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Original Article

Implementation of a Customized Light CNN Architecture for Iris Recognition System

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Abstract - *Biometric recognition refers to a technological approach that enables the identification and authentication of individuals by leveraging their distinct physical or behavioral attributes. The utilization of this technology is prevalent in the domains of security, access control, and authentication of identity. Unlike traditional identification methods such as passwords or PINs, biometric recognition relies on the distinctive traits of an individual, making it more secure and difficult to fake. Commonly used biometric approaches include fingerprint, iris, facial, palmprint, and retina. Among them, iris recognition is used widely and has unique patterns in the colored part of the eye (iris) to identify and authenticate individuals. The iris is the ring-shaped part of the eye surrounding the pupil and is known for its distinctive and stable characteristics. Even identical twins have different iris patterns, making iris recognition highly accurate and secure. However, the security aspects of the system are still unexplored. Therefore, we proposed a convolutional neural network (CNN) architecture-based approach to identify fake iris images. The suggested model includes preprocessing, saliency detection, feature extraction, and classification by CNN. All these experiments were carried out on the CASIA-Iris-Interval and CASIA-Iris-Syn databases. Through this process, the implemented technique attained 100% accuracy.*

Keywords - *Biometric recognition, Fake iris, Feature extraction, Saliency, Convolutional neural networks.*

1. Introduction

Iris recognition is a biometric technology that involves the identification of individuals based on the unique patterns found in their irises. The iris is the colored part of the eye that surrounds the pupil, and it has a complex, distinctive pattern of lines, ridges, and furrows that are different for each individual, even among identical twins [1]. The process of iris recognition involves capturing a high-resolution image of the person’s iris using specialized cameras or scanners. The unique features of the iris are then extracted and converted into a digital template, which is a mathematical representation of the iris pattern. This template is then stored in a database for comparison with other iris templates during identification [2]. Iris recognition is widely used in various applications such as airport security and border control, time and attendance tracking, law enforcement, healthcare, and other access control centers such as government buildings, data centers, and research labs due to the following factors [3]:

- High accuracy
- Uniqueness
- Non-instructive
- Resistance to forgery
- Speed
- Long-term stability
- Medium Collectability

Despite its benefits, the iris system is vulnerable to a variety of attacks that can pervert it and reduce its security level. This type of attack aims to trick the system into accepting the fraudulent iris image as a genuine image, leading to a false identification, which is known as iris spoofing [4]. Iris spoofing, also known as iris biometric spoofing, refers to the act of attempting to deceive an iris recognition system by using fake or manipulated iris images to impersonate a legitimate user.

The main factors for iris spoofing are printed iris images [5], contact lenses [6], artificial eyes [7], presentation of high-quality videos or images, and contactless masks [8]. Distinguishing between real and fake iris images can pose significant challenges due to their potential similarity. Therefore, developers and researchers have been working on various anti-spoofing techniques, such as multi-factor authentication, Presentation Attack Detection (PAD), Liveness detection, texture analysis, and infrared imaging [9]. Among them, texture analysis is the most prominent approach since it relatively extracts the texture variations within the iris to distinguish between genuine and fake irises. To meet this criterion, we proposed a Convolutional Neural Network (CNN) - based anti-spoofing system in this work. The remaining part of the work is organized as follows:

2. Related Works

Over the past few decades, researchers have developed numerous models to recognize fake iris images [4]. In this section, we discuss a few recently implemented well-received approaches. Fathy WS et al. [8] proposed a Liveness detection methodology using Wavelet Entropy (WE), Local Binary Patterns (LBP), and support vector machine (SVM). Through this process, the authors achieved 99.92% accuracy. Mamta Garg et al. [10] implemented an effective iris recognition system through Principal Component Analysis (PCA), genetic algorithm (GA), and Back Propagation Neural Networks (BPNN). Through this model, they obtained approximately 96.40% classification accuracy. S Adamović et al. [11] suggested a novel framework for iris recognition using Gabor Wavelets (GW) and Random Forest (RF), and they yielded an accuracy of 99.99%.

K. Saminathan et al. [12] developed a kernel-based SVM (KSVM) approach for iris recognition and attained 98.5% accuracy. Maram. G Alaslani et al. [13] presented an AlexNet-followed SVM classifier for iris recognition and achieved a 98% recognition rate. Afsana Ahamed et al. [14] proposed a curvelet and Particle Swarm Optimization (PSO) based iris recognition system. By this framework, the authors obtained 99.4% recognition accuracy. Prajoy Podder et al. [15] suggested a new feature extraction technique, namely, LBPX, and they reached approximately 97.2% accuracy.

Smita Khade et al. [16] developed a machine learning-based strategy using discrete cosine transform fragmental coefficients and an RF classifier. By this technique, the authors produced an accuracy of 99.18%. Arun Singh et al. [17] suggested VGG16 architecture for iris recognition, and they attained a 96% recognition rate. Rahmatallah et al. [18] presented canny edge detection and CNN frameworks for enhancing iris recognition, and they obtained 94.88% accuracy. Danlami et al. [19] suggested a Legendre wavelet filter (LWF)-based feature extraction technique to recognize the iris images, and they generated 88.2% classification accuracy.

By analyzing the above state-of-the-art approaches, we made the following observations:

1. A few authors utilized conventional CNN frameworks, such as AlexNet and VGG16, to identify the iris subjects. However, they required a huge number of parameters to train the model.
2. For a few approaches, researchers employed handcrafted features (Gabor wavelets, wavelet energy, and DCT coefficients) to recognize iris images. Here, the selection of decomposition levels is quite complex.
3. A few authors implemented iris recognition systems without performing normalization/segmentation, which resulted in low accuracy.
   To conquer the aforementioned issues, we developed a light CNN model for an efficient iris recognition system.

The significant highlights of the proposed study:

1. A saliency and thresholding-based approach have been implemented for effective segmentation.
2. Employed a light CNN architecture for the detection of spoofing iris images with a smaller number of training parameters.
3. Minimize the overfitting issues by initializing the weights into layers using the 'he_uniform' initializer.

3. The Proposed Model

In this paper, the suggested iris recognition model has the following stages represented in Figure 1:

1. Data collection
2. Saliency detection
3. Segmentation by histogram-based gray level thresholding and
4. Feature extraction and classification by CNN.

3.1. Data Collection

To build the proposed methodology, we collected 2090 iris images with a resolution of 640×480 from CASIA-Iris-Interval and CASIA-Iris-Syn databases. Figure 2 illustrates the sample images of the abovementioned datasets.

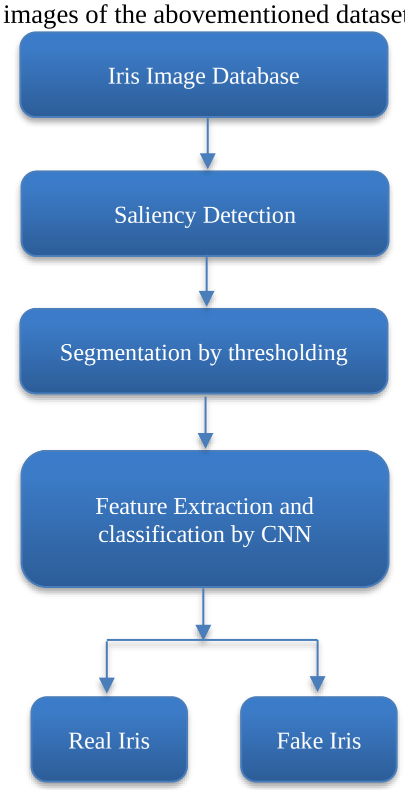


Fig. 1 Block diagram of the proposed iris recognition system

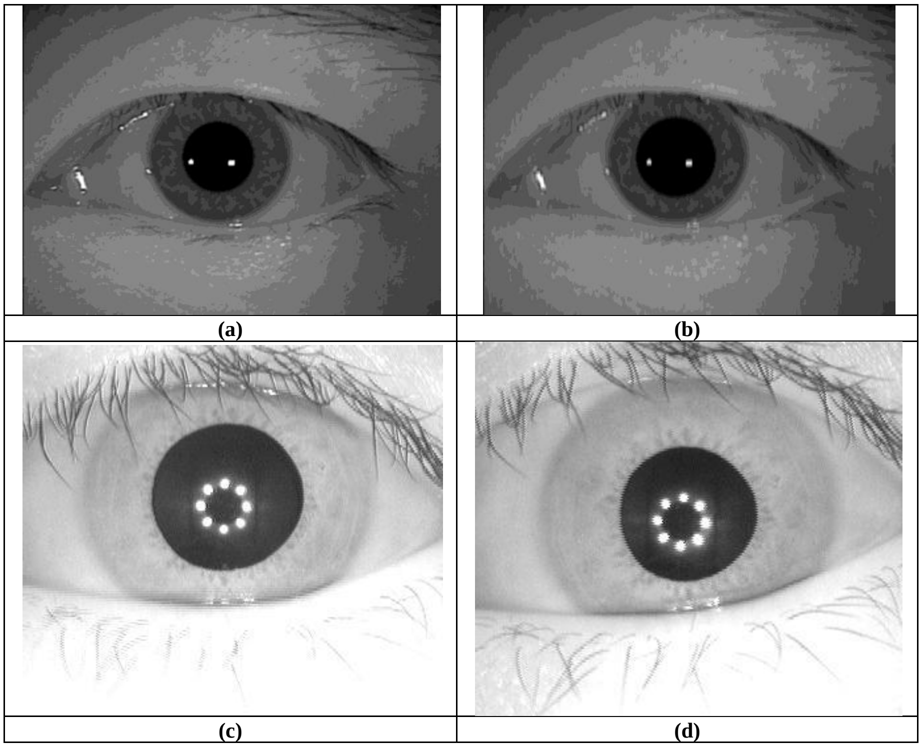


Fig. 2 Sample images for (a)-(b) CASIA-Iris-Interval; (c)-(d) CASIA-Iris-Syn

3.2. Saliency Detection

The main motive of saliency detection is to identify the most visually significant or relevant regions within an image or a scene. These regions are known as saliency maps or saliency regions. The idea of saliency originates from human visual perception, in which certain aspects of an image attract attention due to factors such as contrast, color, orientation, motion, and spatial arrangement. Hence, saliency is used in various applications, including computer vision and pattern recognition, human-computer interaction, image processing, etc. Based on this idea, we adopted the saliency concept to our iris recognition system. The process to obtain the saliency map is as follows:

1. Initially, extract the R (Red), G (Green) and B (Blue) channels from the given image.
2. Convert the given RGB image into LAB color space using 'rgb2lab' inbuilt MATLAB function.
3. Calculate the mean of L, A and B channels, and says thatm_l,m_a, and m_b.
4. Estimate the saliency map by the following formulation:

$$S = (L - m_1)^2 + (A - m_a)^2 + (B - m_b)^2 \tag{1}$$

5. Finally, we refine the saliency map by Equation (2) and the corresponding outcome is illustrated in Figure 3.

$$S_m = \frac{S - min(S)}{max(S) - min(s)} \tag{2}$$

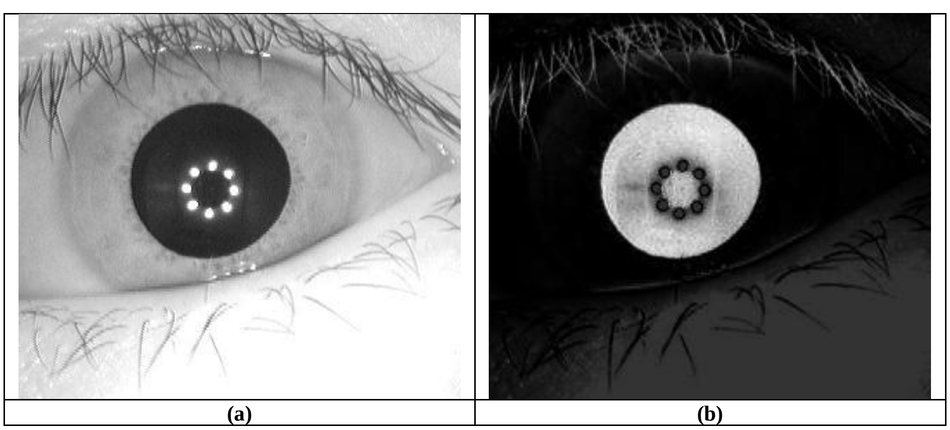
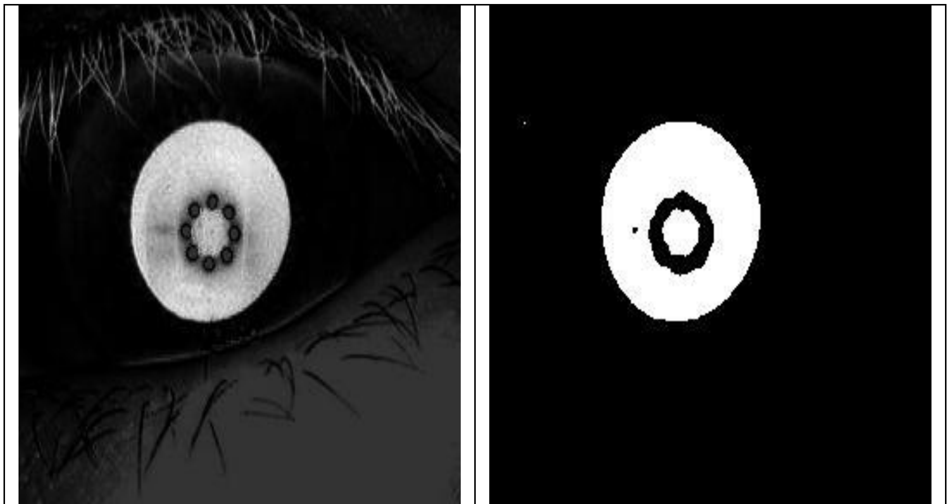


Fig. 3 (a) Source image; (b) Saliency map



(a)	(b)

Fig. 4 (a) Saliency map; (b) Segmented image

3.3. Segmentation

Image segmentation is a computer vision task that entails breaking an image up into different segments or regions based on attributes like color, intensity, texture, or other visual properties. The main goal of image segmentation is to partition an image into meaningful and distinct parts to facilitate further analysis, understanding, or manipulation. In this work, the histogram-based thresholding approach. The sequence of steps involved in the proposed segmentation technique is as follows:

1. Divide the image into two equal regions, say thatR_1, andR_2.
2. Estimate the histograms of both regions defined in step 1, which are denoted byH_1andH_2.
3. Obtain the difference of their histograms and then estimate the threshold value T using Otsu's method [20].
4. Finally, segmentation on the saliency map will be performed based on the thresholding value obtained in step 3, and the corresponding findings are illustrated in Figure 4.

3.4. Feature Extraction and Classification

Feature extraction is a fundamental concept in various fields, including computer vision, machine learning, and signal processing. It involves selecting or transforming relevant information from raw data to create a more compact and representative representation (features) that can be used for analysis, classification, or other tasks. Feature extraction is particularly important when dealing with high-dimensional data, as it helps reduce the complexity of the data while retaining significant patterns or characteristics. In image processing and computer vision fields, feature extraction involves identifying and quantifying distinctive attributes or patterns within an image. These attributes can be edges, textures, shapes, colors, or other visual properties. By extracting relevant features, the goal is to capture the essential information that can help discriminate between different objects or classes in the data. In this study, we used CNN to extract relevant features from the segmented iris image.

3.4.1. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a type of deep neural network that has been developed for interpreting and analyzing visual data like images and videos. CNNs have revolutionized the field of computer vision by achieving remarkable performance in tasks like image classification, object detection, image segmentation, and more.

They are particularly effective at capturing spatial hierarchies and patterns within images. Typically, CNNs are designed with the help of several layers, such as convolutional, batch normalization, non-linear activation, pooling, dense or Fully Connected (FL), and SoftMax. Based on this idea, we developed a customized light CNN architecture, as shown in Figure 5.

The primary goal of our model is to reduce the number of learning parameters and training time while maintaining accuracy. To meet this criterion, we construct a CNN model with six convolutional blocks, as shown in Figure 5. All blocks are quite similar, including convolutional, batch norm, ReLU, and max pooling layers in sequence. The last blocks are different from the others since they hold a softmax followed by an FC layer. The sizes of the convolutional kernel in the first six blocks are 3 × 3 with 32, 64, 128, 192, 256 and 512 channels, respectively. Similarly, in blocks 1 to 6, 2 × 2 max pooling with stride 2 is applied. Besides, the batch norm is also employed for all the blocks with 32, 64, 128, 192, 256 and 512 channels. It needs to be noted that the proposed CNN model contains six convolutional layers, one fully connected layer, and a softmax layer. In addition, six batch norm, ReLU, and max pooling layers are also present. Using these layers, the proposed model obtained high-level features automatically.

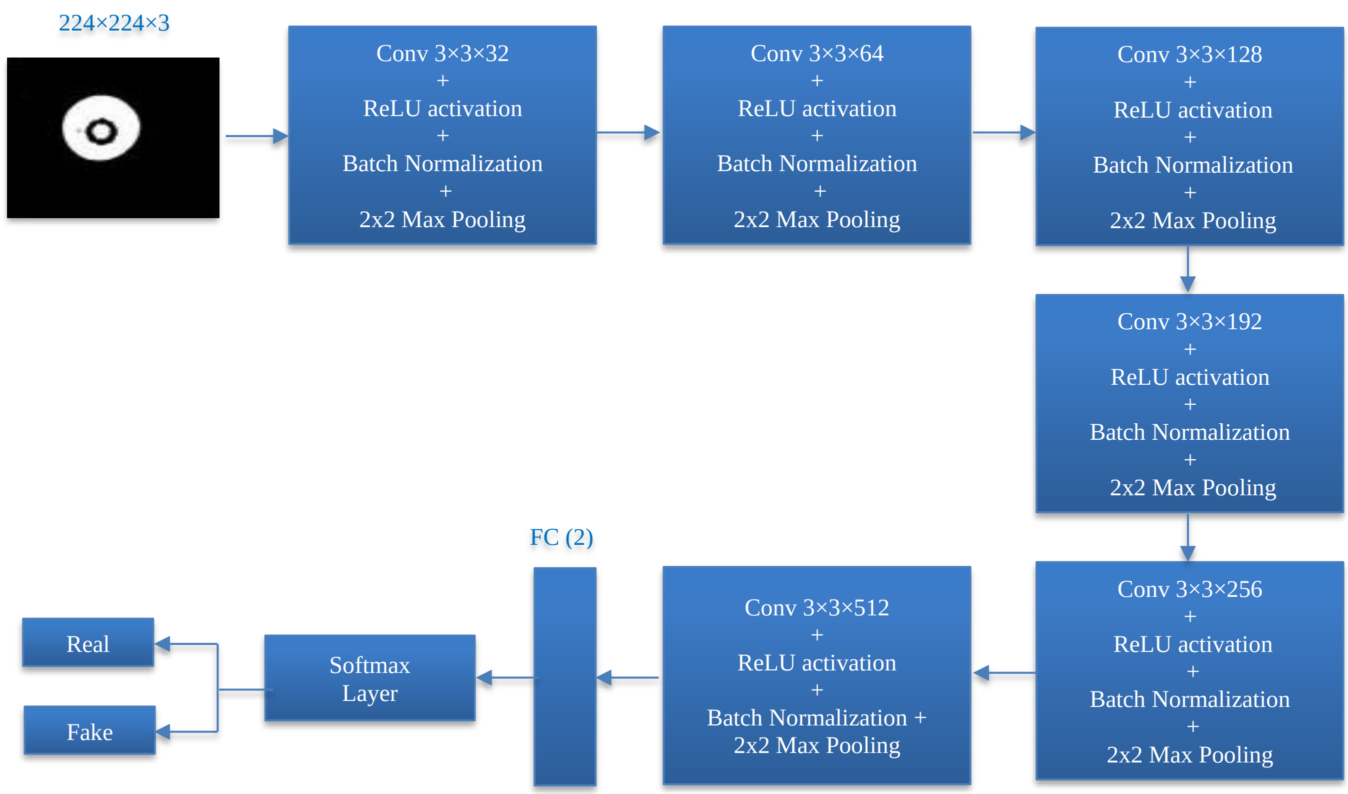


Fig. 5 The proposed customized light CNN model

3.5. Evolution Measures

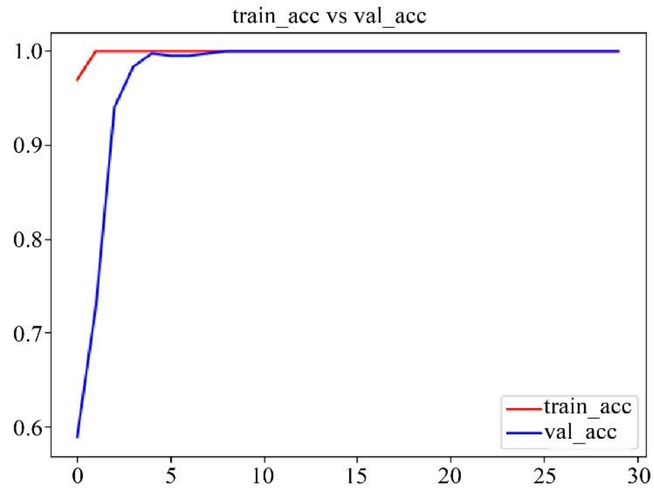
Performance measures in machine learning are used to assess the quality and effectiveness of a model's predictions. These measures help evaluate how well a model is performing on a given task and provide insights into its strengths and weaknesses. The choice of performance measures depends on the specific task at hand, whether it is classification, regression, clustering, or other types of machine learning problems. In this paper, we deal with the metrics that are related to classification tasks, such as recall, specificity, precision, f1-score, Area Under the Curve (AUC), and accuracy [21].

4. Results and Discussions

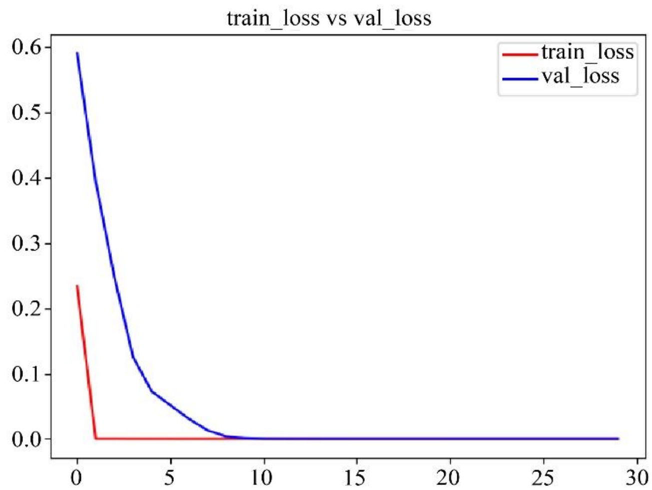
This study implemented an effective light CNN architecture to recognize iris images. Initially, we obtained saliency region and employed thresholding operation to yield segmented iris images. As a result, we can enhance the classification performance. Finally, we differentiate them into real and fake iris using the suggested CNN framework. MATLAB 2022b and Google Colab were used to run the experiments on an Intel (R) Core (TM) i3-5005U CPU at 2 GHz. Here, to train the model, we randomly split the dataset into 80% training and 20% testing, using a batch size of 32 and 30 epochs. In addition to that, Nadam [22] optimizer with a learning rate of 0.001 is taken into consideration to minimize the loss function. Figure 6 illustrates the model's training progression. As the number of epochs increases, training loss decreases, leading to improved accuracy. Similarly, Figure 7 depicts the confusion matrix of the implemented model, and Figure 8 depicts the Receiver Operating Characteristics (ROC) curve. As a result, we determined that the presented method achieved a high level of performance with 100% recall, specificity, precision, f1-score, AUC, and accuracy.The proposed model is compared with the well-known approaches that are discussed in Section 2, as shown in Table 1. As a result, we can conclude that the proposed customized CNN approach outperforms existing techniques in terms of recognition accuracy (approximately 0.08%) on the given benchmark dataset. The following are the main benefits of the suggested strategy:

1. Approximately 1,951,362 fewer parameters are required to train the model, with 1,948,994 trainable and 2,368 non-trainable parameters.
2. Low time complexity.
3. CNN can extract complex features without human involvement.
4. Significantly extract the Region of Interest (ROI) using the histogram-based thresholding technique.

Due to the above-mentioned benefits, the suggested framework significantly distinguishes genuine and fake iris images compared to the existing CNN-based approaches ([13], [17] and [18]).



(a)



(b)

Fig. 6 Training progress of the presented CNN architecture

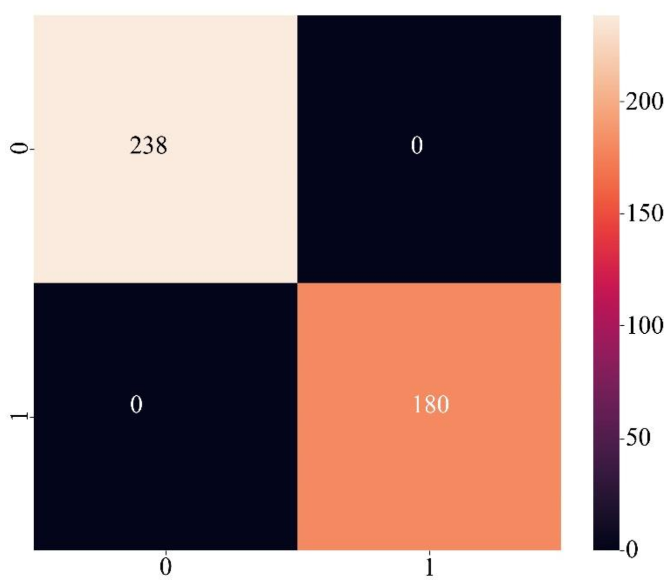


Fig. 7 Confusion matrix of the implemented approach

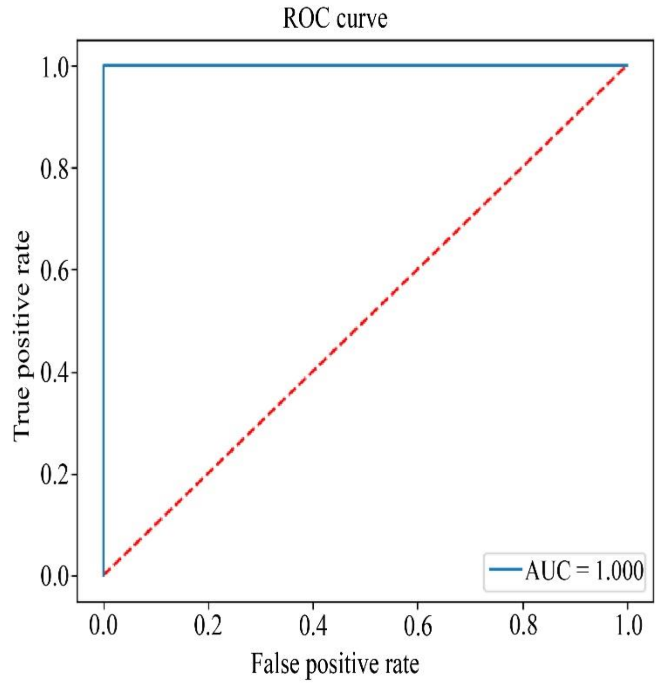


Fig. 8 ROC curve of the proposed model

Table 1. Comparison between the implemented and existing models

Method	Recognition Accuracy (%)
WE + LBP + SVM [8]	99.92
PCA + GA + BPNN [10]	96.4
KSVM [12]	98.5
AlexNet + SVM [13]	98
Curvelet + PSO [14]	99.4
LBPX [15]	97.2
DCT + RF [16]	99.18
VGG 16 [17]	96
CNN [18]	94.88
LWF [19]	88.2
The Proposed Model	**100**

5. Conclusion and Future Scope

In this article, we have developed an efficient, customized CNN framework for recognizing iris images. Primarily, the saliency map will be extracted using the suggested saliency detection approach, and the segment will be segmented using a histogram-based thresholding approach.

The segmented iris images are fed to CNN to identify fake/spoofing iris images. From the experimental analysis, we observed that the proposed model yields a high recognition rate in comparison with well-received strategies. Hence, the proposed model can be used as a supportive tool for iris recognition. In the future, we would like to implement a cost-effective iris recognition system with the help of Internet-of-Things (IoT).

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