Iris Recognition System Using Convolutional Neural Network

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***Abstract*—Identification system is one of the important parts in security domains of the present time. The traditional protection methods considered to be inefficient and unreliable as they are subjected to the theft, imitation or forgetfulness. In contrast, biometrics such as facial recognition, fingerprints and the retina have emerged as modern protection methods, but still also suffer from some defects and violations. However, Iris recognition is an automated method that considered as a promising biometric identification due to the stability and the uniqueness of its patterns. In this paper, an iris recognition system based on Convolutional Neural Network (CNN) model was proposed. CNN is used to perform the required processes of feature extraction and classification. The proposed system was evaluated through CASIA-V1 and ATVS datasets, after the required pre-processing steps taken place, and achieved 98% and 97.83% as a result, respectively.**

***Index Terms*—Fuzzy Operation, Deep Learning, Segmentation, Convolution Neural Network.**

I. Introduction

Data essentially is the plain facts that need to be collected during any daily life activity or interaction. However, the data itself may not be very informative, but it is quite important to gain the necessary information that considered to be a very crucial in business. The exponentially growing in the internet has brought many technologies, that with no doubt helps in increasing the use of desktop, web and mobile applications. Tremendous amount of data has been produced by those applications and the data still growing every day. The confidentiality, integrity and availability of those resources still in need of providing an adequate protection that can maintain the data sensitivity according to regulatory compliance requirements. Achieving such requirements via traditional protection methods like passwords, signatures and cards is a crucial issue and is not an easy task, because those means are subjected to the theft, imitation, or forgetfulness, and considered to be insufficient and unreliable. In contrast, biometrics such as facial recognition, fingerprints and the retina have emerged as modern protection methods, but still also suffer from some defects and violations. However, the iris recognition system considered a promising biometric due to the stability and the uniqueness of its patterns, and can play a vital role in the identification system. Several methods in the literature have been devoted to tackle such issues and to improve the efficiency of the identification system [1].

In 2016, Liu et. al. [2] proposed a DeepIris verification system for heterogeneous irises based on a deep learning technique. The dataset is acquired via different sensors that placed in different distances. To improve the learning ability of the proposed system, DeepIris uses Pairwise Filter Bank (PFB) to find the similarity of the non-linear function between the pairs of iris images that acquired from different sources. The experiments were performed in two databases: Q-FIRE and CASIA cross sensor, and resulted in 0.15% and 0.31% Equal Error Rate (EER), respectively.

The study in [3] attempted to improve the iris recognition system by using a method called Visual Geometry Group (VGG)-Net that was implemented on CASIA-iris-1000 and IIT Delhi iris database. The iris region was not segmented in this method, and the entire image of the eye was used, however, the accuracy achieved was over 98% on both datasets.

Min et. al. [4] proposed a different method for iris recognition using three common convolutional neural networks (CNN). To handle the noise, the iris and periocular images normalized at the first place, then, the required features were extracted. This method implemented on noisy Iris Challenge Evaluation-Part II (NICE-II) dataset, Mobile Iris Challenge Evaluation (MICHE) database, and CASIA-Iris- database. A good result was achieved on CASIA-Iris-database with a 3.04% error rate.

A deep representation using VGG and residual network

(ResNet-50) were also introduced by [5] for iris recognition in unconstrained environments. Both methods implemented on the NICE-II database that has non-segmented and non-normalized images. The experimental results showed that the learning model based on the ResNet-50 was pretty good and achieved the best result with a 13.98% error rate, whereas the VGG model comes next with a 17.48% error rate.

In [6], a system using convolutional neural network-based feature extraction for iris recognition was introduced. The multiclass Support Vector Machine classifier used to evaluate the features of the segmented images that have been extracted from the pre-trained Convolutional Neural Network (Alex-Net Model) and to perform the recognition task. Four public datasets IITD, iris databases CASIAIris-V1, CASIA-Iris-thousand and CASIA Iris- V3 Interval were used for this purpose. The classifier achieves a good result on all databases with accuracy rates (100%, 98.3%, 98% and 89 %), respectively. However, the performance of the system has degraded a little bit after the normalization process takes place.

In 2018, Nguyen et al. [7], combined Five different pre-trained CNN models AlexNet, VGG, Inception, ResNet and DenseNet to find the highest peak iris recognition accuracies. The introduced system evaluated on two large datasets (LG2200 dataset with 1,352 classes and the CASIA-Iris-Thousand with 2,000 classes) that selected as 70% for training and the rest (30%) for testing. The training images were used only to train the multi-class SVMs, while the pre-trained CNNs were kept untouched. However, among all five CNNs DenseNet and ResNet achieved the highest peak recognition accuracy (over 98%) on both datasets.

Another, learning transfer approach for iris recognition using ResNet-50 was proposed by Shervin et al. [8]. The visualization technique was also used in this work for detecting the most important regions of the iris prints. The experiments carried out on the IIT Delhi iris database that contains 2240 iris images and captured from 224 different people. As a result, the method achieved 95.5%, and it was superior with its accuracy compared to the Multiscale Morphologic Features method that obtained 87.94%.

In 2019, Ming Liu et al. [9] introduce a method that can help with reducing the noise that hinders the detection and segmentation of the iris without any external influences such as eyelashes and eyelids. This could be done by detecting the boundaries of the iris and pupils using canny edge detection and Hough transform circle. Then, fuzzing it using the Gaussian and median filter. Reducing the pixel's noise and improving the iris segmentation process can play a vital role in improving the performance of iris recognition. This method tries to avoid the noises (e.g., make up, false lenses, eyeliner or pupil reflections) by using the CNN and capsule network to train samples.

In 2020, Weibin et. al. [10] proposed system for iris recognition, that is trying to extract the pupil edge using the dynamic threshold analysis and contour pupil extraction. They used a deep learning framework represented by AlexNet model. The iris was detected by edge detection and gray calculation. The experiments conducted on (CASIA-V3-Interval and UBIRIS-V3) databases. A promising result was achieved with an accuracy rate around 98.61% and 98.04% on both datasets, respectively. In [11], an iris recognition system using CNN deep learning framework was presented. The implementation carried out on the two databases named: CASIA-Iris-V4-Thousand and CASIA-Iris-V4-Distance. The rate achieved by the proposed framework on both datasets was 5.3% and 3.25% EER, respectively, and Area Under the Curve (AUC) obtained was 0.018% and 0.004%.

A system called IRISNet [12] was proposed as an iris recognition system using deep learning techniques, for features extraction and classification. The Convolutional Neural Network layers were including in the architecture of IrisNet to perform the features extraction and the Softmax layer to imply the classification task. The performance this system was evaluated on IITD-V1 iris dataset. The results showed 97.32% and 96.43% as the accuracy for original and normalized images, respectively.

An iris and sclera recognition system was presented by Chia-Wei et. al. in [13]. The system used YOLO-V2 model to joint an iris and sclera regions without considering the segmentation process in this work, then the model was applied on two types of datasets: (self-made and visible light eye dataset). The system reaches the accuracy rate of 99%.

In [14], as network architecture based on the dual spatial attention mechanism was introduced as iris recognition system. This system is called DualSANet and consists of two parts named as encoder and decoder, the encoder uses ResNet-18 to extract the features, and the decoder used spatial attention feature fusion module to fuse multi-level features. The architecture evaluated using CASIA-Iris-V4-Thousand, CASIA-Iris-V4-Distance and IITD datasets and obtained 0.31%, 10.67% and 0.54% as a False Rejection Rate (FRR) and 0.27%, 3.23% and 0.45% as Equal Error Rate (EER), on all datasets, respectively.

II. METHODOLOGY

A. IMAGE ACQUISITION

CASIA-Iris-V1: CASIA-Iris-V1 [15] is a dataset that has been captured with a homemade iris camera with 850nm, NIR illuminators are circularly arranged around the sensor to make sure that iris is uniformly and adequately illuminated. The pupil regions of all iris images in CASIA-Iris-V1 were automatically detected and replaced with a circular region of constant intensity to mask the specular reflections out from the NIR illuminators before public release. This version of the CASIA dataset includes 756 iris images of 108 eyes. For each eye, 7 images are captured in two sessions with a self-developed device. CASIA close-up iris camera, where the three samples are collected in the first session the fourth one is collected in the second session. All images are stored in BMP format with 320×280 of resolution.

ATVS-FIr DB: The ATVS-FIr DB [9] is an iris database provided by the ATVS Biometric Recognition Group. It was first made for liveness detection since it contained both real and fake examples. The real samples are taken from 50 random users and contain the iris samples of their both eyes ($50 \times \ 2 = 100$ different irises). Four iris samples of EOU3000 obtained by high quality printed images, each iris sample was captured in 2 acquisition sessions with the LG Iris Access EOU3000. That's why the dataset comprises $100\ irises \times 4\ samples \times 2\ sensors = 800$ real image samples. while the fake samples were also acquired by the LG Iris Access samples. The structure of the fake sample is the same as one of the real samples, thus, the dataset comprises $100\ irises \times 4\ samples \times 2\ sensors\ = 800$ fake image samples.

B. PREPROCESSING

Preprocessing is required to remove and control the unwanted type, colour and light, that may exist in the dataset, to make it ready for use at the following steps of detection and localization.

SPLITTING THE DATASET: The dataset was divided into two parts: 80% for training and 20% for testing, using train_test_split python's functions.

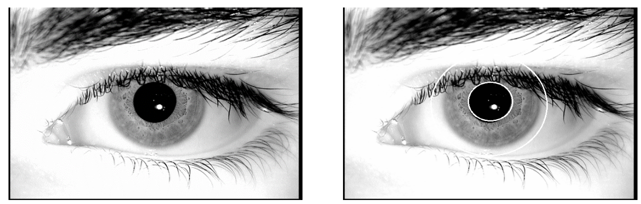
C. IRIS DETECTION AND LOCALIZATION

CANNY EDGE DETECTION: defined as an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges within the iris images. Such detection can take place according to the given threshold and sigma values.

CIRCULAR HOUGH TRANSFORM: The Hough transform is one of the computer vision applications that can be used to isolate features of a particular shape within an image, and most commonly used for detecting the regular curves such as lines, circles, and ellipses, etc. In iris segmentation, the Hough transform method is used for detecting the curves, to make the pupil and iris patterns approximately circular, and to deduce its center coordinates and radius, as illustrated in both Figures 1 and 2. The circle is defined in Eqaution 1.

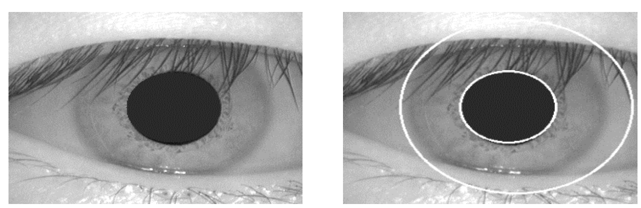
$$(x-a)^2 + (y-b)^2 = r^2 \tag{1}$$

where (a/b) is the centre of the circle, r is the radius, and (x, y) points.



(a) Original Image (b) Localized pupil and iris

Fig. 1: The result of the localization stage on ATVS



(a) Original Image (b) Localized pupil and iris

Fig. 2: F. The result of the localization stage on CASIA-V1

D. NOISE REMOVING

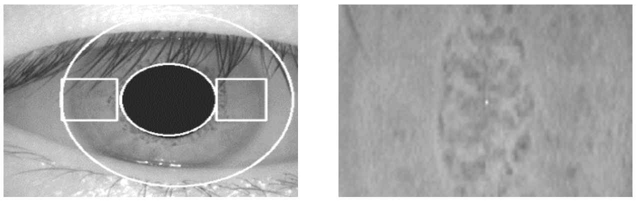
Two well-known approaches are usually used for handling the noise that may exist within the dataset:

FUZZIFIED IMAGE TECHNIQUE: A Triangular Fuzzy Median Filter, is the standard median filter that used to eliminate impulse noises and preserve the edge of the image. A non- linear digital filtering technique often used to remove the noise from an image, and it can preserve useful information about the noise.

GAUSSIAN FILTER: usually used for smoothing the pixels of the image, the pixels in different positions are given different weights, which can smooth the images while retaining more gray distribution features out of the images.

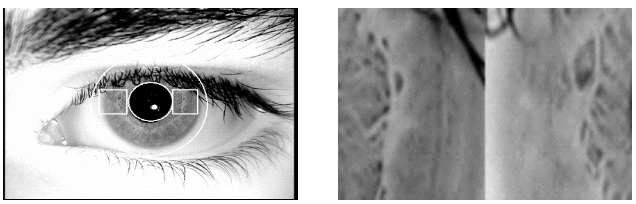
E. SEGMENTATION

FINDING IRIS REGIONS: after successfully detecting the iris and pupil, two iris' regions on each side of the pupil are localized using some python's functions. After that, cropping both regions and composing them together, is needed to construct the required shape of the iris region as depicted in Figures 3 and 4.



(a) Finding iris regions (b) Merging two regions

Fig. 3: The iris regions and the removed noise on CASIA-V1

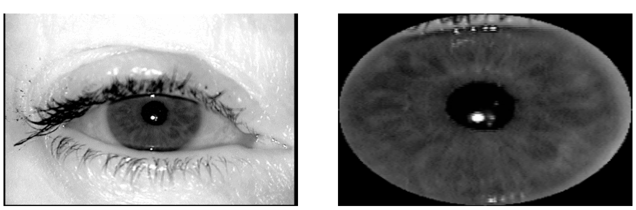


(a) Finding iris regions (b) Merging two regions

Fig. 4: The iris regions and the removed noise on ATVS

The iris region here is segmented and both sides of the pupil are trimmed, as this area is completely free of noise or external influences, so the resolution obtained was 100%.

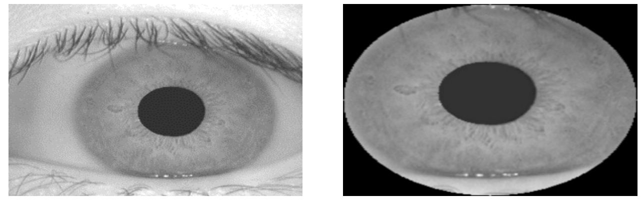
CROPPING ENTIRE IRIS: after detecting iris and pupil, the entire region of iris is cropped using some python's functions, without sclera, image background, eyelashes and other noises, as shown in Figures 5 and 6.



(a) Finding iris regions (b) Merging two regions

Fig. 5: The cropped iris and the removed noise on ATVS

With the second segmentation method, the circular shape of the entire iris is cropped out. Thus, eliminating a lot of noises, and can justify the increased accuracy and the improved results.



(a) Finding iris regions (b) Segmented image

Fig. 6: The cropped iris and the removed noise on CASIA-V1

F. FEATURE EXTRACTION AND CLASSIFICATION

THE CONVOLUTIONAL NEURAL NETWORK (CNN): CNN is a type of Artificial Neural Network (ANN) that is used for image processing and recognition. More specifically, it designed to process the pixel data, which is a part of deep learning techniques that commonly used to analyze visual imagery. Comparing to other image classification algorithms, CNN uses minimal preprocessing computation, meaning that, the network learns from the filters that typically are hand-engineered in other systems [16].

THE CONVOLUTIONAL LAYER: Convolution layers are used for extracting features from the input images as illustrated in Figure 7, while the kernels are generated randomly to do the convolution operations using the Back-Propagation Algorithm (BPA).

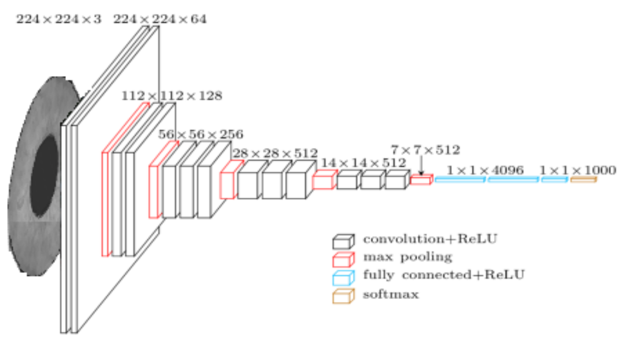


Fig. 7: The architecture of CNN

THE MAXPOOLING LAYER: CNN also contains the pooling layers which usually used immediately after convolutional layers to simplify out the information that obtained in the output through the convolutional layer. The pooling layer takes the output of each feature map from the convolutional layer to construct a condensed feature map. Then, each unit in the pooling layer may summarize a region of neurons in the previous layer [17].

THE FULLY CONNECTED LAYER: CNNs are using the fully connected layers after the pooling layers to produce the required classification for the images. After flattened, each value, gets a vote through one or more fully connected layers [18].

SOFTMAX LAYER: This layer used in the output. The idea of softMax is to define a new type of output layer for Neural Networks (NN), that usually used in the categorical classification while classifying the data into k classes output.

III. EXPERIMENTAL RESULTS

A. EXPERIMENT SETUP

In this framework, different pre-processing and actual applications are performed to recognize the iris image using CNN. The input instances of iris are segmented and the data cleansing technique is used for cleaning up the dataset from any form of noise or defects. For the identification purpose, the proposed framework goes through different stages i.e., image acquisition, pre-processing, localization, segmentation, feature extraction and classification to obtain the prediction required for the identification as illustrated in Figure 8. The dataset is divided into two parts: training and testing. The Pre-Processing stage carried out, then, the processes of detection, localization and segmentation take place, and the fuzzified technique was used to remove the unwanted noise. After that, a CCN was used as a deep learning technique to extract the features, train the data and to classify the patterns. Finally, the prediction stage takes place after validating the training data, to carry out the recognition rate of the identification events.

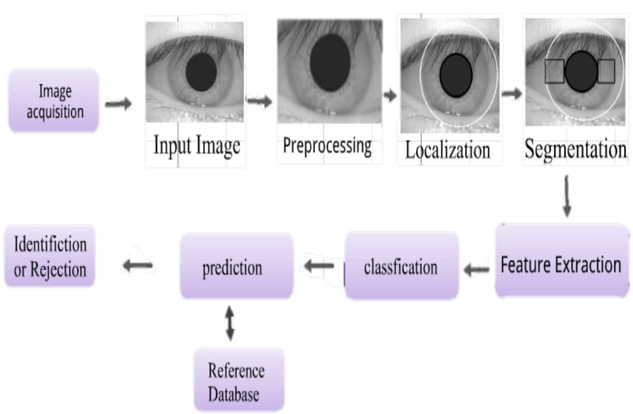


Fig. 8: The Iris Recognition System Framework

B. PERFORMANCE ANALYSIS

The results of the training process have shown that, some level of decrement in the rate of the data loss is exists during the training and testing process, and this is due to the simple structure of the network as it suits the amount and the nature of the data as shown in Table I.

TABLE I: The parameters and the configuration of the proposed framework

PARAMETERS		CONFIGURATIONS
Loss Function	**CATEGORICAL ENTROPY**	**INPUT IMAGE (400*400 GRAY SCALE IMAGE)**
OPTIMIZER	**Adam**	1*conv
		size: 5; ch: 64; stride: 4
		BatchNormalization
		MaxPooling
		1*conv
		size: 5; ch: 64; stride: 4
		MaxPooling
EARLY STOP	**Loss_Val;Patience =10**	FC
		FC-256
		FC-Class Number
		Softmax

The early stopping technique has been used to preserve the data from loss as a result of the repetition of the training stages, after the stability of the accuracy on the training and testing set, as shown in Figures 9 and 10. However, the classifier has achieved a good accuracy rate, on both sides of training and testing, which means that, the dataset was perfectly cleaned from the noises during the segmentation process. Moreover, the dropout layer and the early stopping technique efficiently handled the problem of overfitting and prevent the training data from being repeated in the layers after good accuracy has been achieved. The model performance results are shown in Table II and Table III.

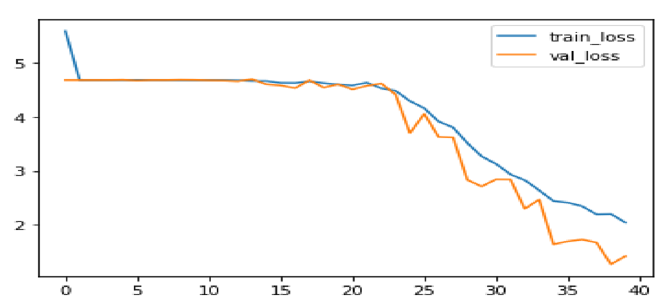


Fig. 9: Loss rate using cropping iris technique on CASIA-V1

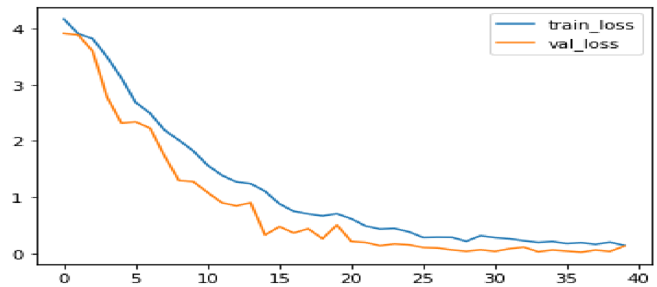


Fig. 10: Loss rate using cropping iris technique on ATVS

TABLE II: The model performance on the ATVS dataset

SEG-TECH	Accuracy	Loss	Recall	Precision	F1-Score
Croped IRIS	97.70%	0.0118	0.88075	0.8703	0.8632
IRIS-Region	97.83%	0.1428	0.93201	0.9249	0.9171

TABLE III: The model performance on the CASIA- V1 dataset

SEG-TECH	Accuracy	Loss	Recall	Precision	F1-Score
Croped IRIS	97.82%	0.0527	0.90175	0.8803	0.8732
IRIS-Region	98%	0.0701	0.96557	0.9416	0.9311

IV. CONCLUSIONS

Iris recognition stands as a vital topic in biometrics, that has great potential as a protection means for many real-life applications. In this paper, we presented a CNN deep learning framework for iris recognition, along with a simple demonstration of recognition stages. The different stages of workflow (localization, segmentation, noise removing, feature extraction and classification) were investigated and carried out on different datasets (CASIA_v1 and ATVS). The obtained results were quite integrating, and it has shown the importance of the segmentation process and its effects on the rest of the iris recognition system.

ACKNOWLEDGMENT

This work was supported by Universiti Malaysia Pahang through the Research Grant RDU190333 and Ministry of Education Grant No FRGS/1/2018/ICT02/UMP/02/6 (RDU190173).

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