97.3	98.2	94.6	94.2	94.7	95.8	94.7	97.7	92.6	95
	5. EGEI+ LWCNN	92.5	95.2	97.9	**98.5**	93.2	94.4	94.1	95.6	97.7	98.2	94	96
	6. MCLAHE+EGEI+CNN	92.9	96.1	**98.8**	93.2	**99.0**	94.7	94.2	95.7	98.1	**98.3**	94.4	96
	7. MCLAHE+EGEI+LWCNN (Proposed)	**96.5**	**97.9**	98.5	98.3	98.9	**99.1**	**99.2**	**99.1**	**98.4**	96.5	**96.5**	**98**
Bag	**1.** Original	90.5	94.2	95.6	97.1	93.9	92.5	94.1	95.4	95.6	95.7	90.7	94
	2. GEI + CNN	91.6	94.2	96.7	97.8	94	93.1	93.1	93.4	94.9	96.7	92.9	94
	3. GEI + LWCNN	91.2	94.9	97.2	96.8	92.1	93.4	93.3	94.5	96.5	95.2	92.7	94
	4. EGEI+ CNN	91.1	94.8	96.7	97.5	93.6	94	94.6	95.5	94.2	96.8	92.1	95
	5. EGEI+ LWCNN	91.9	94.4	97.2	97.9	92.7	94.1	93.6	95.5	97.3	98.1	93.7	95
	6. MCLAHE+EGEI+CNN	92	**95.9**	**98.1**	**98.8**	93	**94.2**	93.4	95.4	97.4	**98.3**	94	**96**
	7. MCLAHE+EGEI+LWCNN (Proposed)	**94.9**	95.2	97.9	98.1	**97.5**	93.7	**96.8**	**95.6**	**99.2**	97.8	**96.9**	**97**
Clothes	**1.** Original	89.6	93.3	95.4	96.4	93.7	91.7	93.7	95.3	95.4	95.4	89.9	94
	2. GEI + CNN	90.9	93.3	96.6	97.5	93.4	93	92.5	93.4	94.6	96	92.6	94
	3. GEI + LWCNN	90.4	94.2	97	96.3	91.2	92.5	92.3	94.1	95.6	94.8	91.9	94
	4. EGEI+ CNN	90.6	94.5	96.4	96.9	93.1	93.8	93.7	95.4	93.5	96.8	91.4	94
	5. EGEI+ LWCNN	91.4	93.8	96.7	97.8	92.1	94.1	92.8	94.7	97.2	98	92.8	95
	6. MCLAHE+EGEI+CNN	91.7	**95.5**	97.4	**98.2**	92.5	93.6	92.9	94.7	96.6	**98.3**	93.1	95
	7. MCLAHE+EGEI+LWCNN (Proposed)	**95.8**	95.4	**98.3**	97.8	**96.2**	**95.7**	**96.8**	**95.5**	**98.8**	97.2	**97.6**	**97**

proposed model GRLNet (MCLAHE+EGEI+LWCNN) outperforms the other model and increased the recognition rate with view angle 0◦, 72◦,90◦, 108◦, 126◦, 144◦ and 180◦ with mean accuracy of 97%.

4.3. Wearing Different Clothes Condition with different view angle

Normal gait image (NM01 – NM04) is taken as the gallery dataset against the probe set (CL01 – CL02). The proposed model GRLNet (MCLAHE+EGEI+LWCNN) outperforms the other models and increased the recognition rate with view angle 0◦, 18◦,90◦, 108◦, 126◦, 144◦ and 180◦ with mean accuracy of 97%.

4.4. Comparison of proposed GRLNet with other state of art deep neural networks on CASIA B Dataset

The proposed GRLNet is compared with the performance of other deep neural networks such as CNN, Vgg-19, Xception and Mobile net for gait recognition on CASIA B dataset. Table 5 provides a comprehensive performance comparison of the proposed GRLNet with several state-of-the-art deep neural networks, such as CNN, Vgg19-CNN, Xception, and Mobilenet, across various essential metrics. The accuracy (%) metric evaluates the model's proficiency in correctly classifying gait patterns, and the proposed GRLNet achieves the highest accuracy at 97.95%. In terms of model complexity, measured by the number of learnable parameters (in million), the GRLNet excels with a remarkably efficient 2 million parameters. Training time (in seconds) reflects the duration needed for model training, with the GRLNet demonstrating exceptional efficiency by completing training in 1103.94 seconds. Testing speed (in seconds) gauges the model's inference efficiency, and the GRLNet performs exceptionally well with a testing speed of 8.4 seconds. Lastly, floating-point operations (e + 02 G) measure computational intensity, and the GRLNet stands out with the lowest requirement at 1.5e+02 G, highlighting its efficiency. In summary, the GRLNet outperforms other models in accuracy, model efficiency, training time, testing speed, and computational requirements, making it an excellent choice for real-world gait recognition applications that prioritize both accuracy and efficiency.

5. Conclusion

In conclusion, the task of real-time individual recognition based on gait sequences presents significant challenges. These challenges include handling various environmental factors such as fluctuating lighting conditions, multiple view angles, the presence of carried objects, and different clothing attire. To address these challenges, the research introduces GRLNet, a lightweight Convolutional Neural Network (CNN) designed specifically for gait recognition. The approach enhances gait silhouette images using the innovative Modified Contrast Limited Adaptive Histogram Equalization (MCLAHE) technique and introduces a novel Hamming Correlated Gait Cycle Detection method to improve the quality of gait energy image generation. The architecture of GRLNet leverages depth-separable convolution to reduce computational demands in terms of parameters and floating-point operations. This optimization significantly accelerates the training and testing processes for gait image recognition. To evaluate the effectiveness of the proposed method, experiments were conducted using the CASIA B dataset, encompassing various view angles (ranging from 0° to 180°), scenarios involving the carrying of bags, and diverse clothing types. The findings demonstrate that GRLNet achieves substantially improved performance, with an impressive recognition rate of 97.95%. Importantly, the results of gait recognition on enhanced silhouette images highlight the superior performance of the model in terms of recognition accuracy, parameter count, floating-point operations, and computational speed. GRLNet's lightweight architecture positions it as a suitable solution for deployment on low-performance edge computing devices, with promising potential for future integration into smartphone terminals.

Author contributions

Nithyakani P: Conceptualization, Methodology, Software, Field study, Visualization, Investigation Writing Writing-Reviewing and Editing **Ferni Ukrit M:** Data curation, Writing-Original draft preparation, Software, Validation, Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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