An Efficient Contact Lens Spoofing Classification

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Abstract: Spoofing detection, when differentiating illegitimate users from genuine ones, is a major problem for biometric systems and these techniques could be an enhancement in the industry. Nowadays iris recognition systems are very popular, once it is more precise for person authentication when compared to fingerprints and other biometric modalities. Nevertheless, iris recognition systems are vulnerable to spoofing via textured cosmetic contact lenses and techniques to avoid those attacks are imperative for a well system behavior and could be embedded. In this work, attention is centered on a three-class iris spoofing detection problem: textured/colored contact lenses, soft contact lenses, and no lenses. Our approach adapts the Inverted Bottleneck Convolution blocks from the EfficientNets to build deep image representation. Experiments are conducted in comparison with the literature on two public iris image databases for contact lens detection: Notre Dame and IIIT-Delhi. With transfer learning, we surpass previous approaches in most of the cases for both databases with very promising results.

1 Introduction

Nowadays, the term biometry (bio, life, plus metry, measure, the measure of life) has been associated with the measurement of physical, psychological or behavioral features of a living being. Biometric-based person identification systems have been developed rapidly in the last two decades. It is commonly applied not only to distinguish but also to identify someone based on their uniqueness, physical and biological characteristics (Prabhakar et al., 2003).

What makes biometric measurements reliable is the premise that each one is unique and has different physical and behavioral characteristics (the voice, way of walking, etc.). Today, various parts of the human body can be used, such as fingerprint, face, iris and palm.

Among all the body parts, the iris is considered the most promising, reliable, and accurate biometric trait, providing a rich texture that allows high discrimination among subjects and its uniqueness factor (Flom and Safir, 1987; Daugman, 1993).

Daugman (1993), proposed the first functional iris recognition method, whereas, in (Flom and Safir, 1987) the first patent using iris texture as biometric modality are presented. Since then, several iris recognition approaches have been proposed in the literature (Bowyer et al., 2008; Song et al., 2014) and the modality has become popular in commercial biometric systems. Hence, iris modality becomes a target for attacks (Sequeira et al., 2014b; Yadav et al., 2014; Bowyer and Doyle, 2014) due to its use in forensics systems (Yang et al., 2020).

There are several manners to attack an iris biometric system (Agarwal and Jalal, 2021; Morales et al., 2021), such as using printed iris images (Sequeira et al., 2014b), or by contact lenses (Yadav et al., 2014; Bowyer and Doyle, 2014), for instance. These sort of attacks are usually referred to in the literature as a spoofing attack (Ming et al., 2020), specific as iris spoofing. Upon this fact, Daugman (2003) presented a method for contact lens patterns detection. Some works were proposed to dealing with this problem (Bowyer and Doyle, 2014; Menotti et al., 2015; Raghavendra and Busch, 2015). However, some au-

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thors use different definitions of iris spoofing detection, where liveness and counterfeit detection terms are used with different meanings and, in some cases, interchangeably (Sun et al., 2014). Works as in (Sequeira et al., 2014a; Menotti et al., 2015; Galbally et al., 2014) classify an iris image as real/live or as fake, where a fake image is not a live one (e.g., printed image). In addition, some works consider counterfeit iris with printed color contact lenses as fake images and iris images with soft/clear or no lenses as real images (Wei et al., 2008; Baker et al., 2010; Zhang et al., 2010; Kohli et al., 2013; Doyle et al., 2013; Komulainen et al., 2014).

Several works in the literature emerged to solve the contact lens detection issue (Zin et al., 2021), and several of them have reported accuracy over 98% (Wei et al., 2008; He et al., 2009; Zhang et al., 2010). However, since contact lens technology is under constant development, robust detection has become a difficult task (Bowyer and Doyle, 2014). In addition to this, studies found in the literature are favored by their methodology due to the use of datasets containing contact lenses from a single manufacturer among both training and test data (Bowyer and Doyle, 2014; Wei et al., 2008). According to (Doyle et al., 2013), in a more realistic scenario, methods whose accuracy is close to 100% could decrease to below 60% when a cross-sensor evaluation is performed.

In that sense, the datasets presented in (Yadav et al., 2014) introduces a more complex three-class image detection problem, in which iris images may appear with textured (colored) contact lenses, soft contact lenses (prescripted) and without lenses (no). Addressing that, Raghavendra et al. (2017) proposed an approach using a Deep Convolution Neural Network (D-CNN) for contact lens detection. A new architecture called ContlensNet is elaborated, which consists of fifteen layers. The proposed approach is tested in three scenarios: Intra-sensor (training and testing with data from the same sensor), Inter-sensor (training and testing with data from different sensors), and Multi-sensor (training and testing with data from multiple iris sensors combined). The authors reported a Correct Classification Rates (CCR) which overcomes the current state-of-the-art for the two well known datasets for iris spoofing (both used in this work).

Choudhary et al. (2019) introduced a Densely Connected Contact Lens Detection Network (DCLNet) to detect contact lenses in iris images captured from heterogeneous sensors. The authors customized DenseNet121 and fine-tuned it with Near Infra-Red (NIR) iris images. The experimental CCR results reported for the IIITD Cogent dataset are of 99.10% and 92.10% for the intra-sensor and the multi-sensor scenario, respectively.

This work addresses a three-class problem, as well as the one presented in (Silva et al., 2015), exploring the Inverted Bottleneck Convolution (MBconv) blocks (Tan and Le, 2019) which were used to report state-of-the-art results for the ImageNet dataset (Tan and Le, 2019). Our approach is compared against three works on the literature (Yadav et al., 2014; Silva et al., 2015; Raghavendra et al., 2017) in three evaluation scenarios using two public datasets: 2013 Notre Dame Contact Lens Detection (NDCL) dataset and IIIT-Delhi Contact Lens Iris (IIIT-D). The proposed approach outperformed the current state-of-the-art approach in five out of ten scenarios and presents comparable results in the five remaining.

The paper is organized as follows. First of all, we present and describe in Section 2 the datasets used in our experiments. The methodology proposed to handle the spoofing detection is detailed in Section 3. Experiments and results are described and discussed in Section 4. Finally, conclusions and directions for future work are outlined in Section 5.

2 Datasets

In (Yadav et al., 2014), a three-class dataset is created to evaluate an approach for contact lens iris detection. In this section, the characteristics of the datasets used in our experiments are summarized in Table 1 and the following subsections. Both datasets, NDCL and IIIT-D, are available upon public request and all images are gray-scale with 640×480 pixels.

2.1 Notre Dame Contact Lens Dataset

The 2013 Notre Dame Contact Lens Detection (NDCLD'13 or simply NDCL) is a dataset where all images were acquired under near-IR illumination using two sensors, LG4000 and IrisGuard AD100. The dataset is divided into two subsets according to this two sensors: *LG4000* with 3000 images for training and 1200 for verification; *AD100* with 600 for training and 300, verification. This dataset contains a total of 5100 images (Doyle and Kevin, 2014), all of them are 640×480 pixels. Some samples of the NDCL and its cameras and classes can be found in Fig. 1.

The images are equally divided among three classes: (1) wearing cosmetic contact lenses, (2) wearing clear soft contact lenses, and (3) wearing no contact lenses. Each image is annotated with some information: an ID to the subject it belongs, eye (left and right), the subject's gender, race, the type of con-

Table 1: Main features of the datasets considered herein and introduced in (Yadav et al., 2014).

Dataset	Sensor	# Training				# Testing/Verification			
		Text.	Soft	No	Total	Text.	Soft	No	Total
NDCL	IrisGuard AD100	200	200	200	600	100	100	100	300
	LG4000 iris camera	1000	1000	1000	3000	400	400	400	1200
	Multi-camera	1200	1200	1200	3600	500	500	500	1500
IIIT-D	Cogent Scanner	589	569	563	1721	613	574	600	1787
	Vista Scanner	535	500	500	1535	530	510	500	1540
	Multi-scanner	1124	1069	1063	3256	1143	1084	1100	3327

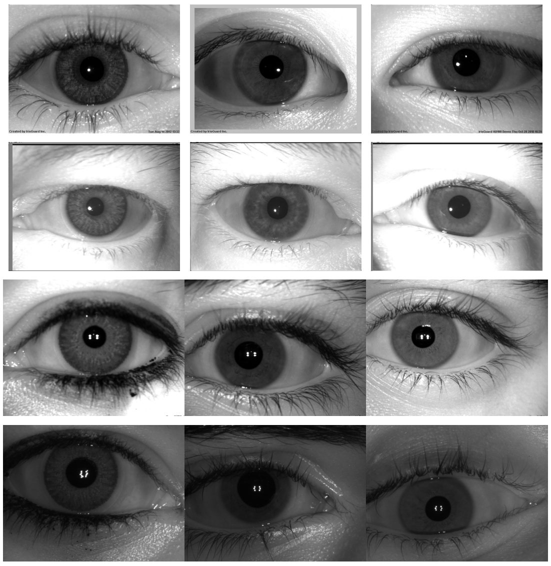

Figure 1: Samples of images in the 2013 Notre Dame Contact Lens Detection (NDCL) dataset and IIIT-Delhi Contact Lens Iris (IIIT-D). In the first row present samples from NDCL IrisGuard AD100, the second, NDCL LG4000 iris camera, while in the third, IIIT-D Cogent Scanner and the last line, IIIT-D Vista Scanner. The first column presents samples with textured/cosmetic contact lenses. The second column presents samples with soft/clear/prescript contact lenses. The third column presents samples with no contact lenses.

tact lenses used, and the coordinates of pupil and iris. More specific details of this dataset can be found in (Doyle and Kevin, 2014, Section II.B).

2.2 IIIT-D Contact Lens Iris Dataset

The Indraprastha Institute of Information Technology (IIIT)-Delhi Contact Lens Iris (IIIT-D) is a dataset where the iris location information is not provided. Nevertheless, for this work, we manually annotate all images to assess segmentation impact. There is a total of 6583 iris images from 101 different subjects. For each individual: (1) 202 iris classes (different iris) because both eyes, left and right, were captured; (2) it was used different textured lenses (colors and manufacturers); (3) the iris images were captured with soft and textured lens and without - the three classes considered here. Images of this dataset are illustrated in Fig. 1. More specific details of this dataset can be found in (Doyle and Kevin, 2014, Section II.A).

3 Proposed approach

This work methodology for iris contact lens detection is based on deep representations with the state-of-the-art inverted bottleneck convolutional blocks (Sandler et al., 2018) and transfer learning (Goodfellow et al., 2016).

We adapt the EfficientNets architecture (Tan and Le, 2019) for the current problem, preserving some pre-trained layers (from ImageNet). This section presents a brief explanation of EfficientNets as well as the new architecture proposed. The evaluation protocol is also detailed.

3.1 EfficientNet and Proposed Architecture

EfficientNet is a set of architectures based on Mobile Inverted Bottleneck Convolution (MBconv) blocks (Sandler et al., 2018). They were first presented in (Tan and Le, 2019), where the authors proposed a uniform scaling of the network's width, depth, and resolution using a compound coefficient (ϕ) that determines the dimensions of the model as follow:

$$depth = \alpha^{\phi} \quad (1)$$

$$width = \beta^{\phi} \quad (2)$$

$$resolution = \gamma^{\phi} \quad (3)$$

$$s.t \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$

$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

in which α, β and γ are constants obtained with a grid search performed in (Tan and Le, 2019). Figure 2 exemplifies the proposed scaling effect on the network dimensions.

The EfficientNet is used in this work due to a superior accuracy performance compared to previous CNN on ImageNet (Russakovsky et al., 2015) while being 6.1x faster and 8.4x smaller (Tan and Le, 2019). It is worth mentioning that in (Tan and Le, 2019), the authors proposed a CNN family with eight architectures (B0 – B7) obtained with different ϕ values.

In this work, we have empirically chosen to use the EfficientNet - B3 model, as it demonstrated the best cost-benefit ratio between CRR and network size. More details of the architecture are found in (Tan and Le, 2019).

The EfficientNet models were originally proposed to be used on ImageNet (Russakovsky et al., 2015). However, we propose its use in a new classification problem based on iris and contact lens. To better suit our specific problem, we included extra blocks at the end of original architecture. A fully connected layers (FC) is included to adjust the final classification to the new classes and other layers with activation, optimization, and regularization. Among these, we have Dropout, a technique widely used in neural networks to avoid overfitting by dropping random units during the training (Srivastava et al., 2014) and batch normalization (BN), used to normalize the values in intermediate layers to zero-mean and constant standard deviation (Bjorck et al., 2018). The activation used in these blocks was the Switch activation function (Ramachandran et al., 2017). Table 2 summarizes the model obtained named as EfficientNet B3 Lens Detection (EB3LD).

Table 2: Proposed architecture, considering B3 EfficientNet model as the base model. (NC = Number of Classes)

Stage	Operator	Resolution	# channels	# layers
1-9	EfficientNet	300 x 300	3	1
10	BN/Dropout	10 x 10	1536	1
11	FC/BN/Swich/Dropout	1	512	1
12	FC/BN/Swich	1	512	1
13	FC/Softmax	1	NC	1

The new layers are added after the Average Pool Layer ("avg_pool") of the original EfficientNet - B3.

3.2 Pre-processing and transfer learning

The Convolutional Neural Networks are capable of extracting relevant features from input images, so they do not require heavy pre-processing in many cases. In this way, the only processing performed in our database was the clipping of the iris in the image, adding a 10% margin around it. The NDCL base already comes with the annotation of the iris coordinates. However, the IIIT-D database required manual marking of the same for later clipping.

To improve the model's performance without the need to generate new samples, we chose to use transfer learning. In transfer learning, the weights learned in a different problem are used for fine-tuning in another one (Pan and Yang, 2010). This technique is based on the idea that the initial layers can extract intermediate features from the input images, thus, the weights learned from a wide database can be reused as a starting point in training a new network. It is useful when the training data is scarce and also to speed up training convergence (Pan and Yang, 2010). Once the pre-trained weights were loaded, the network was trained with the new classification layers and blocks specified in Table 2.

3.3 Evaluation

We evaluate the performance of our system in three scenarios: intra-sensor, inter-sensor, and multi-sensor. In the first case, we trained the proposed model with samples from a single sensor and tested with different samples from the same sensor and database. Thus, we trained and tested the model with sensor LG400 from the NDCL database and repeated the process for the IrisGuard AD100 sensor. We also trained and tested the model with the IIIT-D Cogent Scanner and Vista Scanner, separately.

The second scenario proposed here is the inter-sensor scenario. In this case, we used one sensor for training and tested with a different one, both from the same database. So, we trained with LG400 and tested with AD100, and vice versa, and performed the analog experiment with IIIT-D sensors. The objective here is to evaluate a scenario closer to real applications, where the system is not always used with the same sensor used to capture the training samples.

Finally, we investigated the impact of stacking samples captured with different sensors for training, characterizing the multi-sensor scenario. For this, we trained the network with images obtained with both NDCL sensors and tested with both as well, but never using the same image for training and testing. Likewise, we trained the network with the two IIIT-D sensors and evaluated the model with samples from both.

The metric used to evaluate our approach was the correct classification rate (CCR) (Silva et al., 2015).

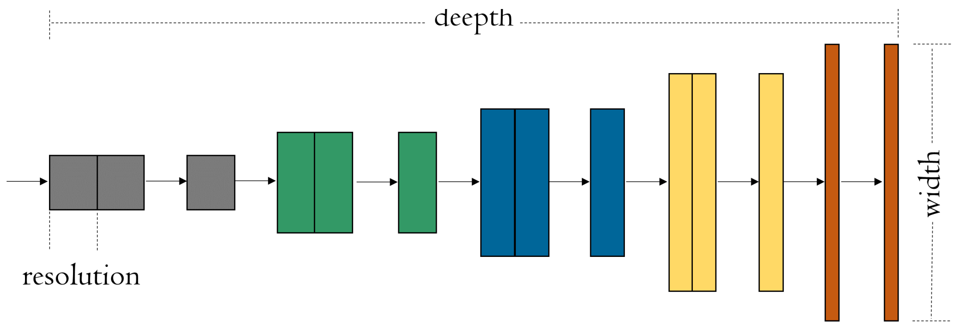

Figure 2: Compound scaling method and the effect of fixed ratio on the three dimensions. (Adapted from (Tan and Le, 2019))

Table 3: CCR(%) results for Intra-sensor on the NDCL and IIIT-D databases.

Methods	NDCL		IIIT-D	
	AD100	LG4000	Cogent	Vista
MLBP (Yadav et al., 2014)	77.67	80.04	73.01	80.04
CLDnet (Silva et al., 2015)	78.33	86.00	69.05	72.08
ContlensNet (Raghavendra et al., 2017)	**95.00**	**96.91**	86.73	87.33
EB3LD	89.67	94.33	**93.11**	**96.89**

4 Experiments and Results

The EB3LD approach implementation is conducted using the Keras/TensorFlow framework. This model requires all images resized to 300×300 pixels and 3 channels (RGB). Since our datasets are in grayscale, the three channels are replicated using the grayscale image. The CNN models are trained on a GPU GeForce Titan X with 12GB with a Intel(R) Core(TM) i9-10900 CPU @ 2.80GHz and a RAM of 128GB.

The EB3LD model is trained for 20 epochs using the Adam optimizer with a mini-batch size of 20 and the categorical cross-entropy loss. The training data is shuffled and 10% is used as validation data. The initial learning rate is set to 10^{-3} with the callback of reducing learning rate on the plateau by a factor of 0.5 and patience equal to 2 if the accuracy on validation data stopped improving. Furthermore, the ImageNet weights are used for transfer learning.

The results obtained are compared against the literature (Yadav et al., 2014; Silva et al., 2015; Raghavendra et al., 2017). Tables 3, 4 and 5 present CCRs for contact lens classes detection problem on three scenarios: intra, inter, and multi-sensor evaluations, respectively. These results are analyzed as follows.

4.1 Intra-sensor evaluation

According to Table 3, the proposed EB3LD approach outperforms the literature in the IIIT-D sensors, in which the difference among the other methods was meaningful.

The worst performance is observed in AD100 sensor from the NDCL dataset which has a small number of training data, only 600. It is also observed when compared to the results reported by Raghavendra et al. (2017). A comparable performance is ob-

Table 4: CCR(%) results for Inter-sensor on the NDCL and IIIT-D databases. The first sensor is the train one, and the second, test.

Methods	NDCL		IIIT-D	
	AD100 LG4000	LG4000 AD100	Cogent Vista	Vista Cogent
MLBP (Yadav et al., 2014)	60.08	61.03	77.79	65.29
CLDnet (Silva et al., 2015)	78.00	75.33	45.54	43.08
ContlensNet (Raghavendra et al., 2017)	**90.45**	88.00	**84.80**	**94.80**
EB3LD	78.83	**91.00**	82.85	70.71

Table 5: CCR(%) results for Multi-sensor on the NDCL and IIIT-D databases.

Methods	Database	
	NDCL	IIIT-D
MLBP (Yadav et al., 2014)	73.20	72.96
CLDnet (Silva et al., 2015)	82.80	69.28
ContlensNet (Raghavendra et al., 2017)	94.65	92.60
EB3LD	**94.73**	**94.73**

served on LG4000 (NDCL) sensor. However, the approach proposed in (Raghavendra et al., 2017) has more pre-processing (segmentation and normalization) and each image has to be processed 32 times by the network. In contrast, the proposed approach is a single feed-forward in the network.

4.2 Inter-sensor evaluation

According to Table 4, the proposed approach outperformed the literature results for the NDCL database when training with images from the LG4000 sensor. Overall, the transfer learning approach has shown less efficiency for the inter-sensor scenario. Although the EB3LD method did not overcome the literature in the IIT-D sensors scenario, results show that iris location improves EB3LD and ContlensNet classification. Our hypothesis to lower performance on the inter-sensor evaluation is overfitting. Both network architectures (ContlensNet and EB3LD) generate high dimension representation vectors, which could cause overfitting due to overtraining. We hypothesize that the models captured specific details of the sensors.

4.3 Multi-sensor evaluation

According to Table 5, The EB3LD method outperforms the literature results in the multi-sensor scenario for both NDCL and IIIT-D database. In this sense, for this case, the transfer learning has obtained impressive results. Our hypothesis for low performance for the inter-sensor case and high performance for the multi-sensor is specialization in the sensors signature. Models could be learning specific details regarding sensor technology and causing overfitting when only one sensor is used for the training. The Multi-sensor scenario is the closest to the real test, once the models would be trained with data from several sensors, which would decrease specialization on a specific sensor. Thus, multi-sensor results shown the suitability of our method for contact lens problems.

4.4 Discussion

The proposed approach had converged for all datasets, even for the smallest one (NDCL-AD100). However, it is latent that the EB3LD takes advantage of more data as seen in all training using the sensors NDCL-LG4000, and IIIT-D Cogent and Vista.

In the inter-sensor scenario, the model did not generalize well for the IIIT-D sensors. Two hypotheses arise: (i) over-training on the sensors' data, or (ii) the learned characteristics from a sensor are not useful for the other. The second hypothesis is supported by the results presented in Table 5 in which the EB3LD approach presented state-of-the-art results.

5 Conclusions and Future Work

In this paper, we proposed deep image representations through the Inverted Bottleneck Convolution (MBconv) blocks by adapting the EfficientNet B3 network for contact lens detection problem. The proposed model could be embedded and work as one step of the iris recognition pipeline.

The proposed model is called in this work EB3LD. Experiments results revealed that the proposed EB3LD model approach surpasses the literature in five out of 10 scenarios, including NDCL and IIIT-D databases. The proposed method allows the usage of a deeper network with a reduced number of images. The main limitation of the proposed approach is related to the small number of training images such as the one observed in the NDCL-AD100 dataset.

One future research direction would be to investigate the transference of learning from another domain or task, such as face or eye. Another direction is to use a different representation of the image and apply Data Augmentation techniques and evaluate the proposed approach in an embedded scenario to be used in industry.

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