Blink Detection for Off-Angle Iris Images using Deep Learning

Hasan Palta, Timi Omoteso, and Mahmut Karakaya
Dept. of Computer Science, Kennesaw State University, Marietta, GA USA 30060

ABSTRACT

Iris recognition is one of the well-known areas of biometric research. However, in real-world scenarios, subjects may not always provide fully open eyes, which can negatively impact the performance of existing systems. Therefore, the detection of blinking eyes in iris images is crucial to ensure reliable biometric data. In this paper, we propose a deep learning-based method using a convolutional neural network to classify blinking eyes in off-angle iris images into four different categories: fully-blinked, half-blinked, half-opened, and fully-opened. The dataset used in our experiments includes 6500 images of 113 subjects and contains images of a mixture of both frontal and off-angle views of the eyes from -50^o to 50^o in gaze angle. We train and test our approach using both frontal and off-angle images and achieve high classification performance for both types of images. Compared to training the network with only frontal images, our approach shows significantly better performance when tested on off-angle images. These findings suggest that training the model with a more diverse set of off-angle images can improve its performance for off-angle blink detection, which is crucial for real-world applications where the iris images are often captured at different angles. Overall, the deep learning-based blink detection method can be used as a standalone algorithm or integrated into existing standoff biometrics frameworks to improve their accuracy and reliability, particularly in scenarios where subjects may blink.

Keywords: iris recognition, blink detection, convolution neural network, deep learning

1. INTRODUCTION AND BACKGROUND

The Coronavirus pandemic will have far-reaching consequences on human behavior and society, including the adoption of new protection measures such as social distancing and the wearing of masks. As a result, the need for non-invasive and touchless biometrics has become more essential during COVID-19. Among these techniques, iris recognition stands out as one of the most accurate, distinct, universal, and dependable biometric approaches, enabling accurate identification of individuals without requiring contact with a surface or removal of the mask [1]. However, the accuracy of iris recognition is greatly impacted by angle, dilation, and occlusion, particularly in standoff iris images, which are frequently acquired in non-cooperative settings [2]. Eye blinking poses an additional challenge for iris recognition, as it can lead to difficulty in collecting accurate and reliable biometric data.

Blinking is a complex physiological process that plays a vital role in protecting the eyes from external factors such as dryness, bright light, and foreign objects like dust or smoke. It involves the rapid closure and opening of the eyelids, which serves to moisten and lubricate the cornea and protect it from potential harm. In addition to its protective function, blinking also assists in the processing of visual information by resetting the visual system and improving the clarity of visual perception. However, blinking is a challenge for iris recognition since part of the iris texture is occluded during the blinking. The images captured during a blink can be blurry, or the iris may not be visible at all, leading to difficulties in collecting accurate and reliable biometric data. Moreover, in many cases, it is challenging for subjects to keep their eyes fully open for a substantial amount of time, which can further complicate the collection of accurate and reliable iris images. In standoff iris recognition, where the iris images are captured at a distance and under non-cooperative settings, blink detection becomes even more crucial to ensure that the collected images are of high quality and can be used for accurate identification. Therefore, it is essential to investigate the impact of blinking on iris recognition and develop effective approaches for dealing with this issue.

To improve iris recognition performance, recent research in iris identification algorithms has primarily focused on dealing with non-ideal iris images caused by occlusion, lighting shift, and blur [3, 4, 5]. However, few research have addressed the issues in standoff iris images, such as elliptical unwrapping [6] and perspective projection [7]. Current

* Email: mkarakay@kennesaw.edu; Phone: +1(470) 578 6983.

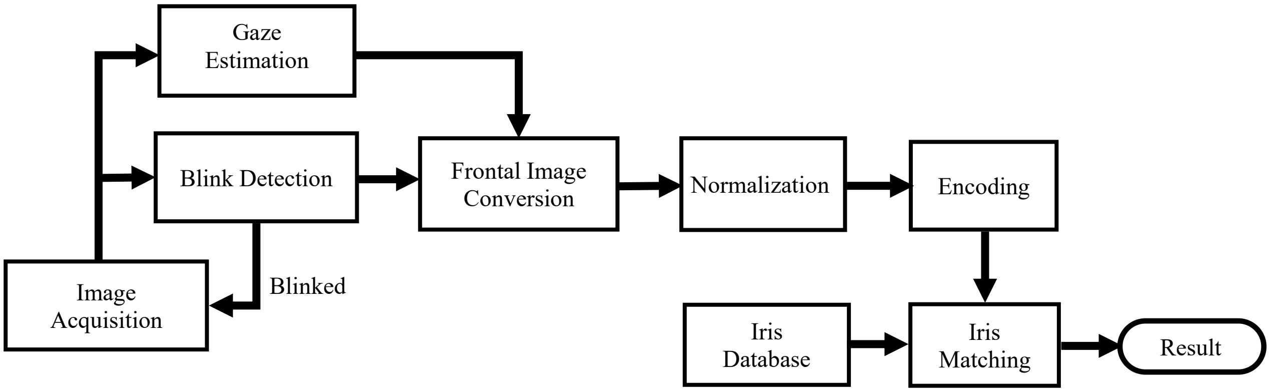

Figure 1: Flowchart of the traditional iris recognition framework for off-angle iris image with gaze and blink detection.

research indicates a modest improvement in recognition accuracy due to the following flaws: neglecting the light refraction at the cornea, disregarding limbus occlusions at the iris's outer border, and the requirement for adjustments according to industrial norms. Since traditional iris recognition systems are only designed for frontal iris images, the binary iris codes in databases for matching are only derived from frontal images. Future standoff iris recognition frameworks are required to be compatible with existing iris databases in order to match them by generating frontal binary iris codes, including both frontal and off-angle iris images. Blink detection is crucial in this situation, as it provides information concerning the images that can still be utilized in iris recognition or many other applications.

In this paper, we present a deep learning-based blink detection approach for off-angle iris images that can be used in standoff iris recognition frameworks. Figure 1 shows the flowchart of traditional iris recognition framework for off-angle iris image including the frontal reconstruction framework, gaze estimation, and blink detection. Since detecting the eye blink is the first essential component of the off-angle iris recognition process, this paper will address blink detection based on deep learning. The rest of this paper is organized as follows: Section II presents related works in blink detection. In Section III, we present our proposed deep learning-based blink detection method. Section IV describes the experimental setup. The results are presented in Section V. Finally, the conclusion is given in Section VI.

2. RELATED WORK

Blinking is a common challenge in iris recognition, as it can lead to incomplete or inaccurate iris images, hindering the performance and reliability of iris recognition systems. To address this issue, several approaches have been proposed to detect and cope with blinking in iris images including flow image methods, template matching, and convolutional neural networks (CNNs).

Using the flow image methods is a common approach to detect eyelid movements in video images [8-12]. For instance, Divjak and Bischof [8, 9] present real-time video-based approaches for detecting blink rates using a combination of intensity and motion-based features. They also utilized a support vector machine (SVM) to classify eye blinks as fatigue-related or spontaneous based on blink duration and frequency. In [10], they utilize the variance of motion vectors (VVM) to distinguish between blinks and other motions to address the large variation in illumination and moving objects issues where the image intensity and optical flow-based methods do not perform well. Fogelton and Benesova [12] combined recurrent neural networks with flow image methods, outperforming the performance obtained with finite state machines. These methods have shown promising results in detecting eye blinks and estimating their duration.

In a recent study, Medeiros et al. [14] developed a machine learning approach to detect volunteer eye blinks in real-time, which can be used as a signal for human-computer interaction. They utilized a computer vision detector that was capable of handling data captured through a generic webcam. Ayudhya and Srinark [15] presented a method based on image processing techniques for detecting human eye blinks and generating inter-eye-blink intervals. They used a Haar Cascade Classifier for face detection and a Camshift algorithm for tracking the face, allowing the extraction of the region of interest (ROI) around the eyes. Then, image processing techniques were applied to detect and measure the blinks based on changes in the ratio of the height of the ROI before and after the blink.

Han et al. [16] proposed a hybrid method that used convolutional neural networks and a support vector machine to detect blinks in visual data generated by smartphones. The deep learning model extracts features from the image and SVM was used for classification. In [17, 18], template matching methods used patches of the subject's open eyes on a specific phase as templates. Open and blinking eyes were identified by comparing the templates and the current eye patches using a similarity score. In [19], the variance map of the pixels in the entire face region and space-time filtering methods were used in order to locate the head and extract features of the eye. Panning et al. [20] developed an algorithm using the distance of the pixel values to a fixed threshold computed at the initialization phase for different color channels to detect eye blinks and other potential eyelid movements.

Danisman et al. [21] proposed a function for measuring eye openness by using the horizontal symmetry of open eyes as a baseline. The method is mainly based on extracting, normalizing, and splitting the patch region into the lower and upper halves. The closed eyes are measured based on high scores after measuring the asymmetry between these two halves. Additionally, many studies have used convolutional neural networks (CNNs) with facial images or videos to determine whether the eye is open or closed [22, 23] for driver fatigue detection and human-computer interaction. They successfully specified the occurrence of blinking using CNNs. However, no results related to any intermediate states.

Overall, various methods have been proposed to detect eye blinks in order to improve the accuracy of iris recognition algorithms. These methods have used different approaches, such as flow image methods, template matching, and CNNs, to detect eye blinks. Most of the methods and approaches described above require images or videos of the entire face of the subjects. In addition, traditional iris recognition systems are mainly designed for frontal iris images only. In addition, the existing binary iris codes in most databases used for successful matching are generated mostly from frontal images. In our study, the purpose is to perform iris recognition with maximal accuracy using both frontal and off-angle images. We want to determine whether the images of subjects' eyes can still conveniently be utilized in iris recognition or other biometric applications even if a full or partial blinking occurs. Therefore, further research is needed to develop more efficient and accurate methods for detecting intermediate states of the eye, which can improve the accuracy of iris recognition systems.

3. METHODOLOGY

The development of deep learning techniques has revolutionized various fields, including computer vision, natural language processing, and robotics. Particularly, Convolutional Neural Networks (CNNs) have gained significant interest from various research communities. In this study, we develop a deep learning-based blink detection method for off-angle iris images, which is a crucial task in iris recognition frameworks. CNNs are popular deep learning techniques used in various applications such as image classification and segmentation. Therefore, we have adopted a CNN-based AlexNet [24] and transfer learning was adopted to pursue our investigation.

AlexNet architecture consists of five convolutional layers, three max-pooling layers, two normalization layers, two fully connected layers, and one softmax layer. Each convolutional layer comprises convolutional filters and a nonlinear activation function called ReLU. The convolutional layers consist of filters that learn features from the input image, while the max-pooling layers help reduce the dimensionality of the output of the convolutional layers. The fully connected layers at the end of the network perform classification on the learned features, and the softmax layer outputs the probabilities for each class. AlexNet has been trained in using over a million images and is capable of classifying images into a thousand different regular object classes such as animals, computers, backpacks, pens, etc. During classification, the network takes an image as input and returns a corresponding label for the object detected in the image with a probability score for each of the object categories.

However, training a deep learning model from scratch requires a large dataset, significant computational power, and time. Due to these constraints, this study employs transfer learning, a technique that uses a pre-trained network as a starting point to learn new tasks. Transfer learning retrains the final softmax layer on a fresh dataset with a different number of classes using general-purpose features learned in lower layers. Compared to training a network with randomly initialized weights from the beginning, transfer learning is typically much faster and easier. Thus, we can transfer the learned features to a new task using fewer training images.

The use of transfer learning allows us to adapt the pre-trained network to the blink detection task with minimal training images, thus reducing the time and computational power needed for training. The resulting blink detection model achieves high accuracy in detecting blinks in off-angle iris images, making it a promising tool for iris recognition frameworks.

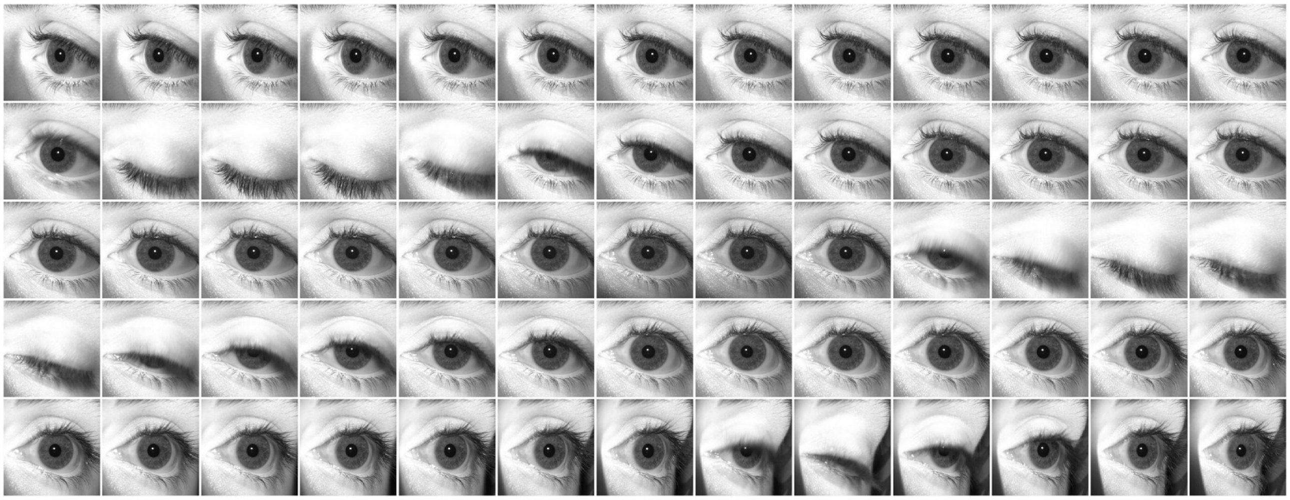

Figure 2: Example of eye images in the continuous off-angle images dataset captured from -50° to 50° with 1° step-size. Note that it also includes blink images in different gaze angles.

4. EXPERIMENTAL SETUP

A novel dataset consisting of off-angle iris images is used to train and test a deep learning-based blink detection approach. The dataset was acquired using two near-infrared (NIR) sensitive cameras, which capture frontal and off-angle iris images simultaneously. Each camera has a resolution of 1280x1024 pixels and is equipped with an 18-108 nm changeable focal length lens, with focal lengths of 108 mm and 40 mm for the frontal and off-angle cameras, respectively. To improve image quality, the iris texture is illuminated by a 780 nm near-infrared light emitted from a Power LED light source. In the data acquisition system, the frontal camera is placed at a fixed position (with 0° gaze angle) to capture frontal images, while the off-angle camera is attached to a horizontally moving arm that can move between 50° and -50° in angle to record off-angle iris images. Two separate configurations were used to acquire frontal and off-angle iris images from 100 different participants.

In the first setup, the off-angle camera starts its movement from 50° and captures 10 images per stop for each subject, stopping every 10° as a step-size until it reaches -50°. A total of 110 images are retained for each participant. In the second setup, the off-angle camera moves back to its starting point (50°) at a steady speed from -50° in angle, and 10 iris images are recorded every second during this continuous movement. Each camera takes around 975 images of each participant during the 30-second image acquisition session. The angle difference between two consecutive off-angle photos is approximately 0.1°. Two types of off-angle iris datasets are produced: a steady image dataset and a continuous image dataset. Each iris image was originally grayscale and had a size of 1280x1024 pixels. Fig. 2 shows sample continuous images of a subject recorded at angles ranging from -50° to 50° with a 2° step-size. To prepare the images for use with the AlexNet model, the images were cropped by 128 pixels from the right and left edges, enlarged, and converted to RGB format.

The dataset was organized into four main groups based on the degree of eye opening: (a) Full-blinked, (b) Half-blink, (c) Half-opened, and (d) Fully-opened. Fig. 3 shows the sample images from each group where they have a similar number of images in the dataset. The dataset contains 6,500 frontal and off-angle iris images, with the number of images in each category given in Table 1. We manually selected blink images from the original iris image dataset that includes. In order to generate ground truth labels for each image, at least two different investigators verify the blink category. To study the effect of gaze angle on blink detection, the dataset was further divided into two groups as frontal (F) and off-angle (O). The ground-truth gaze angle for each image is precisely known since images are acquired at constant points in our first data gathering configuration. Our algorithms were implemented in MATLAB, and we employed image processing and deep learning toolboxes. The algorithms were implemented in MATLAB, and image processing and deep learning toolboxes were used. A workstation desktop computer with a Nvidia GeForce RTX 2080 SUPER with 16GB of memory was used for faster computation.

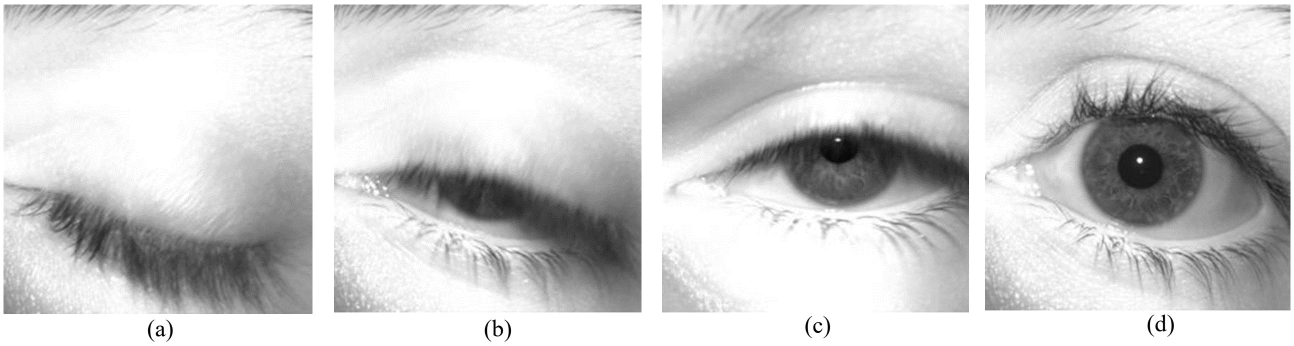

Figure 3: Example of eye images in the dataset (a) Fully-blinked, (b) Half-blinked, (c) Half-opened, and (d) Fully-opened.

TABLE I: OFF-ANGLE BLINK DATASET FOR OFF-ANGLE IRIS IMAGES

Class Name	Total # of Images	# of Frontal Images	# of Off-angle Images
Full blinked	1,833	880	953
Half blink	1,431	602	829
Half opened	1,807	590	1217
Fully opened	1,444	1022	422

TABLE II: ACCURACY FOR DIFFERENT HYPERPARAMETERS (LEARNING RATE AND MINIBATCH SIZE)

Learning Rate \ Minibatch Size	4	8	16	32
$4.0 \cdot 10^{-6}$	94.70%	94.47%	94.17%	93.04%
$1.2 \cdot 10^{-5}$	92.56%	93.55%	93.55%	94.32%
$2.0 \cdot 10^{-5}$	92.79%	94.32%	93.78%	93.94%
$2.8 \cdot 10^{-5}$	92.79%	92.56%	94.55%	93.78%
$3.6 \cdot 10^{-5}$	91.10%	93.71%	92.79%	94.63%

5. RESULTS

In our initial set of experiments, we divided the complete dataset into two distinct groups for the purpose of training and testing the deep learning network using various parameter settings. This task mainly involved selecting appropriate hyperparameters, such as the learning rate, batch size, and range, to achieve optimal performance. To this end, we tried different combinations of these hyperparameters, and the results are presented in Table II. Our results show that the dataset was successfully trained using the chosen hyperparameters, with the algorithm generating a validation accuracy of more than 91% for all the combinations of learning rates and minibatch sizes tested. This indicates that the proposed deep learning-based approach is capable of accurately detecting the eye blinks from off-angle iris images, even when subjected to different hyperparameter settings. However, further experiments are required to validate the algorithm's robustness and generalization capability.

The second set of experiments used iris images in the frontal (*F*) and off-angle (*O*) groups for network training and testing to investigate the blink detection performance for frontal and off-angle iris images. The blink detection results were analyzed using ROC curves for different categories of eye blinks, as shown in Fig. 4. The solid-blue line represents fully-blinked, the solid-red line represents half-blinked, the solid-green line represents half-opened, and the dotted-black line represents fully-opened blinks. Fig. 4(a) illustrates the performance of blink detection when trained and tested using frontal images. Since the frontal image subset (F) is used for network training and testing, the performance is very high for fully-blinked, half-blinked, half-opened, and fully-opened blink category where their area-under-the curve (AUC) scores are 0.993, 0.990, 0.998, 0.999, respectively.

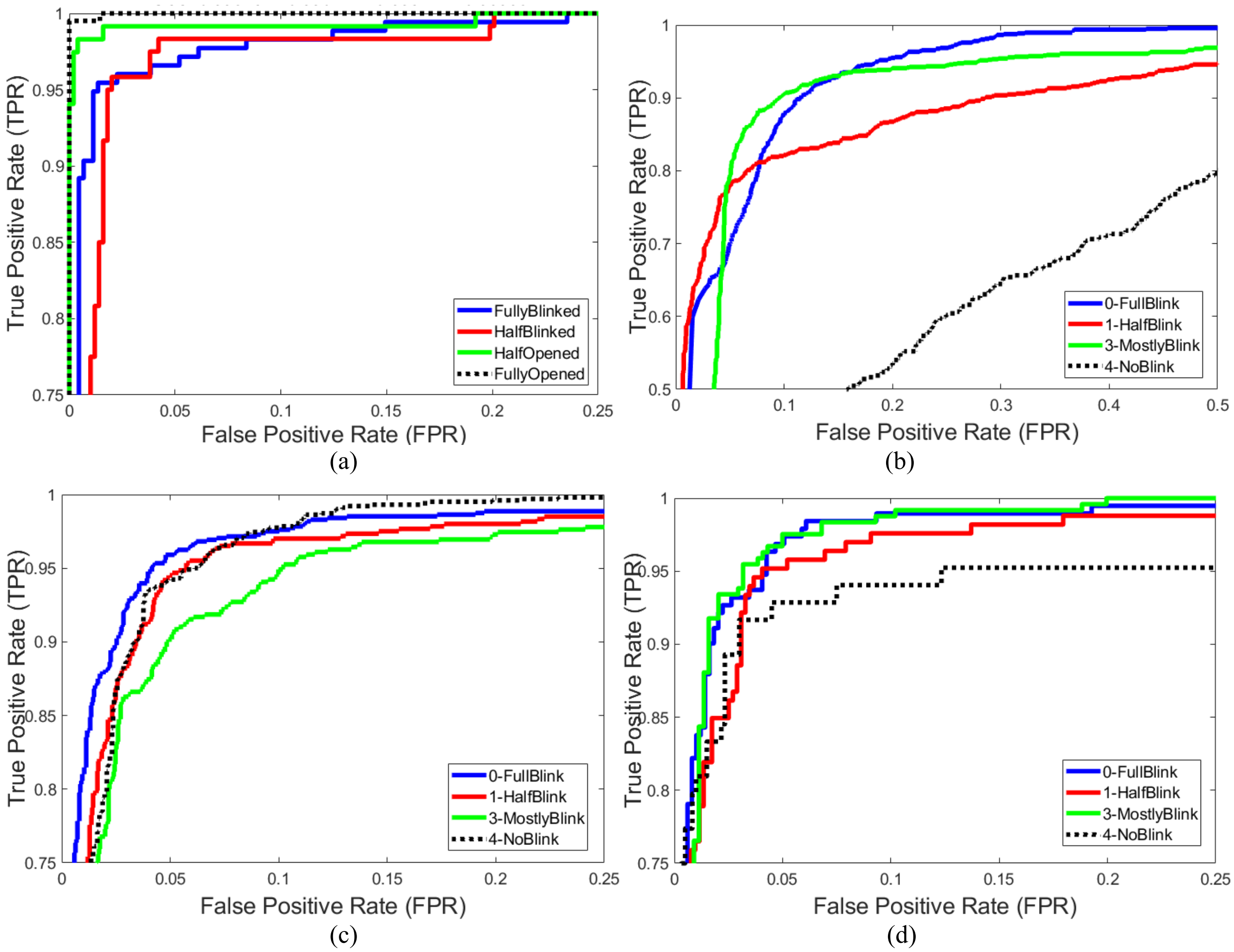

Figure 4: Performance analysis using ROC curves for different categories of eye blinks including fully-blinked, half-blinked, half-opened, and fully-opened. (a) CNNs are trained with frontal image subsets (*F*) and tested with off-angle image subsets (*F*), (b) CNNs are trained with frontal image subset (*F*) and tested with off-angle image subset (*O*), (c) CNNs are trained with off-angle image subsets (*O*) and tested with off-angle image subsets (*F*), (d) CNNs are trained with off-angle image subset (*O*) and tested with off-angle image subset (*O*).

Fig. 4(b) shows the blink detection performance analysis for training with frontal images and testing with off-angle images. Since only frontal image subset (F) is used for network training and network is tested with off-angle images, the performance is lower compared with Fig. 4(a). For the fully-blinked, half-blinked, half-opened, and fully-opened blink categories, the AUC scores are 0.954, 0.922, 0.936, and 0.763, respectively. These scores indicate that the performance of the blink detection model decreases when tested on off-angle iris images. The main reason for the performance drop when testing the blink detection model on off-angle iris images is that the off-angle iris images have a different viewing angle and are more challenging to detect blinks compared to the frontal iris images. This leads to a difference in the distribution of the features learned by the model during training and those present in the off-angle images during testing. Therefore, the model may not generalize well to off-angle images, resulting in lower performance. Additionally, the off-angle images may have occlusions or other artifacts that are not present in the frontal images, which further affects the model's performance. Therefore, further optimization of the model and training dataset may be needed to improve the performance on off-angle images.

Fig. 4(c) shows the blink detection performance analysis for training with off-angle images and testing with frontal images. The AUC scores are 0.988, 0.979, 0.978, and 0.985 for fully-blinked, half-blinked, half-opened, and fully-opened blink categories, respectively. The higher AUC scores indicate that the model has learned useful features from off-angle images that can be transferred to frontal images. This indicates that the model trained on off-angle iris images performs well when tested on frontal iris images. Interestingly, the performance of the model on frontal images in this case is comparable to the performance of the model trained on frontal images and tested on frontal images (Fig. 4a). This suggests that training the model on off-angle images could potentially lead to better generalization to frontal images. Further investigation is needed to explore this hypothesis and optimize the model's performance on both frontal and off-angle iris images. This could be due to the fact that off-angle images have different characteristics and may not capture all the information needed for accurate blink detection in frontal images.

In our last experiment, the network was trained and tested with off-angle iris images, and its blink detection performance is shown in Fig. 4(d). The AUC scores are 0.990, 0.984, 0.991, and 0.976 for fully-blinked, half-blinked, half-opened, and fully-opened blink categories, respectively. These results demonstrate that the performance of the blink detection model improves when trained with off-angle images. In comparison to Fig. 4(b), where the model was trained on frontal images and tested on off-angle images, the AUC scores in Fig. 4(d) are higher for all blink categories. This indicates that the network has learned robust features that are not specific to off-angle or frontal images. These results also suggest that training the model with a more diverse set of off-angle images can further enhance its performance for off-angle blink detection. This improvement is particularly significant for real-world applications where iris images are often captured at different angles.

6. CONCLUSION

In conclusion, we have presented a CNN-based blink detection algorithm for standoff iris recognition frameworks. Our approach can classify off-angle iris images and determine which ones can still be used in biometric applications such as iris recognition in case of full or partial blinking. Our experiments showed that the performance of the blink detection model improves when trained with off-angle iris images. Compared to the network trained with frontal images, the network trained with off-angle images was able to classify both off-angle and frontal images with a success rate exceeding 97.5%. These results suggest that training the model with a more diverse set of off-angle images can improve its performance for off-angle blink detection, which is crucial for real-world applications where the iris images are often captured at different angles. Furthermore, our approach has the potential to be used in other biometric systems that require accurate detection of blinks. Overall, our work provides a promising approach for improving the robustness and accuracy of standoff iris recognition systems.

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