Binary vs. Multi-Class Segmentation for Off-angle Iris Images using Deep Learning Frameworks

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ABSTRACT

During the pandemic, it is a critical task to recognize individuals and to verify their identity without touching a surface or removing the face mask. Compared with other biometric modalities, iris recognition provides accurate, reliable, and contactless biometrics measure. Traditional iris recognition systems require high quality frontal iris images. The image quality dependency limits its recognition performance in standoff applications. However, standoff biometric systems work in a less controlled environment where the captured images may be nonideal and off-angle. Since segmentation is the first step among recognition tasks, having an accurate segmentation is extremely critical to achieving a high recognition performance especially for off-angle iris images. Recent advances in deep learning enable the usage of some convolutional neural networks (CNN) for the challenging iris segmentation task. During training process, binary iris segmentation masks feed to the CNN framework to learn the iris texture where all other eye structures included in the same class. However, the pupil and sclera segmentation may provide useful additional information for iris segmentation. In this paper, we investigate the CNN-based iris segmentation frameworks for binary segmentation and multi-class segmentation. We first train the deep networks with binary segmentation masks (iris vs. others). Then, additional deep networks are trained with multi-class segmentation masks where pupil, iris texture, sclera, and other eye structures in separate classes. Finally, we compare the segmentation accuracies with off-angle iris images where images are captured from -50° to 50° in angle. Based on the results from real experiments, the proposed method shows effectiveness in segmentation for off-angle iris images.

Keywords: biometrics, iris recognition, segmentation, off-angle iris images.

1. INTRODUCTION

Technology is evolving rapidly every single day. Technologies that used to take years to become obsolete now take mere months; to contribute to this fast-moving wave, it is important to stay up to date and ahead of the curve. In the past decade or so, in the world of Artificial Intelligence, otherwise known as AI, machine learning has taken the world by storm; milestones in computer capability have been achieved that were otherwise deemed impossible only a few decades back, this is especially true in the world of machine vision. One area of research that we have taken an interest in is iris segmentation since, if perfected, can have major implications in many different industries. When strictly considering traditional computer vision techniques, the ability to be able to perform accurate and quick iris segmentation has already been achieved. However, the technology is arguably limited in scope of operability and certain stringent conditions must be met for this segmentation to be accurate. For example, some airports employ iris recognition cameras at their passport control counters most probably for ID verification and security purposes. For the recognition to proceed smoothly, the subject must be facing forward with zero-degree tilt with his/her eyes wide open. Otherwise, the iris segmentation algorithm is likely to fail therefore resulting in a case of failed iris recognition. There are other locations that employ these traditional iris segmentation techniques for iris recognition such as military bases and law enforcement facilities [1].

Traditional iris segmentation tasks using traditional methods is quite challenging due to the elliptical shape, dilation, and extreme off-angle cases [2]. Most of the traditional techniques for segmentation use traditional computer vision techniques such as integro-differential, Hough Transform, and edge detection to achieve segmentation results [4]. These techniques only work in very ideal situations of a visibly clear frontal iris image where boundaries are circles. While some researchers have tackled the issue of off-angle iris segmentation, the vast majority have limited the scope of their research to frontal zero-degree ideal iris images. Due to the recent boom and advancements of machine and deep learning in the past decade, many researchers have chosen to tackle iris segmentation problem using deep Convolutional Neural Networks.

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(a) (b)

Figure 1: Example frontal and off-angle iris images at (a) frontal gaze, 0º and (b) off-angle gaze 50º.

The contribution of this study is in two-fold: First, it conducts research and experiment on the effects of multi-class trained R-CNNs on off-angle iris images. This aspect of the work is mostly a complement and a continuation of the work in [2]. We investigate the deep networks that have been trained on both frontal and off-angle images using duplicate layers or layers that have been modified through masking and other techniques, we may be able to isolate techniques of preprocessing to be able to improve such segmentation. The second aspect of this work is to explore the possible improvements that can be achieved using multiple binary classifiers working in series/parallel as opposed to using one multi-class segmentation network. The intuition behind considering this as something viable is the fact that when we are dealing with a binary segmentation network, as opposed to a multi-class one, the probabilities associated with the classification, and ultimately correct segmentation, of a specific area of an image goes up from >50% to 50%. Furthermore, having multiple networks working in unison can also introduce the ability for the developed algorithm to re-consider the classification of a specific pixel in the image; when one network considers a pixel to be of a specific category and has a higher probability that it belongs to such a category than the other binary network, the algorithm would then consider the former network's classification. This is as opposed to the segmentation being done with a network trained with more than two classes; the algorithm essentially has only one opinion to work with as opposed to multiple; there is only so much that one can do to improve the segmentation of such a network.

The rest of this paper is structured as follows: Section II presents background and related works in iris recognition system. In Section III, binary and multiclass segmentation approaches of off-angle iris images will be discussed. Experiments and results are presented in Section IV. Finally, we conclude in Section V.

2. RELATED WORKS

There are a multitude of works that tackle the issue of iris segmentation whether it be zero degree or off-angle iris segmentation. There are two primary ways of approaching each of the two challenges mentioned above: either (i) using traditional computer vision techniques or (ii) using more novel machine and deep learning methods. Research on the techniques of frontal and off-angle iris segmentation was done using both approaches.

Starting with the traditional approach, as mentioned in the introduction, the already existing research that pertains to iris segmentation has primarily focused on the segmentation of zero-angle frontal iris images; this is done through fitting circles to the iris and pupil boundaries. A recent iris segmentation method that has been adopted commercially is the integro-differential operator proposed by Daugman [4]. This method involves an exhaustive search of the parameter space for the three integral parameters of a circle i.e., the radius and the two-dimensional center coordinates which maximize the angular integral over the radial derivative of the input iris image. Another well-known two-step iris segmentation method is one proposed by Wildes [5] which involves the use of circular Hough Transform to find the iris and pupil edge points. These two methods have been iterated upon and improved over time; rewritten algorithms that reduce computational time [6], ignoring non-important edges due to specular highlights [7], and lastly prioritization of segmentation of the pupil prior to the iris [8]. These traditional methods all have prerequisites to work properly such as a very high-quality image dataset, they do not attempt to segment what is identified as poor-quality images. While recent works [9, 10] have attempted to tackle many of the already present issues plaguing these segmentation methods, such as using methodologies to deal with factors like occlusion, specular reflections etc., these methods do not necessarily work well with off-angle iris images. Considerations that are especially needed for off-angle iris images such as the elliptical shape of the iris and pupils due to a combination of perspective distortion and corneal refraction are not considered.

When considering traditional off-angle iris segmentation, there are not many works tackling this problem. One approach involves the use of nonparametric methods such as active contours [11, 12]. There are authors such as Duagman [11] that propose fitting ellipses to the boundaries of both the iris and the pupil based on the discrete Fourier coefficients of active contours. Other authors such as Shah and Ross [12] use filtering and thresholding methods to detect the pupil boundary and accordingly segment the iris boundary by using a combination of classical snakes and geometric active contours. The methods mentioned may work well in specific scenarios and with specific datasets, however, they are not dataset agnostic. Furthermore, these methods require high computational power since they involve intensive parameter search and training for a new dataset.

Some works try to avoid off-angle iris segmentation problem entirely. [13, 14] avoid this by considering the use of perspective transformation to map these off-angle iris images to a frontal view for use with established aforementioned frontal angle iris segmentation methods avoiding the ellipse issue plaguing the off-angle images. Moreover, a brute force technique proposed by Shuckers et al. [15] involves angle estimates search; this search is meant to pick the best values which maximize the value of integrodifferential operator on iris images. In short, the algorithm attempts to re-project the input image to all possible gaze-angles. The authors of [16] used a boundary segmentation methodology; a look-up table was generated using an ideal biometric eye model and this look-up table was used to find the closest feature points to estimate gaze angles. In [17] Price et al. used computationally intensive raytracing techniques to develop a general virtual eye model which is then used to perspective and refractive distortion correction. Much like with the methods that attempt to tackle off-angle iris segmentation head on, all these additional approaches, which try to remap the off-angle images prior to segmentation, have a major drawback; the reliance on traditional computer vision boundary detection techniques which, we believe to be, inherently flawed for this application. These techniques mainly tend to localize false iris boundaries, especially when considering off-angle iris images. Moreover, many of the aforementioned suggested techniques involve the use of computer synthesized eye models which translates to a model that is highly probable not to perform well in real world scenarios.

More recently, in the past decade or so, computers have gotten much more powerful which has given us the ability to perform calculations that would have been very computationally temporally taxing before. Convolutional neural networks (CNNs) have become a staple in dealing which image recognition, classification, and segmentation as of late; deep learning techniques such as CNNs have the advantage of being able to reduce or even eliminate the drawbacks of the traditional segmentation techniques mentioned above. Aspects such as complex intensive pre-/post-processing of images as well as scenario and dataset dependency can either be reduced or eliminated with the use of this data-driven learning approach. Moreover, the use of these networks introduces the advantage of not only being highly performant but also quite accurate as well when well trained. Arslan et al. [18] proposed the use of a binary CNN, based on the VGG CNN architecture, which classifies the pixels of an image into two classes being 'iris' or 'other'; their results were compiled from various test in non-cooperative/ideal environments. Jalilian et Uhl [19] were able to prove the superior capability of CNNs in dealing with off-angle iris images by comparing three different convolutional encoder-decoder networks they have developed to several traditional methods. In [20] Liu et al. used a hierarchal CNN (HCNNs) and multi-scale FCN (MFCNs) to locate the iris region automatically also in non-cooperative/ideal environments. Jalilian et al. [21] also proposed a domain adaptation technique for iris segmentation using CNNs to prevail over the need of massive quantities of labelled data. The IrisDenseNet model, based on VGG-16, presented in [22] was developed to deal with lower quality iris image dataset. Scenarios that were considered include glasses, off-angle iris images, side views, and rotated eyes. Some like Bazrafkan et al. [23] proposed their own CNN that could also segment lower quality on and off-angle iris images. Rot et al. [24] examined the sensitivity of their own deep multiclass eye segmentation network to the shift of the iris in different directions which include left, right up, and straight. While method proposed by some like Roig et al. [25] involve the multiclass approach for iris segmentation with the aim to improve iris segmentation in non-ideal situations using a CNN. All these aforementioned methods involve the usage of deep learning convolutional neural networks, however, none have explored and analyzed both the performance of multi-class iris segmentation vs binary class iris segmentation nor the quantification of the performance of said segmentation when considering different iris angles; there are many variables that have to be taken into account including but not limited to eyelid occlusion and segmentation parametrization that have not been considered by these previous techniques.

3. METHODOLOGY

The main purpose of this research is to segment the inner and outer boundary of the iris texture with parametrization and to explore the difference between multiclass and binary segmentation of off angle iris images. To find a clean bordered

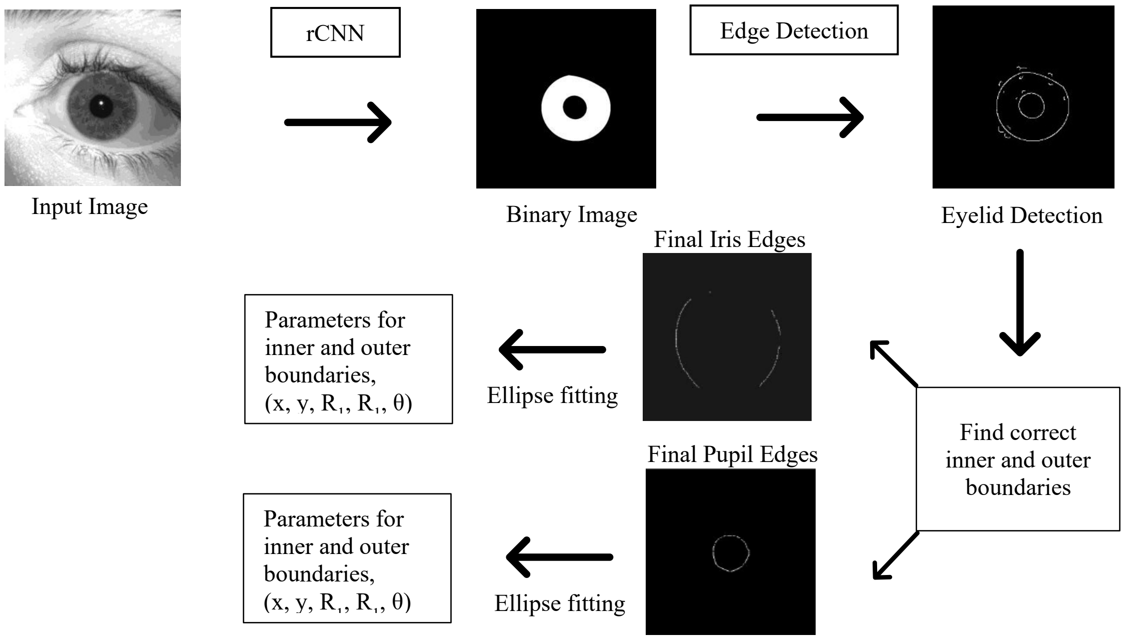


Figure 2: Binary image segmentation pipeline

and accurate iris segmentation comes with many challenges including gaze angle, eyelid occlusion, and limbus occlusion. The iris is bordered by the sclera and gets blocked in numerous ways by the eyelid. It is important to note that while iris segmentation has been a well-explored problem for frontal iris images. However, off-angle iris segmentation needs a more complex solution where we investigate a different deep learning approach for multi-class iris segmentation and compare it traditional binary segmentation. In addition, we also investigate the deep learning based binary segmentation in a serial and parallel fashion wherein multiple binary segmentation networks work in ensemble to segment the iris.

The ultimate goal of iris segmentation is to find the inner and outer boundary parameters of iris texture. For frontal images, boundaries are circular, but off-angle iris images have elliptical boundaries. Therefore, we fit ellipses to pupil and sclera boundaries where each boundary has five parameters: (x, y, R_1, R_2, θ). The x and y parameters being the location of the center of the iris/pupil, the R_1 and R_2 parameters being the horizontal and vertical radii of the iris/pupil respectively, and lastly the rotation θ parameter.

3.1 Binary Iris Segmentation using Deep Networks

In binary segmentation, the input image is segmented into two class as iris texture and others. After the iris texture is segmented from rest of eye structures including pupil, sclera, skin, eyelid, eyelash, eyebrows, two ellipses are fit to inner and outer iris boundaries as shown in Figure 2. First, segmentation process converts the original input image into a binary image where the iris is in white, and the others is in black. To unwrap the iris texture by converting into a dimensionless space, we need to find our five ellipse parameters. Since the ellipse fitting algorithm needs the edge points detection, we first find the edges in the binary image using edge detection methods. However, iris texture is occluded by the eyelid and segmentation result does not corresponds the actual iris boundaries. Therefore, we need to detect eyelid to exclude the edges caused by eyelid occlusion. This is a crucial step since, through this procedure, we can isolate the imperfect and inconsistent boundaries caused by the eyelids. For eyelid detection, the initial binary image is processed by traditional machine vision techniques to fit curves to upper and lower eyelids. After finding the correct inner and outer edges of the iris boundaries, two ellipses are fit to the iris and the pupil and the parameters that are needed are then derived.

Since pupil is the black part of the iris where its value is almost similar and eyelid occlusion is less possible; it is easier to segment pupil compared with the iris texture. Therefore, the traditional iris segmentation algorithms first segment the pupil from the given input image. However, the deep learning-based segmentation methods do not take this as an advantage for segmentation. They use the training masks where iris is marked as one and others are categorized zero. This paper investigates two different approaches to compare the binary networks: (i) a single *Iris_Other* network that tries to perfectly segment iris texture from other eye structures, (ii) multiple binary networks that are used to segment the pupil and iris in different networks. Elaborating on (ii), these two separate binary networks are designed to segment pupil from other eye structures using a binary *Pupil_Other* network and to segment iris from rest using a binary *Iris_Other* network. We investigate two different approaches to fuse the information from these two binary segmentation networks: the (i) parallel approach and (ii) the serial approach.

In the parallel approach, the *Pupil_Other* and the *Iris_Other* networks first work separately in parallel then fuse their results producing the final result. Initially, each binary network is trained separately to segment pupil and iris texture. During testing, the input image is fed to both these binary networks where *Pupil_Other* segments the pupil and *Iris_Other* segments the iris texture. After these separate segmentations, we fuse their results by weighting the pupil segmentation result of the *Pupil_Other* network on the result of the iris segmentation from *Iris_Other* network. In essence, the inner iris boundary (i.e., the pupil boundary) of the iris texture that was segmented by the *Iris_Other* network is adjusted by the *Pupil_Other* network before being deemed a final iris segmentation and having the relevant result metrics be calculated. This process redefines and refines the inner iris boundary.

With the serial format two binary networks are trained, *Pupil_Other* and *Iris_Other* similar with parallel fashion. However, the pupil segmentation network is used to generate the training images of iris segmentation network. In serial fashion, we first train a binary *Pupil_Other* network for pupil segmentation. Second, the resultant the pupil segmentation is used to process the input images by masking the pupils to generate the new masked training set. Third, the *Iris_Other* network is trained with the processed dataset. After training two binary networks, the input image is first fed to *Pupil_Other* network to segment the pupil and which is then masked from the testing input image. Finally, the masked image is segmented using the *Iris_Other*.

There is a big shortcoming for the binary segmentation networks where binary networks ignore the different eye structures (the pupil, the sclera, and skin) in the input image by classifying them as 'other'. Even if all these eye structures have different grayscales and textures, the binary segmentation network puts them into the same class ignoring the loss of additional useful information. Therefore, this loss of what may be considered essential details results in the decrease of overall segmentation accuracy. Ultimately, this means that the binary pipeline requires a separate eyelid detection algorithm. Since eyelid detection is a particularly important stage in the pipeline, it becomes a much more difficult endeavor to fit ellipses to the inner and outer iris boundaries and to extract the relevant ellipse parameters for iris normalization with this separate algorithm.

3.2 Multi-Class Iris Segmentation using Deep Networks

Multi-class iris segmentation enables us to segment all the different relevant eye structures into different classes. Figure 3 shows a pipeline of multi-class segmentation where input image segmented into four classes including the pupil, iris, sclera, and others. The others class includes all the periocular eye structures including eyelid, eyelash, skin, and eyebrows if captured. Since these periocular eye structures are not related to iris texture directly, we put them into same class. Besides, we can design the network for any different number of classes. However, the overall structure of the pipeline will remain the same. Unlike the binary segmentation pipeline, the multi-class pipeline does not require the use of an additional algorithm to find the eyelids. Using edge detection, the boundary of other class is used for the eyelid detection. The edges of where the eyelids intersect are determined to use as the left and right extremities of the eye. We split the eyelid edges into two classes as upper and lower points using connected component analysis and extremist points. Finally, we fit two quadratic curves for the top and bottom eyelids.

For iris and pupil segmentation, canny edge detection method is used on both the segmentation outputs of the iris and the pupil classes. The edges in the iris class are used to find the outer boundary where iris and sclera intersects. The edges in the pupil class are used to find the inner boundary where iris and pupil intersects. In order to remove the eyelid occlusion effect on iris boundaries, we eliminate any edge points of the iris and pupil class if they are above or below the eyelid curves. Since we find eyelid occlusion on the iris texture and eliminate the bad edge points, these final inner and outer iris edges are more accurate iris boundaries. Finally, we fit an ellipse to pupil and iris segmentation edges separately.

Similar to binary segmentation, different variations of the multi-class segmentation network can be designed. The intermediate goal was to find a better network design comparable with the binary segmentation network. For example, we can design a three-class network where it can be trained with modified input images with their first layer being untouched, second layer having the pupil masked, and third layer having the iris and pupil masked. The theory was that since there is a lot of duplicate information, having some variance in the layers may give the feature extraction process the ability to extract more features for better segmentation.

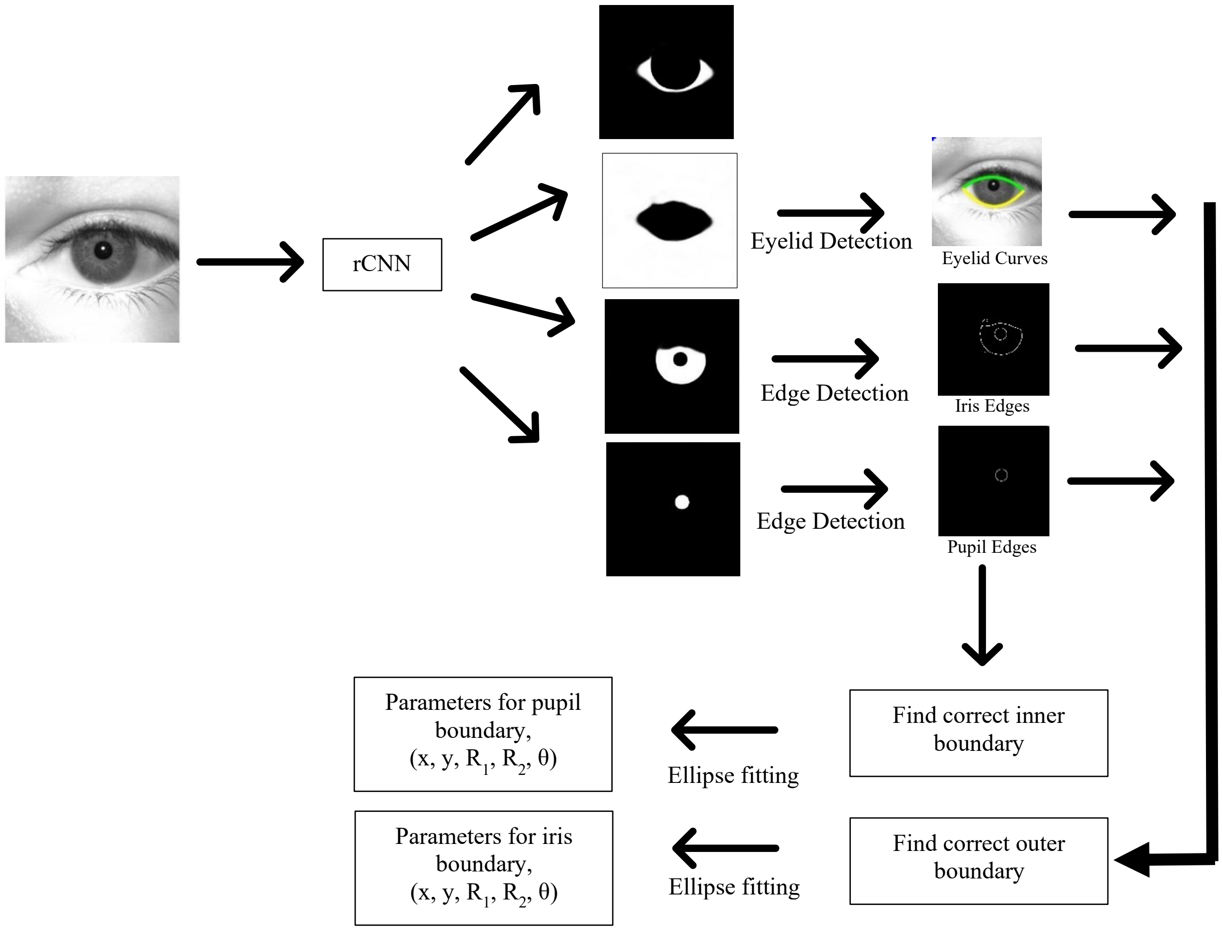


Figure 3: Multi-Class Image Segmentation Pipeline

4. EXPIRIMENTAL SETUP AND RESULTS

To train all models we used MATLAB integrated development environment alongside an Nvidia RTX 3060Ti. Each training session took around 80 minutes to complete. The deep-lab-v3 semantic segmentation architecture alongside the Resnet50 Convolutional Neural Network were used as the basis for training the model. It is important to note that the base case hyperparameters used to train the control binary and multiclass networks were a stochastic gradient descent (SGDM) optimizer, a batch size of 32, a learning rate of $1.00e^{-3}$, a learning rate drop factor of 0.9, a learning rate drop period of 10 epochs, an L2 regularization of 0.005, and lastly 20 number of epochs. About 10,000 images, from around 100 subjects, were used [3]. These images were captured using two near-infrared sensitive cameras. They were of both the left and right eyes of the subjects at angles from -50° to 50° with 10° increments. Images were taken by a horizontally moving camera to capture all the different angles which captured 10 iris images per step which amounted to 10 frontal and 100 off-angles iris images captured from each subject; this totaled to about 220 images per subject. Each of these images had a ground truth mask constructed for it. Example images from every angle can be seen below in Figure 4.

In order to quantify the performance of our networks, many result metrics were used to evaluate the quality of the segmentation performed by a specific trained model. This is including but not limited to accuracy, mean IoU, mean BF score etc. However, the most important metric that were referred to gauge the quality of the iris and other segmentations was the NICE1 segmentation error rate score. The NICE1 protocol, is a metric developed to give an even more in depth look at the performance of the segmentation done on the testing samples in the dataset. The formula consists of adding the summation of the XOR ($\oplus$) between the iris segmentation results of one image and the iris ground truth data from the masks, summing the result, and dividing it by the summation of the summation of the iris ground truth data. The results of each image are then either averaged together to give an average NICE1 score that is used to gauge the overall segmentation

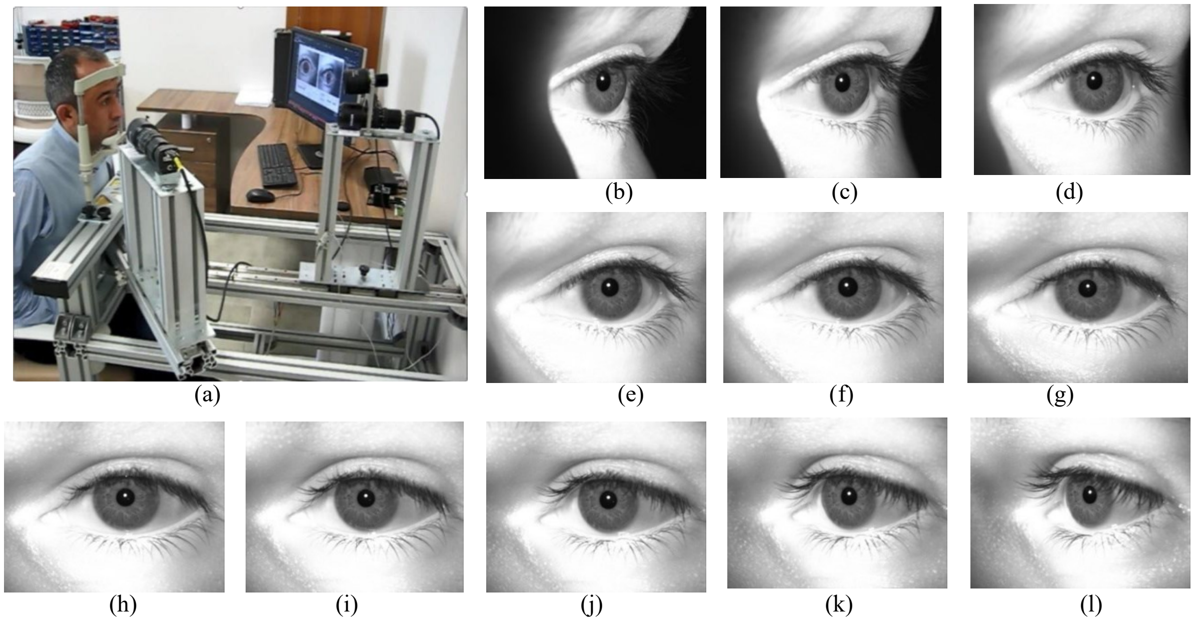


Figure 4: (a) Experimental setup of off-angle iris image capturing of off-angle iris dataset. Example images from off-angle iris at various angles (b)+50°, (c)+40°, (d)+30°, (e)+20°, (f)+10°, (g) 0°, (h)-10°, (i)-20°, (j)-30°, (k)-40°, (l)-50°.

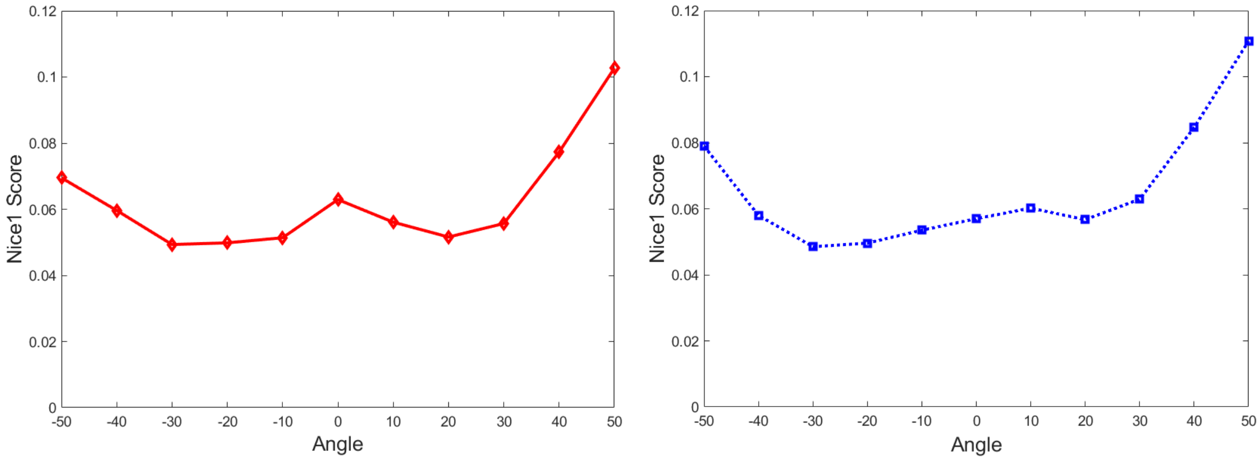
performance of model or plotted on a figure with the iris angle on the x-axis and the NICE1 score on the y-axis to gauge the performance on an angle-by-angle basis. The lower the NICE1 score, the better the segmentation is considered. The NICE1 score is calculated as:

$$NICE1 = \frac{\sum\sum Seg(x,y) \oplus GT(x,y)}{\sum\sum GT\,(x,y)}$$

where x, y are the coordinates of each pixel, *Seg(x,y)* is the predicted segmentation, and *GT(x,y)* is the ground truth.

The serial, as opposed to the parallel binary network produced the best results. We went through several iterations of this network to reach the current optimal hyperparameters which are the ADAM optimizer, a batch size of 16, a learning rate of $1.00e^{-5}$, an L2 regularization value of 0.005, and lastly 30 epochs. From these multiple iterations it was seen that uniformly dropping the learning rate during training was hurting the accuracy of the network, therefore, the learning rate during the training phase of this model was held constant. The NICE1 score of this network was impressive being 0.0624 the highest when compared to all our other binary trained models. However, the mean overall NICE1 error rate is only an indication of overall performance, mean NICE1 error rate on an angle-by-angle basis is needed to paint a clearer and more succinct picture of the performance of this model.

As show in Figure 5(a), the *Iris_OtherS2* network performs the best when segmenting inputs that have been captured from a -30° to 30° angles as it has the lowest mean NICE1 error rate. This model also performs moderately well when segmenting inputs captured for a N40 and P40 angles. However, it fairs worse when dealing with angles of -50° and even worse with the P50 angle. The reason the network performs marginally worse when dealing with the 50° angle is due to the presence of a difference between the angles associated with the actual geometric axis position and visual axis position of the eye. The geometric-axis and the visual-axis of the eye do not overlap. Since we captured images when subject was looking at the camera at frontal images, we labeled gaze images with respect to the frontal where the visual axis is 0° in degree, but geometric axis is 8° in degree. Therefore, the P50° images from the left eye is geometrically 58° rather than 50°. This is the reason why in case of our sample test results of left eyes, the worse NICE1 scores of the positive angles do not mirror the better scores of the negative angles. This is also the case when testing the right eye wherein the results are reversed. For example, it will be the case that the NICE1 score for the 30° in angle should be the same as the NICE1 score for the -30° in angle, however, that is not the case. It is important to note that this axis disparity phenomenon is also present with all the positive angles, in the case of the left eye subset, and all the negative angles, in the case of the right eye subset, however, gets progressively worse the more extreme of an angle is chosen.



(a) (b)

Figure 5: Average NICE1 score for each angle at (a) Binary network and (b) multi-class network

There were many variants of the multiclass network. *ALL2* was the best variant and was trained with the same hyperparameters used to train the *Iris_OtherS2*; they were the ADAM optimizer, a batch size of 16, a learning rate of $1.00e^{-5}$, an L2 regularization value of 0.005, and lastly 30 epochs. This did indeed improve network segmentation performance netting us a NICE1 score of 0.0652. While this is better than the base case multiclass network, it remains a higher score than what the final binary iteration was able to achieve meaning at first glance, it performed worse than its binary counterpart. However, much like with the binary segmentation network, the mean overall NICE1 score does not tell the full story of this segmentation network. We calculated the per angle mean NICE1 scores for this network as shown in Figure 5(b). We observed that this network performs the best when considering the -20° to 20° in angles compared with the best binary network *Iris_OtherS2*. Overall, when considering more extreme off-angle iris input images such as angles of -30° to -50° or 30° to 50°, the model's performance dips considerably in comparison to the best binary network variant. Much like *Iris_OtherS2* this network's segmentation accuracy also suffers substantially when segmenting the 50° in angle, which again, we believe is attributed to the difference present between the geometric and visual axes.

5. CONCLUSION

To improve segmentation of off-angle iris images, we have investigated many different models with variations of the multi-class and binary models such as parallel and serial. Overall, the *Iris_OtherS2* and the multi-class model *ALL2* produced the best results in their respective categories. These results show a clear advantage of the serial binary network. To recap, the mean NICE1 score of the serial binary network is 0.0624. When initially compared to the 0.652 of the *ALL2* multiclass network, the scores are awfully close, however, when looking at the mean NICE1 scores of each angle respectively, it can be ascertained that the serial binary network does an arguably much better job at segmenting the iris when considering the extreme off-angles. Despite the metrics, the multi-class network might still seem superior to the due to it outputting feature information but, it still does have its own shortcomings as well. By virtue of there being four classes considered and trained for instead of only two, the probability that a pixel in an image is classified to be part of the correct class drops from 50%, as is the case for the binary segmentation network, to 25%. This ultimately means that, although the overall segmentation accuracy might be higher using a multi-class network, the segmentation and parametrization accuracy of the most important part of the image, the iris itself, suffers. Furthermore, while the segmentation of the sclera is important in order to exclude it from the 'other' class in a multiclass model, experimentation shows that the sclera itself is problematic and difficult to segment and, therefore, is likely to negatively affect the segmentation 'other' since the sclera's outer boundaries are the 'other' class's inner boundaries; this is especially the case for off-angle eye images. Therefore, this phenomenon may compromise the correctness of the eyelid detection and arc fitting which can also compromise the soundness of the final modifications done to the iris segmentation before ellipse fitting. Henceforth, the exclusion of sclera as a class within the binary segmentation network architecture means that this issue can be avoided and can be seen as a positive aspect for that type of segmentation network. The impacts of improving iris segmentation accuracy can have a sizable impact on many modern industries. Currently, more research is needed to perfect the methods used for building a binary segmentation pipeline, however, we believe that there when pursued there may lie tremendous potential.

ACKNOWLEDGMENTS

This project was made possible by support from Secure and Trustworthy Cyberspace (SaTC) program of The National Science Foundation (NSF) under grant award CNS-1909276 and CNS-2100483.

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