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Iris Reflection Segmentation from Ocular Images Acquired in Uncontrolled and Uncooperative Conditions

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***Abstract*—The segmentation of reflections from the iris region is a relevant task for biometric systems, human-machine interaction technologies, and photo editing applications. This task is particularly complex for ocular images acquired from uncooperative users in uncontrolled illumination and environmental conditions. Furthermore, to the best of our knowledge, all of the studies in the literature on methods specifically designed to detect reflections in the iris texture are based on algorithmic approaches. In this paper, we present the first study on deep neural networks for segmenting reflection regions from iris images. Specifically, we propose a modified version of the U-Net architecture based on an encoder (downsampler) characterized by a relatively low computational complexity, and designed with the aim of being applied on edge devices. Experiments have been performed for a dataset of 3,286 ocular images acquired from websites and social media in completely uncontrolled and uncooperative conditions. The obtained results prove that our proposed method can accurately segment the iris reflections for particularly challenging images. A detailed qualitative analysis also confirm the robustness of our method for non-ideal application contexts. Furthermore, experiments show that our method can increase the accuracy of state-of-the-art iris segmentation techniques based on deep neural networks.**

***Index Terms*—Reflections, iris, segmentation, deep learning, edge computing, biometrics.**

I. Introduction

The segmentation of iris reflections is a particularly relevant task in biometrics, human-machine interaction systems, and photo editing applications. In biometrics, methods for segmenting the iris reflections could increase the iris segmentation accuracy [1]. In human-machine interaction, the iris region is frequently segmented to analyze the gaze of the user [2] for different applications, like driving assistance systems [3]. Photo editing applications could also introduce automatic methods to remove reflections from the iris region, with the aim of obtaining visually pleasing portrait pictures by using artificially generated textures [4].

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Most of the methods in the literature have been designed to segment the reflection regions from ocular images acquired from cooperative users by using biometric scanners, which usually capture ocular images at a distance of less than 30 cm from the camera and adopt near infrared illuminators to enhance the visibility of the iris texture and pupil-iris contrast [1]. Most of these methods are based on statistical analyses of the image intensity [5].

However, accurately segmenting the iris reflections from ocular images acquired from uncooperative users in uncontrolled illumination and environmental conditions is more challenging with respect to segmenting ocular images acquired by using biometric scanners since the less-constrained acquisition conditions can introduce additional non-idelities in the samples [6]. Examples of relevant non-idealities are: strong occlusions, specular reflections with heterogeneous shapes and intensities, shadows, gaze deviation, poor pupil-iris contrast, poor iris-sclera contrast, blur, motion blur, frame interlacing, and unknown spatial resolution.

Recent iris segmentation methods based on deep learning can estimate the pixels describing the iris texture by excluding occlusion regions [7], both from images acquired by using iris scanners and from ocular images captured from uncooperative users in uncontrolled illumination and environmental conditions. However, the reflection regions are not always properly described and these iris segmentation methods do not compute a binary map representing only the reflections, which could be useful for a set of contexts, like photo editing applications. In the literature, there are also studies based on machine learning able to compute segmentation masks representing the reflections of the iris region [8]–[10]. However, they are not based on deep learning strategies.

We present a method for segmenting the reflections of the iris based on deep neural networks (DNNs) designed to cope with ocular images acquired from uncooperative users in uncontrolled illumination and environmental conditions. Our method can be used in unconstrained iris recognition systems, thus improving the security [12] of different applications by increasing the accuracy of identity recognition methods [15],

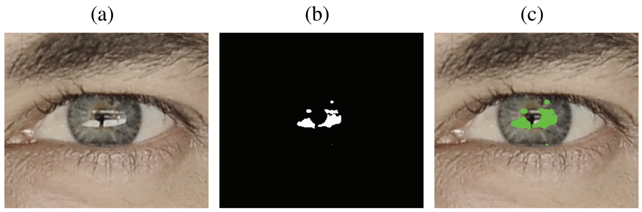

Fig. 1. Example of segmentation the iris reflections from an ocular image acquired from an uncooperative user in uncontrolled illumination and environmental conditions: (a) ocular image; (b) binary mask representing the iris reflection regions resulting from the segmentation task; (c) ocular image with the segmented reflection regions enlightened in green.

as well as it can be suitable for human-machine interaction and photo editing applications. Fig.1 shows an example of segmentation result in the considered application context. Specifically, we propose a segmentation technique based on a modified U-Net [11] architecture. We use an encoder (downsampler) requiring a limited number of computational resources to obtain a segmentation method easily portable on edge devices (e.g., mobile phones, portable biometric recognition systems, and embedded systems). In fact, in distributed systems, it should be preferable to perform most of the computation on edge devices in order to reduce the computational load of the server as well as to reduce privacy risks by not sending biometric samples over the network [13].

The contribution of this paper is twofold.

- First, we present a novel method able to accurately segment reflections of the iris region based on DNNs.
- Second, our segmentation method is designed for edge devices and thus uses encoders requiring limited computational resources.

We experimentally validated our approach for I-SOCIAL-DB [6], a dataset of $3,286$ ocular images acquired from websites and social media, obtaining better accuracy with respect to state-of-the-art algorithms. We also proved that our method can increase the accuracy of iris segmentation methods based on DNNs.

The reminder of the paper is structured as follows. Section II describes related works on iris segmentation and reflection segmentation techniques. Section III presents our proposed segmentation technique. Section IV presents the experimental protocol and achieved results. Section V concludes the work.

II. State of the Art

This section presents related works on iris segmentation and on methods for segmenting iris reflections.

A. Iris Segmentation

Iris segmentation methods in the literature are based on either algorithmic approaches or on DNNs. A large number of methods based on the algorithmic approaches approximate the internal and external iris boundaries as two circles or ellipses by analyzing the edges of the ocular images [14]. More recent approaches approximate the iris contours without applying any assumption on its shape [15]. Only a relatively small number of algorithmic approaches is designed to deal with samples acquired from uncooperative users in uncontrolled illumination and environmental conditions [16]. Algorithmic approaches for iris segmentation cannot directly estimate the iris regions affected by reflections. Therefore, these methods are frequently coupled by techniques for reflection segmentation.

Encouraged by the impressive performance of DNNs in different application contexts, researchers recently proposed iris segmentation methods based on DNNs [7]. Differently from algorithmic approaches, DNNs can classify every pixel of the ocular image in “iris” and “non-iris”, discarding reflections and occlusions. Furthermore, recent studies based on DNNs obtained significantly better accuracy and robustness to non-idealities with respect to algorithmic approaches. In this context, the mostly used techniques are encoder-decoder Convolutional Neural Networks (CNNs) and approaches based on U-Net. Methods based on encoder-decoder CNNs can be based on a fine-tuned SegNet [17], [18] or RefiNet [19]. Many approaches are based on modified versions of the U-Net architecture. As an example, the method presented in [20] is based on Dense-U-Net (dense layers combined with U-Net). Furthermore, U-Net can be combined with Attention Net [21] or Squeezenet [22]. Although many DNNs for iris segmentation can remove reflection regions with sufficient accuracy for biometric recognition systems, this class of segmentation methods do not return a binary mask describing the reflection regions.

In the literature, there are also semantic segmentation approaches for ocular images based on DNNs [23]. However, none of them consider a class representing the iris reflections.

B. Segmentation of the Reflection Regions

Most of the methods in the literature for segmenting the iris reflections perform simple statistical analyses of the image hystogram [24]–[26]. However, their accuracy is limited in case of ocular images acquired from uncooperative users in uncontrolled illumination and environmental conditions.

There are also studies based on artificial intelligence classifiers and handcrafted features. As an example, the method presented in [8] uses artificial neural networks with features extracted by computing the Radon transform of the sample. The method proposed in [9] extracts reflections and occlusions by using a classifier that evaluates images transformed using the Rubber Sheet Model [14]. Other studies perform a semantic segmentation of the ocular region by using trained classifiers [10].

However, to the best of our knowledge, there are no studies on DNNs designed to segment iris reflection regions.

III. The Proposed Approach

We present a study on a highly accurate DNN for segmenting the iris reflection regions. Our proposed method can be divided into four main steps: ROI (region of interest) estimation, preprocessing, DNN, and postprocessing. Fig. 2 shows the schema of our method. In the following, we describe each of the computational steps.

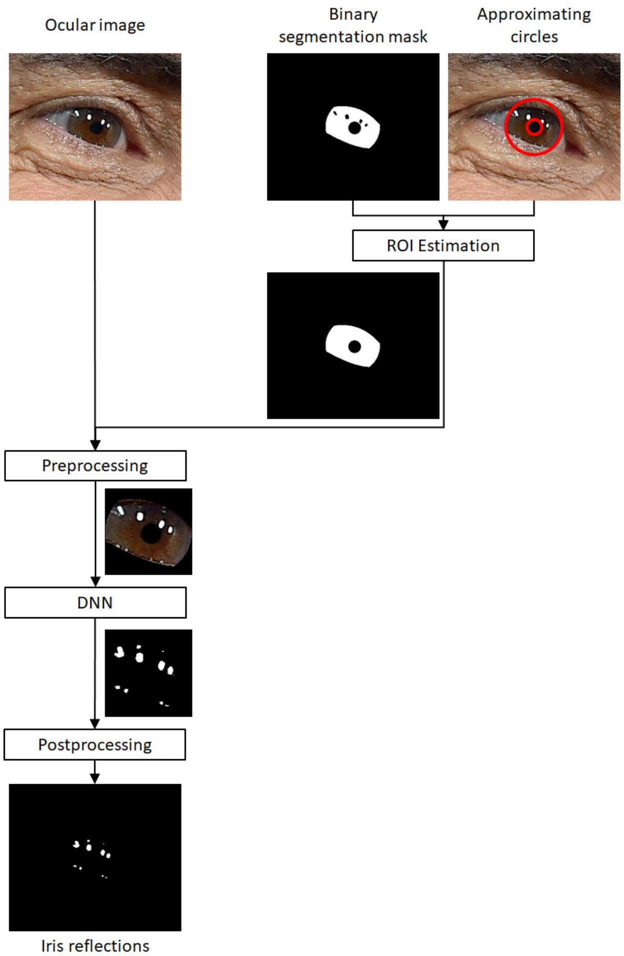

Fig. 2. Schema of our proposed method for segmenting iris reflection regions.

A. ROI Estimation

This step computes a binary image R of the ROI, which describes the iris texture including possible reflections. To this purpose, we extract information from a binary segmentation mask M describing the iris region and from a set of parameters representing the circles approximating the inner and outer iris boundaries. The mask M as well as the circles approximating the iris boundaries can be estimated by a human expert or by using automatic algorithms [1]. The design of novel algorithms for iris segmentation or for estimating circles approximating the iris boundaries is out of the scope of this paper.

To remove the reflection regions from M, we apply a morphological closure by using an empirically tuned structuring element s_e. The obtained image Q does not describe anymore the pupil region. Therefore, we subtract the circular region representing the pupil from Q, thus obtaining the binary image R. Fig. 3(a) shows an example of R.

B. Preprocessing

The preprocessing step consists of first creating an image I' representing only the region decribed by the binary image R.

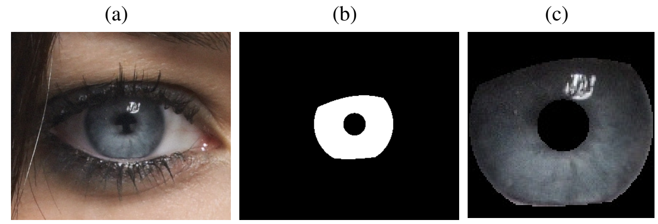

Fig. 3. Example of preprocessing: (a) ocular image I; (b) binary image R representing the ROI; (c) preprocessed image X.

Specifically, for every pixel j, $I'(j)$ is computed as follows:

$$I'(j) = \begin{cases} I(j) & \text{if } R(j) = 1 \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

I' is then cropped according to the bounding box of R. The obtained squared image X is finally resized to fit the input size accepted by the proposed DNN. Fig. 3(b) shows an example of squared image X.

C. DNN

This step computes a binary image representing the iris reflections Y starting from the image X.

Since semantic segmentation methods based on U-Net achieved impressive results for iris segmentation and for a wide set of semantic segmentation applications [27], we selected the U-Net architecture as the basis of our method. To reduce the computational complexity of the method, we choose an encoder requiring a limited amount of resources. Furthermore, to simplify the learning task, the selected encoder has previously been trained for ImageNet dataset [28]. Fig. 4 shows the computational schema of the proposed neural architecture. The decoder is based on the pix2pix framework [29], while the encoder is based on a MobileNetV2 [30], which is an efficient model for mobile and embedded vision applications. Similarly to MobileNet [31], the MobileNetV2 structure is built on depthwise separable convolutions, which require less parameters to be trained with respect to the normal convolutions. Furthermore, MobileNetV2 introduced the linear bottleneck and inverted residual structure to further reduce the computational cost with respect to MobileNet. The architecture of MobileNetV2 contains an initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers.

D. Postprocessing

This step refines the binary mask of the iris reflections Y estimated by the DNN to obtain the binary output image O representing the iris reflections of the ocular image I.

First, we compute the binary mask Y' by resizing Y to the same size of R.

Second, we remove the estimated reflection regions that do not occlude the iris texture. Specifically, we compute the binary image O as $O = Y' \wedge R$, where $\wedge$ is the AND operator.

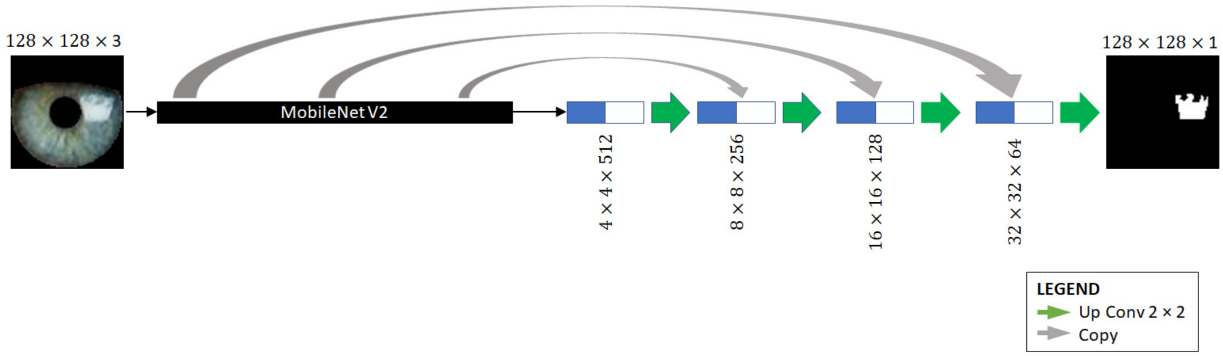

Fig. 4. Schema of our proposed DNN architecture.

IV. Experimental Results

This section presents the used dataset, describes the process used to train the DNN, evaluates quantitative segmentation results, analyzes qualitative results, and describes the results obtained by integrating our method in a state-of-the-art iris segmentation approach.

A. Dataset

We evaluated the performance of our proposed method for I-SOCIAL-DB [6], a dataset of ocular images collected from uncooperative users in uncontrolled light conditions and acquisition environments. Specifically, the dataset is composed of images obtained from websites and social media. It includes 3,286 ocular images, extracted from 1,643 high-resolution face portraits of 400 individuals. For each ocular image, the dataset include a segmentation mask created by a human expert.

For each ocular image I, we computed the labels of the reflection regions as a binary image L obtained by processing the iris segmentation masks created by human exprercts for I-SOCIAL-DB. The reflection mask L is computed as follows:

$$L = M_h \oplus R_h, \tag{2}$$

where M_h is the iris segmentation mak created by a human experts, R_h is the ROI computed as described in Section III-A for M_h, and $\oplus$ is the XOR operator. We refer to data related to the knowledge of human experts by using the subscript h.

We used 80% of the samples to create the training set and 20% of the samples to create the testing set. The testing test is composed of 658 samples. Every result reported in the following has been computed for the testing set.

B. Training Process and Parameters

The presented DNN has been implemented in Python by using the library TensorFlow. The weights of the encoder have been previously trained for ImageNet dataset [28]. The DNN has been fine-tuned for 30 epochs. We used Adam Optimization with binary cross entropy as loss function, batch size equal to 32, and a learning rate equal to 0.001.

We used the iris segmentation masks created by human operators for I-SOCIAL-DB to obtain every image X and label L adopted to train the DNN.

The parameter s_e used to include the reflection regions in the binary image R consists of a circular structuring element of diameter equal to 20 pixels. The diameter value has been estimated as the minimum value for includig every reflection region of the considered dataset. Larger diameter values should obtain similar results, by slightly increasing the computational complexity.

C. Quantitative Evaluation

To quantitatively evaluate the segmentation accuracy of our method, we used figures of merit obtained by averaging the confusion matrices [26] computed for every image of the validation set. Specifically, we considered the following figures of merit:

- Accuracy $= (TP + TN)/(TP + TN + FP + FN)$,
- Sensitivity $= TP/(TP + FN)$,
- Specificity $= TN/(TN + FP)$,

where TP are the True Positives, TN are the True Negatives, FP are the False Positives, and FN are the False Negatives.

We compared the performance of our proposed method with a state-of-the-art reflection segmentation technique designed for non-ideal ocular images acquired from uncooperative users in uncontrolled illumination and environmental conditions [32]. For a fair comparison, we considered the results obtained by the state-of-the-art technique [32] only for the ROI R .

To prove the applicability of our method in heterogeneous conditions, we evaluated its perfomance in case of ROI computed from data manually created by a human expert, as well as in case of using data computed by using state-of-the-art techniques for iris segmentation. In the second case, we executed the DNN trained for samples created using manually estimated data on samples created using automatic algorithms. Specifically, we selected the iris segmentation method R-CNN [33] since it achieved the best performance reported in [6]. To estimate the circles approximating the inner and outer iris boundaries, we used the approach presented in [34]. Table I summarizes the obtained results.

Table I shows that our method largely outperforms the baseline algorithm by using ROIs obtained from data estimated by human experts as well as by using ROIs obtained from

TABLE I
ACCURACY OF REFLECTION SEGMENTATION METHODS

Reflection detection	Accuracy	Sensitivity	Specificity
Baseline, manual ROI	0.9973	0.9986	0.6421
Our method, manual ROI	0.9987	0.9995	0.9654
Baseline, automatic ROI	0.9973	0.9988	0.5803
Our method, automatic ROI	0.9982	0.9993	0.8958

data automatically computed by using state-of-the-art methods. The table also shows that our method is applicable in real case conditions, since the Accuracy decreased only of 0.0005 by using ROIs obtained from data automatically computed by using state-of-the-art methods, in comparison to ROIs obtained from data estimated by human experts. This relatively small performance decrease is due to segmentation errors present in the automatically computed iris segmentation masks, which do not include some portions of the iris texture, thus reducing the obtained Specificity of our reflection segmentation method.

D. Qualitative Evaluation

We performed a qualitative evaluation of the results obtained our method for segmenting iris reflection regions. Specifically, a human exeprt classified the segmentation results obtained for every ocular image into "satisfactory" and "unsatisfactory". Fig. 5(a) and 5(b), Fig. 5(c) and 5(d) show examples of satisfactory segmentations. Fig. 5(e) and 5(f) show examples of unsatisfactory segmentations. In Fig. 5, FP pixels are marked in red, while FN pixels are marked in green.

The percentage of satisfactory segmentations is equal to 97.3%. In most of the cases, unsatisfactory segmentations are due to false positive regions returned by our method. This problem mostly happened for light colored eyes.

E. Contribution to Iris Segmentation

To simulate one of the possible applications of techniques for estimating the iris reflection regions, we integrated our method in a state-of-the-art iris segmentation system. For each ocular image I, we computed the corresponding iris segmentation mask M_a by using the method described in [33] and refined the iris segmentation result by using the output of our reflection segmentation method O. Specifically, we compute the refined iris segmentation mask M'_a as $M'_a = M_a \wedge O$. We refer to data computing by automatic iris segmentation algorithms by using the subscript a

Similarly to most of recent studies in the literature on iris segmentation, we used the figures of merit proposed for the competition NICE.I [35]. The first metric (E1) represents the classification error rate and is computed as the proportion of disagreeing pixels between each computed iris segmentation mask M and the corresponding ground truth mask C, as follows:

$$\mathrm{E1} = \frac{1}{n} \sum_i \frac{1}{c \times r} \sum_{c'} \sum_{r'} M_i(c', r') \otimes C_i(c', r') \ , \qquad (3)$$

where n is the number of ocular images, c is the number of columns of every ocular image, r is the number of rows

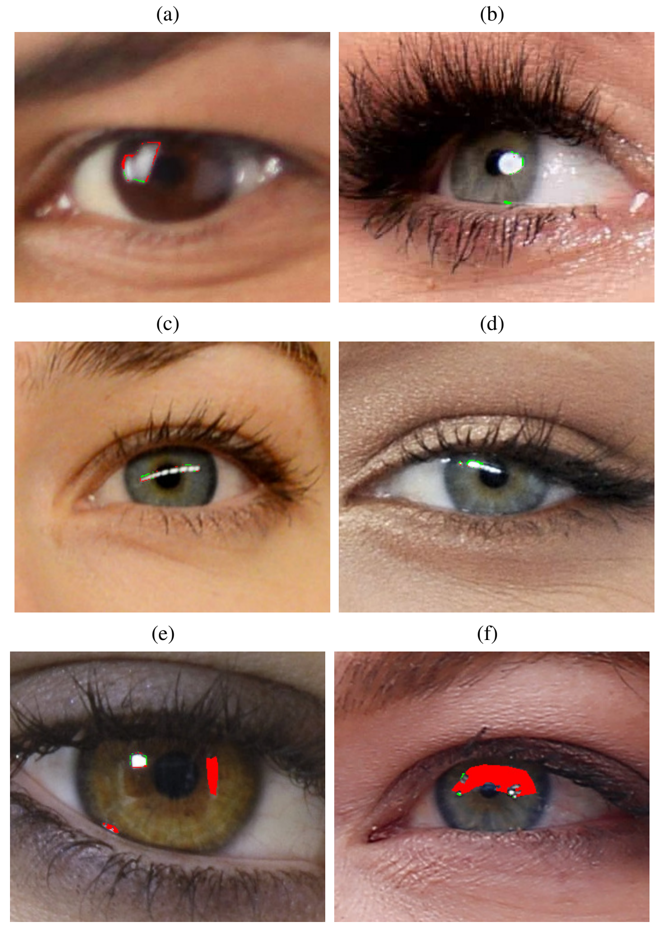

Fig. 5. Examples of reflections segmented by using our proposed method: (a), (b), (c), and (d) are examples of satisfactory segmentations; (e) and (f) are examples of unsatisfactory segmentations. FP pixels are marked in red, while FN pixels are marked in green. In most of the cases, unsatisfactory segmentations are due to false positive regions returned by our method. This problem mostly happened for light colored eyes.

of every ocular image, c' is the column index, and r' is the row index. The second metric (E2) considers the False Positive Rate (FPR) and False Negative Rate (FNR) of the pixel classification, and is computed as follows:

$$\mathrm{E2} = (1/n) \times 0.5 \times \mathrm{FPR}_i + 0.5 \times \mathrm{FNR}_i \ . \qquad (4)$$

Table II summarizes the obtained results.

Table II shows that our method can increase the segmentation accuracy of the best-performing iris segmentation approaches in the literature. Specifically, our proposed method reduced the error E1 from 0.0148 to 0.0142 for both the considered configurations.

V. CONCLUSION

We presented a method based on DNNs for segmenting iris reflection regions. To the best of our knowledge, it is the first study in the literature on deep neural networks for segmenting iris reflection regions. Furthermore, our method is based on a neural network requiring a relatively limited amount of computational resources.

TABLE II
CONTRIBUTION OF REFLECTION SEGMENTATION METHODS TO THE IRIS SEGMENTATION ACCURACY

Reflection detection	E1	E2
No	0.0148	0.0652
Baseline, manual ROI	0.0153	0.0748
Our method, manual ROI	0.0142	0.0680
Baseline, automatic ROI	0.0152	0.0741
Our method, automatic ROI	0.0142	0.0685

We evaluated the performance of our method for ocular images acquired from websites and social media, obtaining remarkable results and outperforming state-of-the-art techniques for reflection segmentation. The obtained results also proved that our reflection segmentation approach increased the accuracy of one of the most accurate iris segmentation techniques based on DNNs in the literature.

A future study should consist in implementing our proposed method on edge devices.

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