Practical Consideration in using Pre-Trained Convolutional Neural Network (CNN) for Finger Vein Biometric

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Abstract—Using a pre-trained Convolutional Neural Network (CNN) model for a practical biometric authentication system requires specific procedures for training and performance evaluation. There are two criteria for a practical biometric system studied in this paper. First, the system's ability to handle identity theft or impersonation attacks. Second, the ability of the system to generate high authentication performance with minimal enrollment period. We propose the use of the Multiple Clip Contrast Limited Adaptive Histogram Equalization (MC-CLAHE) technique to process finger images before being trained by CNN. A pre-trained CNN model called AlexNet is used to extract features as well as classify the MC-CLAHE images. The authentication performance of the pre-trained AlexNet model has increased by a maximum of 30% when using this technique. To ensure that the pre-trained AlexNet model is evaluated based on its ability to prevent impersonation attacks, a procedure to generate the Receiver Operating Characteristics (ROC) curve is proposed. An offline procedure for training the pre-trained AlexNet model is also proposed in this paper. The purpose is to minimize the user enrollment period without compromising the authentication performance. In this paper, this procedure successfully reduces the enrollment time by up to 95% compared to using on-line training.

Keywords—AlexNet, CLAHE, ROC, biometric authentication, finger vein

1 Introduction

Biometric technology has now reached a high level of maturity. Various anatomical and behavioral features have been widely studied, so that a recognition system that is resilient to the attacks of impostors can be developed. Recently, there has been widespread interest in using finger veins as a biometric feature. Most of the research done is focused on the efforts to increase the recognition rate of the biometric system using these finger veins. The structure of the vascular pattern within a finger is unique, and it varies among individuals [1]. It is always protected under the skin, making this modality undamageable, difficult to be manipulated or even forged [2]. The only way to make these finger veins visible, for image capturing process, is to expose the skin area to a near-infrared (NIR) light. Under this condition, the blood vessel will be visible if the blood circulates in the individual's body. This adds to the advantage of using finger vein as a biometric modality, as the individual must be alive during the recognition process [3].

Depending on the type of NIR device used, the images obtained during the acquisition process are expected to produce high-contrast images with a uniformly distributed pixel intensity. Unfortunately, this is not the case because of the moisture and inconsistency of the finger skin thickness area exposed to this light. The simplest solution is to set a different illumination rate for each LED on the NIR device [4]. This is a slightly impractical way of solving this issue since the skin thickness of the fingers varies among individuals and differs even between the fingers of the same person. This leads to the use of contrast enhancement techniques on the acquired images, as one of the pre-processing steps before the unique features of these finger veins are extracted.

The finger vein feature extraction techniques are constantly under investigation and development to produce highly accurate biometric systems. Much effort is devoted to eliminating the use of hand-crafted features [5–7]. The goal is to make biometric systems more autonomous without user intervention. This can be achieved primarily by using deep learning techniques. Deep learning is a subset of machine learning techniques based on neural networks with a depth of three or more layers. It has various architectures according to the application. An architecture capable of extracting features directly from images and directly used for classification is known as the Convolutional Neural Network (CNN).

2 Related work

2.1 Finger vein image enhancement

Images in the FV-USM database are in low contrast. It needs to go through a contrast enhancement process to increase the contrast of the finger vein pattern before its unique features can be extracted. Histogram equalization (HE) is a widely used contrast enhancement process for finger vein images [8–9]. It describes the relationship between gray levels and their corresponding frequencies. HE has been proven to achieve good contrast performance with low computational complexity. However, finger vein images that are usually captured are unevenly distributed and contain low-light criteria with large smooth areas. Using HE for such images results in an excessive enhancement of the finger vein image, making it look unnatural and washed-out [10].

This problem was successfully overcome by enhancing the contrast on local (neighboring) pixel segments compared to the entire image at one time. A contrast enhancement mapping based on the zones surrounding the pixel is produced through this procedure. This technique is called Adaptive Histogram Equalization (AHE) method [11]. AHE is less accepted by vein imaging researchers because it tends to amplify the noise in the respective zone. In some zones, the gray scale distribution of these finger vein images is highly localized. This results in an image with two or more zones that appear to have the same gray scale, mapped to significantly different gray scales [12]. A variation of AHE under the contrast limiting approach is more preferred. This technique, known as Contrast Limited Adaptive Histogram Equalization (CLAHE), can overcome the problem of excessive enhancement using HE and minimize noise-like artifacts in certain zones on the image, which AHE cannot do.

2.2 Convolutional Neural Network (CNN) for finger vein authentication

CNN models have been widely used for image classification [13], computer vision [14], object detection [15], speech recognition [16], and many other fields. This is because of its ability to achieve high accuracy with a minimal error rate. However, the main challenge in making CNN successful in any application depends on the designer's ability to identify the most optimal parameters to produce the highest recognition rate. Various attempts have been made to propose the best architecture and parameters for finger vein recognition.

Among the earliest researchers who used CNN for finger vein recognition was Ahmed Radzi et al. [17]. In his study, he used a CNN with four layers and achieved a 100% recognition rate. However, the results achieved cannot be replicated or verified because of the use of an internal database of finger veins in their work. With the existence of public finger vein databases like FV-USM, more and more CNN architectures have been used in the study of finger vein recognition. Das et al. [18] proposed a CNN model comprising five convolutional layers in their study. They achieved an accuracy rate of over 95% using the proposed architecture. Boucherit et al. [19] achieved a recognition rate of 96.75% on the same FV-USM database, using their proposed CNN model. In their work, they have proposed the use of three convolution layers, three max-pooling layers, two dropout layers, two Dense layers, and one Softmax layer, as their architecture.

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [20], which has been contested since 2012, has produced many of the best CNN architectures every year. In this competition, CNN were used to classify images into 1000 different categories. These architectures that have been pre-trained are then used for finger vein recognition, using the parameters that have been trained in the competition. Using a pre-trained network on new applications reduces the complexity of building a CNN from scratch, which has a tradeoff between accuracy, speed, and size. Training new data to achieve the best accuracy rate using the pre-trained CNN requires less time as it is trained after this architecture becomes sophisticated, as opposed to not being trained at all.

Among the pre-trained networks successfully used in finger vein recognition are VGG-16, AlexNet and ResNet16. Huang et al. [21] and Hong et al. [22] used VGG-16 to train their own finger vein database and successfully achieved an EER of 2.14% and 2.967% respectively. Wang et al. [23] in their study used Multi-Receptive Field Bilinear Convolutional Neural Network (MRFBCNN), AlexNet and ResNet18 on the FV-USM database, and achieved 100%, 92.28% and 96.4% accuracy respectively.

2.3 Contributions

CLAHE will be used as a contrast enhancement technique in this paper. The ability of CLAHE for contrast enhancement depends on the value of the clip limit β. This β value ranges from 0 to 1. Conventionally, CLAHE is often used on a grayscale finger vein image to produce an enhanced version of the image. In our work, 3 grayscale images enhanced by CLAHE using 3 different β values, will produce a single RGB image, which is then used to train our system. The resulting image based on this technique is called a Multiple Clip CLAHE (MC-CLAHE) image. A more in-depth study will be carried out to evaluate the performance of our biometric system, especially to understand the implications of using MC-CLAHE images on the recognition rate, using different combinations of β values.

Despite the successes that have been shown by previous researchers in using CNN for finger vein recognition, improvements and further investigations still need to be done. In a study by Kaixun et al. [23], for example, it was found that although they achieved 100% recognition rate using their proposed architecture, in their work, 200 epochs were needed to train their CNN model to achieve that recognition rate. Using a high number of epochs for biometric authentication applications is inappropriate. The increase in the number of epochs is directly proportional to the increase in training time. For most non-biometric applications, the long training period to train a CNN model is not a big problem. The training process only needs to be done occasionally. Compared to biometric applications, a CNN model needs to be trained every time a new individual is introduced into the system. A high epoch will make the user await the training to be completed before the biometric system can be used. This paper will investigate the effect of epochs on the recognition rate of a finger vein biometric system.

Almost all finger vein-based biometrics researchers use large numbers of users to train their CNN systems [24, 25]. The FV-USM database, for example, has 123 individuals. Most researchers use the entire data that exists in the database to train their CNN models [26–28]. In theory, CNN requires a large amount of data, not only to verify the ability of CNN to discriminate against individuals but also to produce highly accurate CNN models. The practicality of using biometrics should not be limited to systems that have large enrollments. This paper will investigate the implications of using CNNs for biometric systems that have a small number of registered users, and further propose an improvement procedure to make such systems more practical for authentication.

3 Simulation setup

3.1 FV-USM database

Finger vein images from 123 participants were used to develop this database. The demographic information of the participants comprised 83 men and 40 women, aged between 20 and 52 years. Each participant submitted 48 finger vein images from 4 fingers (12 images per finger). The selected fingers were the left index, left middle, right index, and right middle finger. Each captured raw image was 640 × 480 in size with a resolution of 256 gray levels. This database also provided additional images, based on the extracted ROIs using the method described in [6].

3.2 Receiver Operating Characteristics (ROC) curves

Figure 1 shows the overall process of generating the Receiver Operating Characteristic (ROC) curves in our work. As described in the previous subsection, the images in the FV-USM database were taken from 4 different fingers. To simulate the effect of 'Imposter' attacks in our work, these four fingers are considered coming from 4 different groups. AlexNet training was performed separately on these four fingers, immediately after the raw images were processed using MC-CLAHE with three clip limit values, namely β1, β2 and β3.

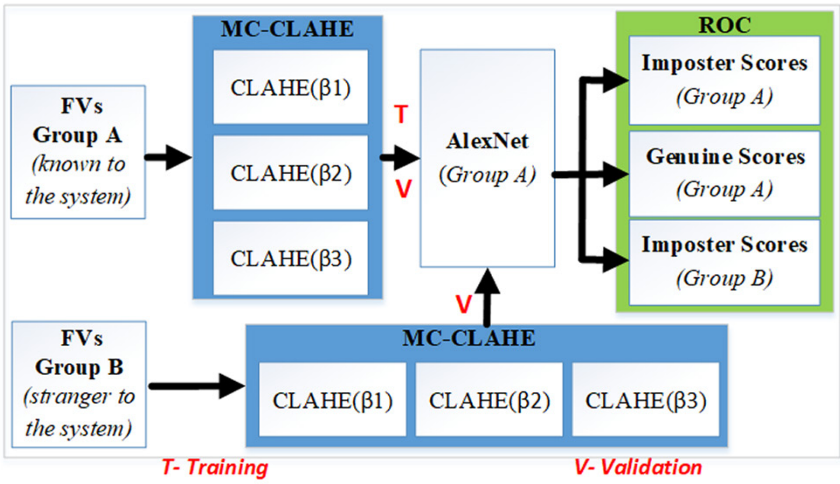


Fig. 1. ROC curves generation

Suppose AlexNet is used to train finger vein images from 1 of these 4 fingers. Let's define these images as finger vein images, FVs from Group A. Images from other fingers, are defined as FVs from Group B. Suppose the images from Group A are used to train the AlexNet. The images submitted by each individual in Group A were divided into training and validation samples. Once the AlexNet is successfully trained using the training sample, it will be validated using the validation sample. The classification percentage value resulting from classifying each individual into the correct class was categorized as a 'Genuine' score. The percentage value of the classification to the wrong classes was categorized as an 'Imposter' score. We define this process as a 'Genuine' attempt to network.

Images from other fingers are defined as FVs from Group B. Suppose the images from Group A are used to train the AlexNet. The images submitted by each individual in Group A were divided into training and validation samples. Once the AlexNet is successfully trained using the training sample, it will be validated using the validation sample. The classification percentage value resulting from classifying each individual into the correct class was categorized as a 'Genuine' score. The percentage value of the classification to the wrong classes was categorized as an 'Imposter' score. We define this process as a 'Genuine Attempt' to network.

Images from Group B were used to simulate the process of an unknown user claiming an identity from Group A. The classification percentage values as a result of validating all images from Group B using the AlexNet is categorized as Imposter Scores. We define this process as an 'Imposter Attempt' to the network. The Receiver Operating Characteristic (ROC) curve plot, plots False Acceptance Rate (FAR) on the x-axis, against the '1-False Rejection Rate (FRR)' on the y-axis. The advantage of this ROC curve is that it is threshold independent. This variation of the threshold value produces 4 conclusions namely 'True Acceptance', 'True Rejection', 'False Acceptance', and 'False Rejection' as shown in Figure 2.

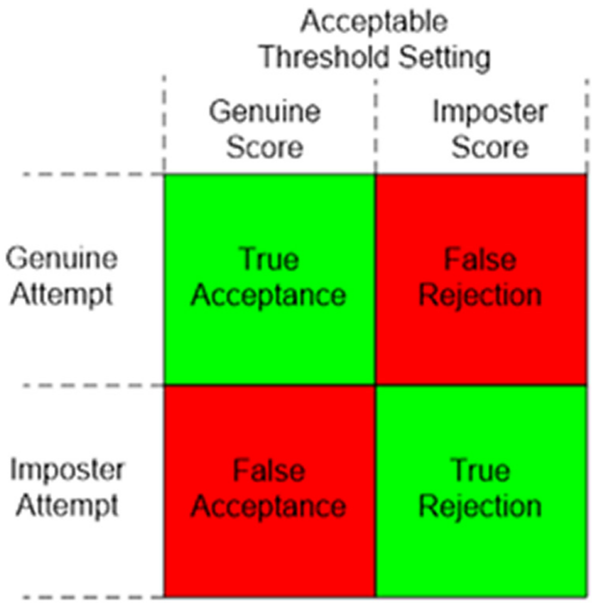


Fig. 2. Confusion matrix

FAR and FRR are defined as in equations (1) and (2) respectively.

$$FRR = \frac{\text{Total number of False Rejections}}{\text{Total number of 'Genuine' Attempts}} \tag{1}$$

$$FAR = \frac{\text{Total number of False Acceptances}}{\text{Total number of 'Imposter' Attempts}} \tag{2}$$

The ROC curves exhibit two important biometric authentication performance criteria, the area under an ROC (AUR) and the Equal Error Rate (ERR)[29]. A higher AUR value indicates a better system performance. When the FRR and FAR represent the same value, this value is known as EER. A practical biometric system requires an EER value approaching 0[30].

4 Results and discussion

4.1 The values of β in the MC-CLAHE equation

Figure 3 shows the comparison of authentication results using Alexnet, based on ROC curves, for finger vein images from FV-USM, before and after processing using MC-CLAHE. Both simulations use AlexNet with the same setting.

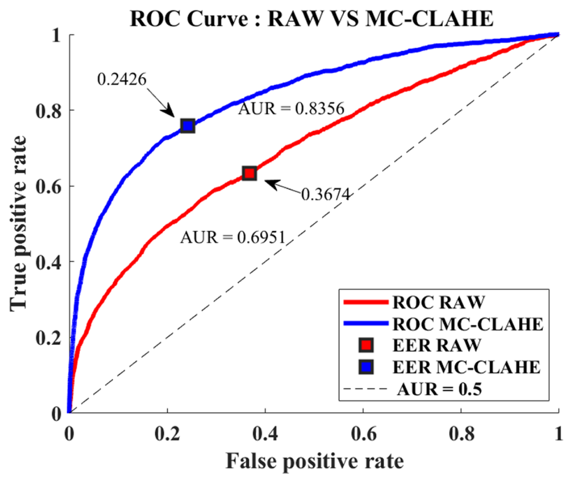


Fig. 3. ROC comparison between images trained with and without MC-CLAHE

Based on Figure 3, it is proved that AlexNet is a good CNN classifier for finger vein verification. This is because, although CNN has been used to train finger vein images that have not yet been processed, it still shows an AUR value above 0.5, which is 0.6951 with 0.3674 EER.

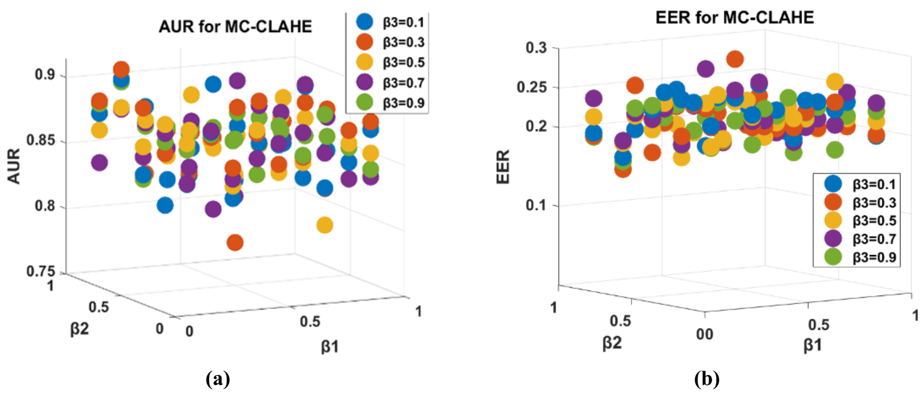
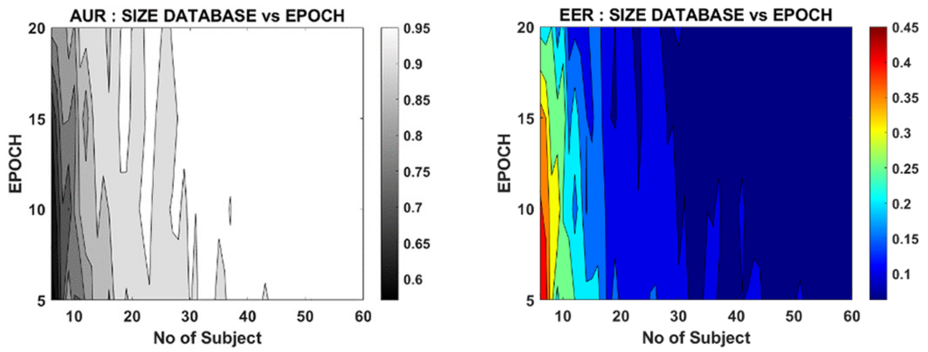


Fig. 4. Performance of MC-CLAHE and AlexNet classifiers using various β1, β2 and β3 values

The application of the MC-CLAHE technique to the FV-USM finger vein images shows an improvement in authentication performance of 20%. The AUR value has increased to 0.8356, while the EER value has decreased by 30%, to 0.2426. In this simulation, the values of β1, β2 and β3 for MC-CLAHE are set to 0.01, 0.02 and 0.03 respectively. The investigation continues to evaluate the ability of the MC-CLAHE based AlexNet classifier, to perform the authentication process, using different values of β1, β2 and β3. As shown in Figure 4a and b, the AUR value for this type of system ranges from 0.7826 to 0.914, while the EER value is between 0.1550 to 0.2917. The best combination of β1, β2 and β3 values to produce the highest AUR value with the lowest EER value is 0.1, 0.7 and 0.3 respectively.

4.2 The total number of samples and users for a CNN-based biometric system

Important factors that need to be considered in choosing a CNN model to be adopted in a biometric authentication application are the ability of the model to classify individuals under the constraints of the size of the database and the number of samples for enrollment. To study the effect of these factors, we use the optimal MC-CLAHE values described in the previous subsection for our simulations.

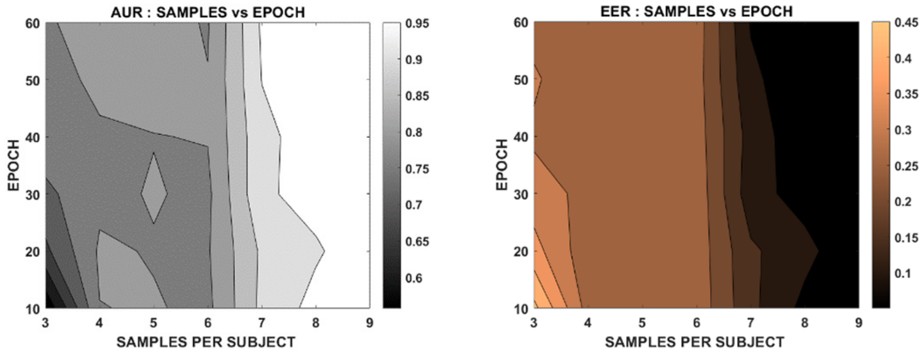


(a) (b)

Fig. 5. Performance comparison between the number of subjects enrolled and the number of epochs during training

As shown in Figure 5a and b, the small number of subjects enrolled in the system resulted in a high EER of up to 0.45. The ability of the model under study to classify individuals is also low. This is shown by the AUR value equal to 0.65. To improve the performance of AlexNet, the number of epochs during training should be increased. As seen in Figure 5a and b, the higher the epoch value, the better the network performance. A similar observation can be observed when the number of samples registered by the user to train the AlexNet model is low.

As shown in Figure 6a and b, a low number of samples will generate high AUR and low EER values. Once again, the AlexNet performance for such cases can be improved by increasing the epoch value during training. In this study, we consider 123 users are registered in the system.



(a) **(b)**

Fig. 6. Performance comparison between the number of samples enrolled by a subject and the number of epochs during training

4.3 Enrollment time

Although increasing the epoch value increases the AUR value and decreases the EER value, it also increases the enrollment time of individuals into the system. This can be seen in our simulation in Figure 7.

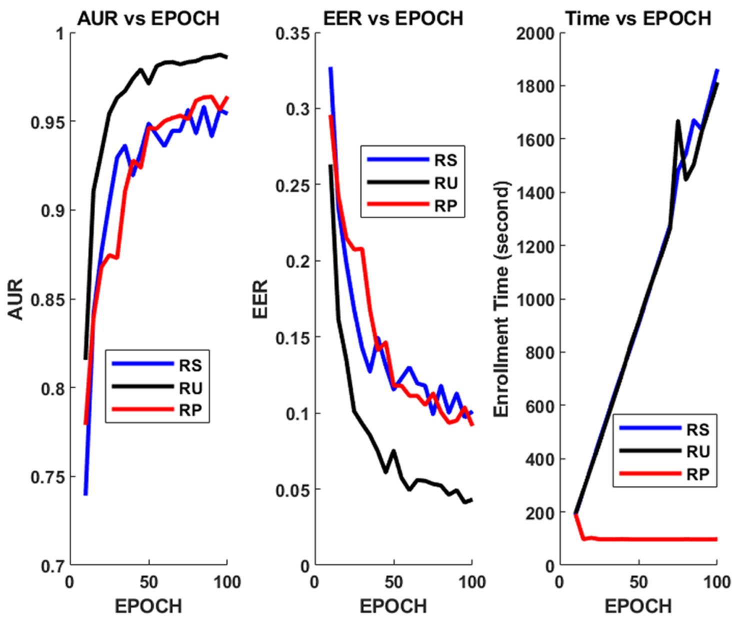


Fig. 7. Performance evaluation using 3 ways of setting the initial training parameters

In this simulation, we use all 123 individuals in FV-USM to train our system. The epoch value is varied between 5 and 100. The effect of changing this epoch on AUR, EER and enrollment time is shown in Figure 7. Our first test in this simulation is to see the effect of using the initial setting of AlexNet based on the value used in the ILSVRC. Whenever a new epoch value is used to train our system, this initial setting is used. In Figure 7, performance evaluation for this experiment is shown by the blue graph and symbolized by 'RT'.

In a practical biometric system, once a CNN model is successfully trained, the same model will be reused whenever training is needed, considering the registration of new users. We simulated this situation in our second experiment and the performance of this experiment is represented by the black graph, denoted by 'RU' in Figure 7. Each time a new epoch is considered, AlexNet is set using parameters resulting from the previous successful training. As seen in Figure 7, AUR and EER performance using this setting improves significantly compared to using the same initial setting every time training is required. In Figure 7, it shows that the duration for enrollment using the settings that produce 'RN' and 'RU', both are directly proportional to the number of training epochs. It can be concluded, based on these two setting methods, users need to take a long time to be registered, to have the best performance of the biometric system. A same approach as in the second experiment, was used in the third experiment to produce the red 'RP' graph. The difference is, we set the maximum epoch value to 5, every time AlexNet needs to be trained. As shown in Figure 7, the 'RP' graph performs similar to the 'RN' graph, in terms of AUR and EER, but the duration of enrollment is always minimum.

4.4 Practical considerations

The three important criteria studied in this paper, in using a pre-trained CNN for biometric authentication are (i) the type of image used, (ii) the number of samples registered per user and (iii) the number of registered users in a system. These criteria affect the user enrollment time and the AUR and EER values of the CNN model. Our solution achieved based on the simulation results above is to use the minimum epoch value during registration and perform offline training repeatedly on existing samples. This approach avoids users taking a long time to be registered into a system. After a user is registered, the system can continue training the CNN model offline while awaiting new user registration. If the number of registered users is small, the frequency of this offline training process can be done more frequently.

Unlike systems that use non-CNN models for biometric authentication, these CNN-based systems need to store registered finger vein images in their database. This is because, every time a new user needs to be registered, the images stored are needed to retrain the CNN model, with the addition of new images from the new registrant. The images used during validation can also be stored together with the images used for training to improve the performance of the biometric system in the future. Two implications of this vulnerability are the need for large database storage sizes and the risk of identity theft through the stored images. The use of MC-CLAHE can help in reducing the risk of identity theft. By using MC-CLAHE, the image stored in the database is a modified version of the original image using various β values. Extracting these images from the database without knowing the combination of these β values prevents the original image from being reconstructed.

5 Conclusion

The results of various simulations and experiments in this work lead to the proposal of a practical framework when using CNN models for biometric authentication. In this paper, we propose the use of the MC-CLAHE technique to process finger vein images before applying them to a pre-trained AlexNet model. From our simulation study, it was found that the combination of MC-CLAHE parameters can achieve AUR values between 0.78 and 0.91, with EER between 0.15 and 0.29. The result of this uniform performance enables MC-CLAHE to be used in preventing the original image from being reconstructed if they are successfully stolen from the database. We also propose an offline training procedure for training CNN models. This approach can improve authentication performance and ensure a short registration period during registration. Based on our simulations using the AlexNet model, the offline training approach can achieve the same AUR and EER performance, or even better than using the online training approach. Offline training procedures have the advantage of being used in biometric systems that have a small database or have a few samples registered in the system.

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