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Textured Contact Lens IRIS Detection Methods: Review

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Abstract— A person's biometric traits can be used to identify them in a variety of ways. One of these characteristics is IRIS detection systems. Iris recognition systems in use today are susceptible to iris presentation attacks. Among the several iris presentation attacks, textured contact lenses are possibly the most difficult to detect. In the last five years, no specific survey focusing on IRIS detection, specifically Contact Lenses Iris Detection Algorithms (CLIDs), has been published. Therefore, the paper reviewed recent CLID algorithms, which were grouped into three categories: CLIDs-based Traditional Features, CLIDs-based Deep Features, and CLIDs-based Hybrid Features. CLIDs-based Traditional Features are techniques that use human feature extraction to detect a counterfeit IRIS image. CLIDs-based Deep Features are the techniques that detect the counterfeit IRIS image automatically from an image. CLIDs-based Hybrid Features are the techniques that detect the faked image manually and automatically from an image. The performance of various current CLID algorithms based on Traditional Features, Deep Features, and Hybrid Features is compared. Finally, we hope that our review has encapsulated the majority of recent CLID studies.

Index Terms— Contact Lenses Iris Detection Algorithms (CLIDs), Concealer Attack Presentation, PAD, Impersonate Attack Presentation, CLIDs-based Traditional Features, Deep Features, Hybrid Features.

1 INTRODUCTION

The human iris is one of the most important and distinguishing traits of every person, and it can be employed in human identification systems at airports, borders, and other locations. Figure 1 depicts the general shape of the human eye.

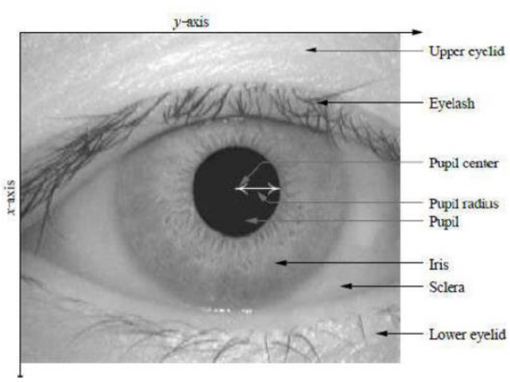

Fig. 1. The General shape of human eye.

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Human discrimination systems can be subjected to a variety of attacks, causing them to make wrong decision, in other words, they are unable to distinguish people well. A genuine iris presentation and an attack presentation are two types of iris presentations. Presentation attacks are the most prevalent type of Iris presentation. The fundamental goal of presentation attacks is to deceive and skew the Iris System detection judgment.

Impersonate and concealment attacks are two types of presentation attacks. In most cases, an impersonate Presentation attack is made up of genuineness iris images. An example is the attacker's goal to acquire access to the system by getting the authorized person's iris image. However, Impostor attack is considered more difficult than the concealer attack, and the reason is that this type requires a discrimination program, which gives you that you are a person known to the system, while the concealer indicates that you are a person unknown to the system.

The Concealer Attack Presentation attempts to hide the identity of the user. Furthermore, the majority of users attempt to to register with a presentation attack model in order to modify and manipulate the system. Printed iris assault [1], [2], textured contact lenses [3], [4], and synthetic [5] iris pictures are the main examples of Concealer Attack Presentation.

Textured contact lenses (colored cosmetic) are the most common Concealer Attack Presentation tool.The majority of contact lenses are designed to change the look of a person's eye (color and texture) as shown in figure 2. When a person wears contact lenses, the natural pattern of the eye is blocked, causing the discriminating system to fail to recognize the original texture of the iris. Furthermore, because of the wide variety of styles, patterns, and colors available, as well as the low cost of contact lenses, the system was unable to distinguish between the fake and original iris. Therefore, an effective and reliable detection system is required for the purpose of distinguishing between the original and the texture contact lenses iris.

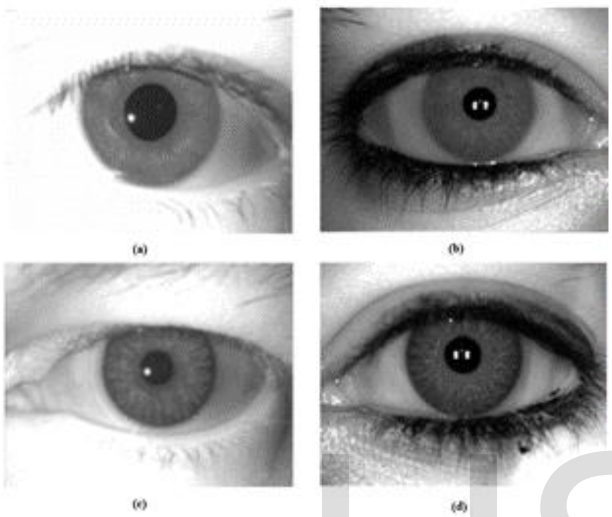

Fig. 2. Examples of Iris Images: normal Iris image (a&b) and textured contact lenses (c&d).

Various methods for detecting textured contact lenses as an iris presentation attack have been explored in the literature. McGrath et al. [6] created a textured contact lens detection method based on 2D iris texture features. Venkatesh et al. [7] created a textured contact lens detection method based on various features such as: LBP, GLCM, image quality - based (BRISQUE), and spectral variation-based (spectral signature). SVM is used for detection.Yadav et al. [8] developed a textured contact lens detection method using popular CNN architecture DenseNet. Their article shows promising findings on previously unknown kinds of textured contacts. Yadav et al. [9] created a textured contact lens detection method based combine the Haralick texture features in the multi-level Redundant Discrete Wavelet Transform (RDWT) domain with VGG features reduced by principal component anaysis.

However, the prior methods include a variety of criteria that influence contact lens detection, such as factory differences, lens colors, and the environment in which a contact lens image is obtained. An effective and reliable detection system is required for the purpose of distinguishing between the original and the texture contact lenses iris. Therefore, this paper review the majority of contemporary Contact Lenses Iris Detection Algorithms (CLIDs) in terms of feature types. CLIDs are divided into three categories: classic, deep, and hybrid.

The following is how the rest of this paper is structured. Section 2 discusses publicly available datasets for CLID evaluation. Section 3 contains performance evaluation metrics. In Section 4, classify and group the current CLIDs based on the features they use. The performance comparison of the CLID algorithms is discussed in Section 5. Finally, conclusions can be formed in Section 6.

2 Existing Publicly Databases

To test the performance of IRIS Detection Methods, multiple IRIS PAD databases are employed. Due to our focus on Textures contact lens images, Table 1 contains information on various databases.

TABLE 1
EXISTING PUBLICALLY AVAILABLE TEXTURES CONTACT LENS IMAGES DATASETS.

Dataset	Year	Total IRIS Images No	Real IRIS Images No.	Attack IRIS Images No.	Kind Of IRIS Images	No. of Subjects
LivDet2013 (Warsaw Subset) [10]	2013	1,667	852	815	Print and Real	-
NDCLD-2013 [4]	2013	5100	-	-	Real and Textured Contact Lens	284
IIIT-Delhi Contact Lens Iris Database[4]	2014	6,570	-	-	Textured Contact Lens	101
LivDet-Iris- 2015 Clarkson [11]	2015	3726	828	2898	Textured Contact Lens	45
NDCLD-2015 [12]	2015	7,300			Real and Textured Contact Lens	326
Combined Spoofing Database [13]	2016	21,525	9325	11368	Real, Print, Textured Contact Lens, and Synthetic Iris	-
LivDet-Iris-2017(NotreDame) [14]	2017	4,800 4,937	2469	2,468	Textured Contact Lens	43
MUIPAD[15]	2018	10,296	-	-	Textured Contact Lens	35
WVU UnMIPA[8]	2019	18,706	9,319	9,387	Textured Contact Lens	81

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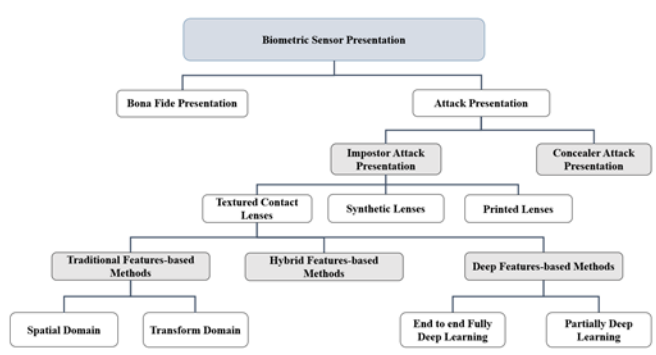

Performance Evaluation Metrics

The performance of Iris presentation attack detection (PAD) is measured using the following metrics, which are based on the International Standard ISO/IEC 30107-3 [16]:

• Total Error Rate: The percentage of misclassified iris images that are incorrectly classified.

• Attack Presentation Classification Error Rate (APCER): The rate at which attacked iris images are misclassified as shown in eq (1).

$$\text{APCER} = \frac{TP}{(TP + FN)} \qquad (1)$$

• Bonafide Presentation Classification Error Rate (BPCER): The rate at which actual iris images are misclassified as shown in eq (2).

$$\text{BPCER} = \frac{TN}{(TN+FP)} \qquad (2)$$

• Half Total Error Rate (HTER): equals the average of BPCER and ACPER as shown in eq (3).

$$\text{HTER} = \frac{\text{BPCER}}{(\text{APCER})} \qquad (3)$$

Where TP (true positive) denotes the number of faked images identified as faked, FN (false negative) denotes the number of faked images identified as true, TN (true negative) denotes the number of true images identified as true, and FP denotes the number of true images identified as faked (false positive).

4 Existing Contact Lences Iris Detection Algorithms (CLIDs)

Capture of Iris Images, segmentation, normalization, feature extraction, and matching are the four processes of traditional IRIS Image Detection. Collect several types of CLIDs algorithms and sort them into groups based on the features they employ. CLIDs-based Traditional Features, CLIDs-based Deep Features, and CLIDs-based Hybrid Features are the three groups. The main taxonomy of IRIS Presentation Attacks techniques is depicted in Figure 3.

Fig. 3. General IRIS Detection Techniques Classification.

4.1 CLIDs Based Traditional Features Extraction

Most of CLIDs methods are based on various types of features that can be found in various domains, such as the spatial and transform domains. Methods for CLIDs are divided into two categories based on the type of features: spatial domain and frequency domain methods.

4.1.1 CLIDs based Spatial Domain

Spatial domain techniques rely on the original image data in the spatial domain, for example an image pixels. Table 2 shows the previous CLIDs sorted by feature extraction in the spatial domain.

The robustness to hidden/unhidden attacks of the best CLIDs may be measured. Table 2 shows that, in terms of accuracy and error rate, the majority of the existing methods produced better outcomes. However, these methods can fall short when it comes to detecting hidden attacks. [19], [21], [7], [22] propose CLIDs that are Poor Robust against unhidden attacks. While the remainder of the methods have certain drawbacks, such as: the outcomes must be improved, the database is restricted, they don't match up to other quality metrics, and they are only effective with soft contact lenses.

4.1.2 CLIDs based Transform Domain

In general, the features generated in the spatial domain have a low level of complexity. However, as computers' computing capacity improves, the high complexity of transform domain features can be reduced.Because these transforms better reflect the multiscale and multi-orientation properties of the Human Visual System (HVS), features taken from other domains become more common.
The fundamental operation of transformation-based approaches is to convert the original image data from a spatial domain to a frequency domain. Features can be extracted from each image using an effective feature transform such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Hough Transform (HT), Fourier Transform (FT), Fast Walsh- Hadamard Transform (FWHT), and combinations of them.

Daugman [23] proposed utilizing the Fourier transform to detect periodic artificial iris patterns that were common in textured lenses at the time in 2003. Multiple layers of printing have lately been added to lenses, making the Fourier response less apparent and textured lens detection by this method less reliable. Furthermore, not all textured lenses employ a dot-matrix printing technique. However, Ridgelet Transform, Contourlet Transform, and Curvelet Transform are examples of Multiscale Geometrical Analysis (MGA) transforms [24] that have been proposed to better represent iris texture.Curvelet Transform (CT) is one of these transforms, which decomposes the original image into a group of subband frequency coefficients of varying sizes, orientations, and positions [25],[26]. To characterize the iris texture, the curvelet transform is a better technique. Contourlet [27] can also be used to extract information from images with smooth edges and contours. Table 3 lists CLIDs that have recently been published, sorted by Feature Extracted from Transform Domain.

TABLE 2
THE PREVIOUS OF CLIDS CLASSIFIED ACCORDING TO FEATURE EXTRACTED FROM THE SPATIAL DOMAIN (2016-2021).

Ref. Year	Features	Classifier	Database	Findings	Limitations
[17], **2016**	Multiscale line tracking (MSLT)	Binary Classification	IIITD-Cogent	Small uneven illumination amount. EER is low.	Only effective against Soft Contact Lenses.
[18],**2016**	GLCM	Multiclass SVM	UPOL	Effective feature extraction method	The outcomes must be improved. The database is restricted.
[19]**, 2017**	Entropy and LBP	SVM	CASIA-Iris-Syn	Both complexity and processing time are low.	Robustness to hidden attacks is poor.
[6], 2018	Binary Statistical Image Features (BSIF)	SVM	NDCLD’15	An open-source baseline method for iris PAD has been proposed.	The outcomes must be improved. The database is restricted.
[20]**, 2018**	BRISQUE and BSIF	Fisher Discriminant	LivDet-Iris 2017	High-precision detection	They don't match up to other quality metrics
[21]**, 2019**	Daugman’s	Discrimination Model	Their Images	High-precision detection	Robustness to hidden attacks is poor.
[7]**, 2019**	LBP	SVM	Their Images	BPCER and APCER are both low.	Robustness to hidden attacks is poor.
[22]**, 2020**	BSIF	Ensemble	NDCLD'15	Extremely robust in a variety of open-set testing settings	Robustness to hidden attacks is poor.

TABLE 3
PREVIOUS OF CLIDS CLASSIFIED UNDER FEATURE EXTRACTED BASED ON TRANSFORM DOMAIN.

Ref. Year	Features	classifier	Database	Finding	Limitations
[28]**, 2016**	Hough Domain	SVM and ANN	CASIAv4	The RBF kernel is marginally better.	Contact Lences Database is not included.
[29]**, 2017**	LBP	SVM	NDCLD’13	Better Results	BSIF outperformed LBP
[30]**, 2017**	DWT	SVM	CASIA v4 Iris-Syn	Better Results	Time complexity
[31]**, 2018**	Contourlet Domain	SVM	IITD	Combined textural and contourlet features achieved better results.	Less CCR only under contourlet features.
[32]**,2019**	Wavelet cepstrum	2D mel-cepstrum	CASIAv3	Low feature vector dimension.	Accuracy improves by a small amount. The database is restricted.
[33]**, 2021**	DCT and Zernike moments	Extreme Learning Machine	[34]	The fusion method yields superior outcomes.	High EER Rate. The database is restricted.

Although there are many works prior to 2016, the research focused on current works, hence Table 3 only displays works from 2016 to 2021. CLIDs based on Hough, DWT, Wavelet, and DCT Transform are proposed in [28], [30], [32] [33]. Geometrical structures with directional moments may be difficult to handle with these methods. However, the features produced via the Contourlet transform are more robust in proposed [31] due to better direction sensitivity. While the remainder of the methods have certain drawbacks, such as: the outcomes must be improved, the database is restricted. In addition to "traditional" effective feature extractors, lately popular Deep learning techniques that learn discriminative features directly from data how to process may be beneficial.

4.2 CLIDs Based Deep Features Extraction

The majority of traditional CLIDs rely on human feature extraction. These strategies are limited by the considerable computing complexity and energy required to determine traditional features. However, deep learning is an automatic feature extraction process that is carried out automatically to learn features from raw data (images). Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), deep belief network, and deep auto encoder are examples of deep learning (DL) models. Deep convolutional neural networks, which are particularly successful for classification and recognition scenarios, are among these DL models that have been frequently employed in iris recognition. The CNN pipeline starts the features extraction process using the various layers to get the best feature from the images, which it then feeds into the basic classifier to detect the texture contact lenses IRIS if it occurs. We may classify existing CLIDs into end-to-end fully deep learning for CLIDs and Partially deep learning for CLIDs based on literature study. Table 5 shows a variety of CLIDs that have recently been classified using deep features extraction.

The most prevalent deep learning approach [35], [39], D5] employed in CLIDs has been Convolutional Neural Networks (CNN), according to the end to end completely DL for CLIDs shown in table 5. Despite the fact that CNN-based algorithms performed well in intra-database setups and against known attacks, they did not generalize well between databases and unknown assaults.

Although the findings of the aforementioned CNN seem promising, they are primarily confined to the network's design due to the amount of the training database limiting the number of layers that can be selected. Among the Partially DL for CLIDs techniques ([38], [41], [42], [43]), [43] used the AlexNet model, which is an enhanced version of the classic LeNet model that relies on a large-scale training database, more computational power, and better GPU operating speed.

TABLE 5
PREVIOUS OF CLIDS CLASSIFIED BASED ON DEEP FEATURES EXTRACTION.

Categories	Ref. Year	Deep Learning Method	DB	Observation
End to end Fully DL for CLIDs	He et al. [35],2016	a multi-patch CNN	ND + CAISA	Obtain the best results. However, they do not generalized well between databases and unknown attacks.
	Raghvendra et al. [36], 2017	15 layer CNN + Softmax	ND + IIITD	Without iris segmentation and normalization, they get the greatest results.
	Singh et al. [37], 2018	ResNet50 + Softmax	ND + IIITD	They're computationally costly.
	Proença et al. [38], 2019	VGG-19 based CNN	CASIA-V4	Matching's computational cost must be minimized.
	Hu et al. [39], 2020	DNN	CASIA Thousand	Due to the lack of utilization of modules to improve efficiency, presentation attack detection performance is low.
	Liu et al. [40], 2021	Condensed 2-ch CNN	CASIA-V1, V3, V4 Thousand	Contact Lences IRIS Image Database is not included.
Partially DL for CLIDs	Minaee et al.[41], 2016	VGG-Net+ multi-class SVM	IIT, CASIA	This finding might be enhanced even more by training a deep network specialized for iris identification,
	Nguyen et al. [42], 2017	Pre-trained CNN (Dense-Net) + SVM	ND2013, CASIA-V4	Because of the computational complexity, duplicate neurons and layers must be removed.
	Alaslani et al. [43], 2018	Pre-trained CNN (Alex-Net) + SVM	IITD, CASIA-V1,V3,V4	The proposed algorithm performance is not Evaluated by various pretrained models in more iris datasets.
	Nguyen et al. [44],2018	CNN based features+SVM	LivDet-Iris-2017	The findings indicate that using CNN features rather than an end-to-end CNN produced better outcomes.
	Boyd et al. [45] 2019	ResNet-50 + SVM	CASIA-V4	Contact Lences IRIS Image Database is not included.
	Meenakshi et al. [46], 2019	CNN based features+SVM	ND+ IIITD	A simpler model is the DCLNet. Without iris normalization, deep CNN models perform better.

4.3 CLIDs Based Hybrid Features Extraction

The most of CLID techniques use a mix of human- engineered features and other classifiers. However, because the textural patterns for genuine and attack iris images are unknown, numerous unique patterns related to the same class are likely to arise. Therefore, a human- engineered feature that was purposefully intended may be insufficient to handle all potential patterns. Convolution neural networks (CNNs) have recently been used to automate feature learning for detection of presentation attacks. However, CNN requires a large amount of training data to learn the discriminatory characteristics, or it will perform poorly. As a result, human- engineered features

are combined with deep features in order to distinguish live iris from contact lens images and improve overall performance. Table 6 shows a variety of CLIDs that have recently been classified based on combined of human-engineered fea tures with deep learning feature.
Among the ([48],[51],[9]) techniques, Fang et al. [51] used the Pre-trained CNN (VGG16), which is trained on a large-scale number of images and is still effective in distinguishing unseen textures. Fusion features in [48], [9] produce excellent outcomes. However, when the deeper layers of the deep network are utilized, the issue of time consumption persists.

Table 6 contains important facts that can be extracted. First, the practice of combining human-crafted qualities with deep-learned features can provide more accurate and flexible features in the process of identifying the kind of lens in the eye. Second, from a huge feature set, identifying features that contribute significantly to class differentiation can greatly improve classification.

TABLE 6
PREVIOUS OF CLIDS CLASSIFIED BASED ON COMBINED OF HUMAN-ENGINEERED FEATURES WITH DEEP LEARNING FEATURE.

Ref. Year	Feature	Classifier	DB	Observation
Federico and Bir [47], 2017	5-layer triplet CNN	Softmax	2013-Warsaw, IIIT, Vista cosmetic	It's simple to use and has a minimal computing complexity. However, it was only used on a few attacks.
Daksha et al. [9], 2018	Haralick texture+ DWT Domain + VGG features	ANN	Combined Iris database	The outcomes are much better. Nevertheless, it is computationally costly.
Domenick et al. [48],2018	BSIF+ LBP+ CoALBP+HoG+ DAISY+ SID+ Pre-trained CNN (VGG16)	CNN	Clarkson Livdet 2013,ND1, IIITD	Good outcomes were obtained.However, propsed's capacity to generalize is not addressed.
Meenakshi et al. [49], 2020	LBP+ SID+SIFT+ CoA LBP+BSIF	DCCNet	ND 2013, IIITD, and Clarkson.	The proposed DCCNet is more efficient and requires less computing.
Kuehlkamp et al. [50],2020	BSIFs	CNN	LivDet-Iris 2017	Fusion features help to increase performance. However, due to the training of 61 CNNs, it requires a lot of computing power.
Fang et al. [51], 2020.	Pre-trained CNN (VGG16)+ scratch network	SVM	LivDet-Iris 2017, ND,IIITD-WVU	The findings show that iris PAD can be competitive by merging features from multiple layers. It's tough to tell the difference in iris patterns.

5 COMPARISON OF CLIDS TECHNIQUES

The performance comparison of the CLID algorithms addressed in this paper is summarized in this section. In terms of datasets, feature extraction, classifiers, and assessment metrics, we find that most techniques differ. Therefore, we categorize them into CLIDs-based Traditional Features [29], [31], [20], [52], [13], CLIDs-based Deep Features [8], [53], [54], [36], and CLIDs-based Hybrid Features [9], [49], [48] when evaluating their performance. Table 7 compares the outcomes of different state-of-the-art CLID methods for various feature extracted groups.

TABLE 7
RESULTS COMPARISON OF VARIOUS STATE-OF-THE-ART CLID METHODS UNDER UNDER DIFFERENT FEATURE EXTRACTED GROUPS.

Group	Ref	Feature Extraction Method	Classifer	Database	Performance Metric			
					Total Error (%)	APCER (%)	BPCER (%)	CCR (%)
Traditional Feature Extraction	[29]	LBP	SVM	NDCLD'13	3.11	N/A	N/A	94.01
	[30]	DWT	SVM, ANN	CASIA V4	5	N/A	N/A	95
	[31]	SGLDM, GLRLM and CT	SVM	IITD	N/A	N/A	N/A	95.63
	[20]	BRISQUE and BSIF	SRKDA	LivDet-Iris 2017 , Clarkson	N/A	N/A	N/A	94.0
	[52]	Local and Global	SVM	IIIT-Delhi	6.80	N/A	N/A	78.50
	[13]	Structural and Textural	NN	Therir images	16.36	18.17	7.32	N/A
Deep Learning Feature	[8]	DenseNet based CNN	CNN	WVU, UnMIPA	9.06	10.15	2.15	N/A
	[53]	LBP	SVM	MUIPAD	13.00	15.36	1.23	N/A
	[54]	AlexNet	SVM	MUIPAD	10.21	11.79	2.28	N/A
	[36]	ContlensNet	Softmax	ND II	N/A	N/A	N/A	92.60
Hybrid Features	[9]	Haralick, DWT,VGG16	ANN	Combined IrisDatabase.	1.01	18.58	0.07	N/A
	[49]	LBP, SID, SIFT, CoA LBP,BSIF,	DCCNet	ND 2013	N/A	N/A	1.500	95.67
	[48]	BSIF, LBP, CoALBP,HoG, DAISY, SID, VGG	CNN	Clarkson Livdet 2013	3.25	N/A	N/A	N/A

The effectiveness of CLIDs approaches based on Traditional Feature Extraction is compared in terms of performance metrics. CLIDs based on spatial domain [29],[20] have a higher CCR rate than other techniques, as can be seen. However, compared to the other techniques, [52] has a lower CCR rate. Also it can be observed that CLIDs based on the transform domain [31] tends to Higher CCR rate than the rest methods. However, [30] tends to lower CCR rate than the rest methods. The effectiveness of CLIDs approaches based on Deep Learning Feature Extraction is also compared in terms of performance metrics. It's clear that [36] has a higher CCR rate than the other approaches. However, compared to the other approaches, [8] has a lower total error and APCER rate. The effectiveness of CLIDs approaches based on Hybrid Feature Extraction is also compared in terms of performance metrics.It's clear that [49] has a higher CCR rate than the other approaches. However, compared to the other approaches, [9] has a lower total error and BPCER rate.

A number of pre-trained CNN models, such as AlexNet, VGG-16, VGG-19, and Caffe, have arisen as a result of the effort and time spent in the training process and might be used to extract features.Several of the above-mentioned models were trained on a subgroup of the ImageNet dataset in order to demonstrate how these models reduced training effort and time.Transfer learning and feature extraction can be utilized to employ learnt features for a variety of image classification problems. Pre-trained CNN models [54],[9],[48] were effectively implemented in the construction of CLIDs, as shown in Table 7.

6 CONCLUSION

There are a number of biometric traits that can be used to identify a person. IRIS detection systems are one of these traits. Current iris recognition systems are vulnerable to iris presentation attacks. Textured contact lenses are perhaps the most difficult to detect among the many iris presentation attacks.

There is no specific survey paper focusing on IRIS Detection, specifically CLIDs, that has lately been published. Therefore, this paper provided a complete review of CLID algorithms by gathering contemporary CLID algorithms and categorizing them into one of three groups based on the features they used: CLIDs-based Traditional Features, CLIDs-based Deep Features, and CLIDs-based Hybrid Features. Various current CLID algorithms based on Traditional Features, Deep Features, and Hybrid Features are compared in terms of performance. Finally, we hope that our survey has covered the majority of recent work in the field of CLIDs.

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