IrisRecognition System:A Detailed Survey Based on Image Processing and Artificial Intelligence Technique

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Abstract:

In recent years, iris recognition algorithms have excelled at identification. Due to its rich iris texture, which provides reliable criteria for finding individuals, iris recognition schemes have attracted much interest in mid-authentication methods. Despite this, settings that allow for unlimited recognition present several difficulties in the stages of segmenting, feature extracting and correctly identifying the iris.To get a good identification performance, such iris areas must have a specificpicture resolution; otherwise, performance deteriorationisdangerous.Thisismuchmoreimportantwhenusingintricatepatternsforirisidentification.The performance of recognition can be improved by acquiring high-resolution pictures using techniques like super-resolution reconstruction in situations when such low-resolution pictures are produced, and the acquisition equipment and environment cannot be improved. A complete summary of research on low-resolution iris recognition has not been included in prior survey publications, which have mostly summarized findings on high-resolution iris recognition. So, we looked at iris detection techniques in both low- and high-resolution images. The classical technique and the deep learning approach to iris identification are both discussed in this article.The researchers also go into thebenefits and drawbacks of earlier methods as well as the drawbacks and advantages of both the conventional and deep learning approaches to iris identification.

Index Terms: Biometric security systems, Deep learning, Iris recognition, super-resolution reconstruction,

1. Introduction

Biometrics are newer-generation security measures that go beyond passwords and other older-generation security measures using unique physiognomic traits [1]. The use of biometrics to prevent theft and hacking is currently being studied and developed. Utilizing distinctive body parts makes it more challenging to steal and hack information and reduces security threats. Because copying and faking body parts are far more complex than breaching conventional security procedures, security is increased even more [2]. The hands, fingers, orface are frequently used in biometric security measures since they are a subject's physiognomy. Facial image- based contactless techniques have been taken into consideration. These recognition techniques frequently top areas (the entire face, an eye, etc.) to capture distinctive regional traits. Contrary to hand-based approaches, there are inherent limitations even if there is no chance of leaving traces because the pictures are gathered and delivered without contact. Furthermore, facial recognition ability suffers if facial characteristics are altered by injuries, cosmetic procedures, or age [3]. Even though these conditions have less of an impact on ear identification, the user should tilt the side view of their face in the camera's direction and take the earring snapshot. Iris recognition, which employs the iris portion of an eye situated in the face, can be used toovercome these concerns. The iris changes very little as a person matures, and because the eyelid shields it, deformations induced byexternal sources areuncommon [4]. Furthermore, because theiris contains uniqueand different traits when employed in biometrics, it has the benefit of adequately identifying the owner. Additionally, iris recognition may be used instantly with the eye picture without requiring extra steps. As a result, it may be utilized in conjunction with iris recognition as an additional recognition mechanism.

A biometric data system carries out recognition based on the data supplied by the acquisition device,and for iris recognition, the data are frequently collected as photographs. The performance of the recognition algorithm substantially declines when a low-resolution image is provided. The fundamental purpose of high- resolution techniques has been to more clearly separate the characteristics of each region [5]. In the current survey,the findingsofstudiesoniris identification utilizing lowandhigh-resolution photographs have collated. This study investigates iris recognition and evaluates existing methods against the most recent deep learning-based innovations. This study analyses the benefits and drawbacks of conventional iris identification using several image processing techniques. This review study covers iris recognition algorithms that employ cutting-edge deep learning techniques.

The fundamental outlines of the iris recognition system are provided in Section 2. In Section 3, we examine the benefits and drawbacks of iris detection using image processing and AI techniques and list their benefits and drawbacks. The survey paper's discussion and conclusion are presented in Sections4 and 5.

2. IrisRecognitionSystem(IRS)Structure

The IRS is typically divided into seven major phases that are executed in the following order: the iris image capture phase, the pre-processing phase, the iris background subtraction phase, the iris standardization phase, the extracting features phase, the attribute selection phase, and finally the iris categorization or pairing phase. The conventional process of Irs recognition system is shown in fig.1.

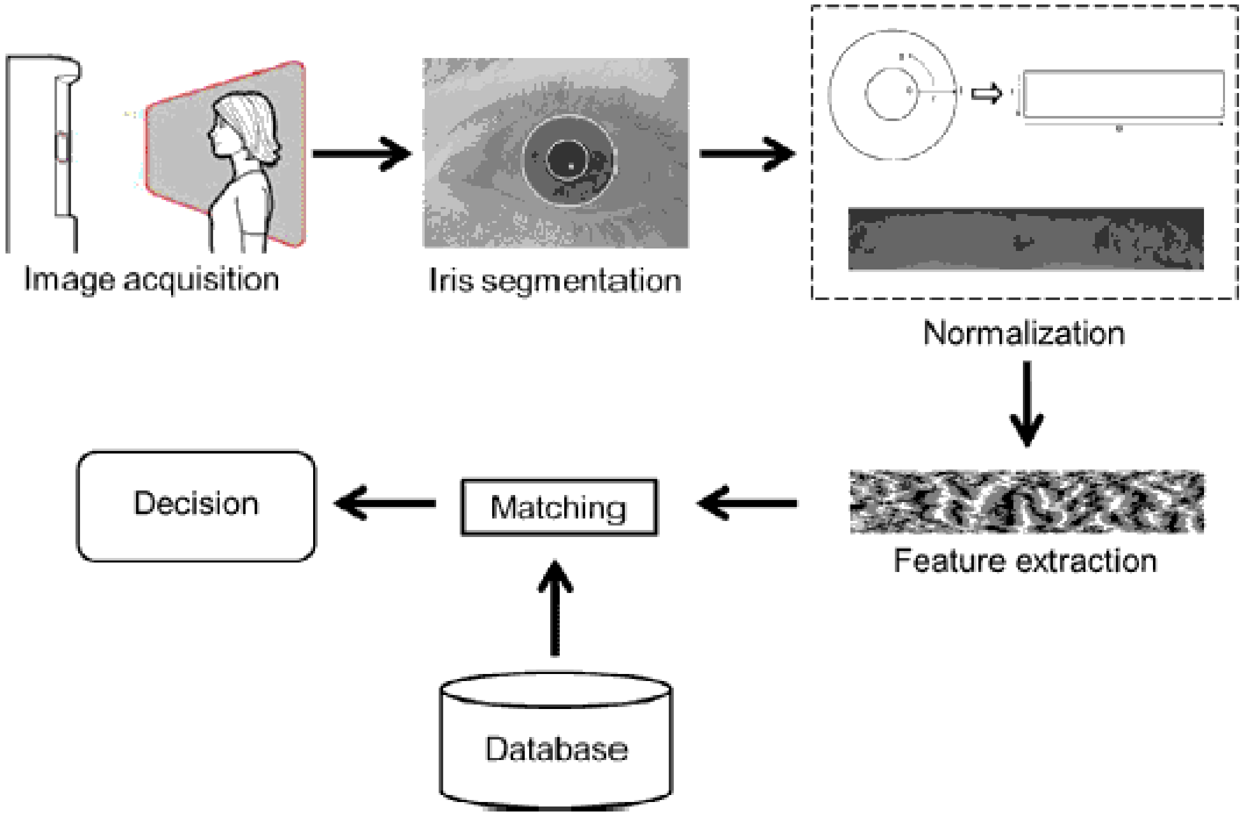

Figure1: IrisRecognitionSystem[6]

AcquisitionofIrisImage

Typically,visibleornear-infrared(NIR)spectrumsareusedtocaptureapictureoftheiris.Lighting,lens,sensor, and console are the four components used to acquire iris images. Instead of the iris' pigmentation, images taken in the NIR range often interact with the region's intricate texture. Additionally, iris photos acquired with the NIR are less susceptible to various forms of noise thaniris photographs taken with the visible spectrum. This improves the performance effectiveness of iris identification bymaking it possible to record the iris texture even while using dark hues.

Pre-processingTechniques

To implement any of the recommended approaches or procedures of the recognition system, a pre-processing method is advised to be developed in the initial step. These methods can aid in the elimination of the various noise types that surfaced during the acquisition of the iris picture. The noise typically present in iris pictures includes distorting, specular reflections, scratches, and other elements induced by eyeglasses, lighting or illumination, closure from the eyelids or eyelashes, distortion, and off-angle iris. The pre-processing stage will improve the IRS's performance accuracy by eliminating this noise. The Hough transform technique, histogram and filtering, structural procedures, and merging are the four approaches to photographic pre-processing.

IrisSegmentationTechniques

After pre-processing, the area of interest (ROI) is instantly extracted. Segmentation, sometimes referred to as localization, is the process of removing the area of interest. The primary goal of the segmentation phase is to separate the iris portion from the useless residual elements, including the skin, eyelids, and sclera around theiris area, as well as the pupil section. The effectiveness of the split region's characteristics is a factor in iris recognition systems. As a result, the segmentation phase's accuracy plays a significant role in the recognition system's performance accuracy. Inaccurate segmentation is mostly to blame for the majority of recognition system failures.

NormalizationTechniques

The process of changing the segmented iris region's circular shape into a rectangular pattern is known as normalization. After segmentation, the normalization phase is used to aid in feature extraction.

FeatureExtraction Technique

After determining the iris' limits and mapping this area, feature extraction techniques should be used to identify the unique characteristics of the region's texture, which vary from person to person. The feature extractionphase is a crucial step in achieving high accuracy in a person's identification since it requires the extraction of each individual's distinctive traits.

FeatureSelection Techniques

To save fewer features in the feature subset, feature selection is an operation to find the best features that can reduce computational complexity while still achieving an accurate performance. The Iris Recognition System's speed is anticipated to grow as processing complexity decreases. The main goals of feature selection are to choose the features, improve the classifier by removing noisy or pointless features, and minimize the computation time and space required to run algorithms.

Classification Techniques

The final stage of the recognition system is categorization. The goal of classification is to assess the similarity between test samples and samples in databases of iris image samples. Frequently, it is impossible to matchthese samples perfectly. The estimated rate of each sample is therefore employed to aid the recognition system in making human identifications.

3. IrisRecognitionMethods

RecognitionBased onImage Processing

RANSAC (Random Sample Consensus), a more precise approach for fitting ellipses around non-circular irisborders, was introduced by **Thomas*et al*.** [7]. Compared to Hough transform-based approaches, it canaccurately determine iris borders. Additionally, the authors employed Dousman's rubber sheet model andcorrelation filter-based matching for iris normalization and elliptic unwrapping and for the determination ofintraclass and interclass distance. The similarity metric for comparing templates is called PSLR (Peak SideLobe Ratio). These make the recognition process better than Daugman's technique. A Watershed transform-based Iris Recognition system (WIRE) was described by **Frucci*et al*.**[8] for noisyvisible wavelength pictures.The picture is binarized using a watershed transformation technique, and the limbus border is then detectedusing a circle-fitting algorithm. The pupil region is discovered using this region and intelligent edge filteringand circle fittingtechniques. Thenewlydiscovered iris region is transformed into arubber-sheet shapeto createan iris code. This iris codeis the utilized as thefoundation forpatternrecognition using theHammingdistanceor cosine dissimilarity to identify the iris.**Alonso *et al.*** [9] discussed a super-resolution approach used toreconstruct iris photographs and was based on the Eigen-transformation of local image patches. Bymaintaininglocal information, the individual reconstruction of each patch enables higher-quality augmented photos.Contrast enhancement is employed to boost the reconstruction quality, and matcher fusion has beenimplemented to enhance the performance of iris identification.

To recognize diverse iris patterns, **Liu*et al.***[10] proposed a code-level method. An adjusted Markovnetwork is used to simulate the nonlinear connection between the binaryfeature codes of the heterogeneous irispictures. Byusingthis approach, thequantityof iris templates in theprobeis converted into ahomogeneous iristemplate that corresponds to the gallery sample. Additionally, the model enables the creation of a weight mapbased on the dependability of the binary codes in the iris template. Utilizing both the learned iris template andweight map is necessary to create an accurate iris matcher that can adapt to changes in imaging sensors,capturing distance and subject conditions. This approach still needs Daugman's rubber-sheet model, but it hasthe disadvantage that if the input image quality is below a certain threshold, the recognition performance maysuffer. The framework proposed by**Deshpande*et al.*** [11] includes thebest frame selection method, amodifieddiamond search technique, a Gaussian process regression (GPR)-based and improved iterated back projection (EIBP)-based super-resolution approach, a fuzzy entropy-based feature selector, and a neural network (NN) classifier. The overview super resolves iris pictures based on the contents of the patches utilizing local patch- based GPR and EIBP methods that employ the linear kernel covariance function without needing an additional database. The NN classifier recognizes pictures of irises using a grey-level co-occurrence matrix, The seven moments, statistical attributes, and features from a discrete cosine transform domain-based no-reference image quality rating model. Integer Wavelet Transform (IWT) characteristics were employed by **Singh*et al***.[12] to create an effective iris identification system that utilized Circular Hough Transform and Total Variation Model for iris localization and segmentation. The segmented picture was divided into sub-band images using characteristicsderived using IWT.Normalized Hammingdistanceis thecriteriaformatchingtemplatesand test images.

Ak*et al.*[13] proposed a novel method for the first identification of the iris region, which uses a morphological filter to eliminate reflected light and a circle-shaped template for the horizontal and vertical axes. Before determining the preliminary location of the iris area, a morphological filter is utilized to filter out pupil-reflected light. The iris area is then more precisely detected using the Hough transform, histogram equalization, Gaussian filter, canny edge detector, and other techniques. Following the refine-connect-extend-smooth (R-C-E-S) approach's detection of the eyelid region, a mask is created to hide it. The iris is identified using a template matching the Hamming distance after generating an iris code using the acquired iris area. The comparison of the above surveyed techniques regarding performance analysis, advantages', limitations, and types of illuminations are shown in table 1.

Table1: ComparsionofimageprocessingmodelsforIrisrecognition

Ref. number	Dataset	Recognition Method	Performance Analysis	Advantages	Limitation	Types of Illuminators
[7]	WVU	The iris area is normalized using Daugman's rubber sheet model and RANSAC for segmentation. Finally, the iris was recognized using the PSLR approach.	Methods only illustrated. There are no graphsexisting in terms of performance Analysis.	Accurate pupil detection	Similar methods are utilized from existing works. And no specific performance parameter was analyzed.	NIR
[8]	UBIRIS v1 session 2, Subset of UBIRISv2	The Watershed method was usedfor segmentation.Then, hamming distance and cosine distance with Daugman’s rubber sheet model was used for Iris recognition.	Measured Decidability 2.0335 for UBIRIS v1 session2,1.385 for Subset of UBIRIS v2	Iris ROI regioncanbe defined even in a noisy visible environment.	The methods usedin this approach are verycomplex.	Visible
[9]	CASIA-iris Interval v3	Feature extraction based on Eigen transformationand Log-Gabor filter withSIFTusedfor iris recognition	EER-lessthan 6% for Log- Gabor filter, less than 8% for SIFT, and less than 5% forLog-Gabor +SIFT	Notrequiredhugedatasets	Reconstructing high-resolution pictures from extremely low-resolution photographs using this technique demonstratesits poor performance.	NIR
[10]	Q-FIRE, NotreDame database	ModifiedMarkov networksusedfor featureextraction and code-level feature matching Usedforiris recognition	EER-98.74%	Resolution independent recognition	Stillrequires Daugman’s rubber-sheet model	NIR

[11]	CASIA-iris database	GPRandEIBPfor feature extraction Neural network classifier for iris recognition	Accuracy-96.14%	use multi-frame photos to lessen the difficultiesof image acquisition	It needs more pre-processing stages to improve the quality of the input image so that the implementation becomes more complex.	NIR
[12]	UBIRIS v2	Handcrafted-based segmentation and Integer wavelet transform are used For iris recognition.	EER-0.12%	No need for additional devices like GPU	Need high complex segmentation	NIR
[13]	CASIA(v1, v4 Lamp), SDUMLA-HMT	The iris area is segmented using the RCES approach. Iris identification using the rubber sheet model of Daugman at a hamming distance.	Accuracy-96.48% EER-1.76%	Accurate detection of pupil region unaffected by specular reflection	It requires a high-resolution image with detectable edges	NIR

The research mentioned above has suggested iris recognition systems that use conventional image processing techniques. A graphic processing unit or any extra computational hardware is not required for traditional methods. On the other hand, if a specific level of input picture quality is not ensured, the identification performance can suffer. The complexity of the implementation approach for the recognition process is another drawback since the image processing methods need to implement the segmentation methodto recognize the iris.

RecognitionMethodsonArtificialIntelligenceMethods

Salve *et al.* [14] provided an enhanced innovative method for employing iris recognition to identify the individual. Support vector machines (SVM) and artificial neural networks were employed in this technique to categorize iris patterns. Before the classifier, theirisregionisdividedusingtheCannyedgedetectorandHough transform. If the effect of the eyelid and lashes is diminished. To increase computational speed and ensure adequate dimensionality, a normalized iris was obtained using Daugman's rubber sheet model. Additionally, by extracting features from a segmented iris picture using a 1D Log Gabor wavelet, a discriminating feature sequence is created. Phase quantization is used during encoding to produce feature vectors. These binary sequence feature vectors are trained to serve as iris pattern classifiers for SVM and ANN.**Nalla*et al.*** [15] developed a brand-new technique that greatlyenhanced cross-domain iris identification byutilizingthe Markov random fields (MRF) model. Real-valued feature representations are used in the proposed domain adaption framework, which is based on the naive Bayes nearest neighbor classification and is capable of gaining domain knowledge. This method outperforms other approaches for cross- spectral iris recognition by estimating equivalent visible iris patterns from the synthesis of iris patches in the near-infrared iris pictures. This research suggested a brand-new type of bi-spectral iris recognition system that simultaneously collects visible and near-infrared images with resolution correspondences.**Zhang *et al.*** [16] investigated auxiliary characteristics toboost mobile device iris recognition accuracy. To begin with, local iris texture is encoded using optimized ordinal measurements (OMs) characteristics. The convolutional neural network is then used to automatically learn paired characteristics to calculate the correlation between two irises (CNN). The pairwise learned characteristics and the chosen OMs features are then combined at the score level.To solve the iris identification problem, Minaee*et al.* [17] assessed the use of deep features taken from the VGG-Net and then a straightforward classification method. Deep features have received a lot of attention recently and are being employed in a widevarietyof contexts. Even though theinitial convolutional network utilized in this study was trained for a different purpose (object identification), it is demonstrated that the features may be effectively applied to biometric recognition.

Alonso-Fernandez *et al.* [18] developed an iris super-resolution reconstruction method based on local image patches and Multilayer Locality-Constrained Iterative Neighbor Embedding to increase the resolutionof near-infrared (NIR) iris images (M-LINE). **Zhao *et al*.** [19] developed a precise and adaptable deep learning framework for iris recognition using a fully convolution network (FCN), which generates spatially matched iris feature descriptors. The implementation of an extended triplet loss (ETL) function follows the discoverythat bit-shifting and non-iris masking are necessary for learning discriminative spatial iris characteristics. Additionally, the authors developed a sub-network to provide important data for identifying major iris regions as an essential input for the recently built ETL. Two deep learning single-image super-resolution approaches, stacked auto-encoders (SAE) and convolutional neural networks (CNN) with the most lightweight structure, were recommended by **Ribeiro*et al.*** [20] to achieve quick speed, maintain local information, and eliminate artifacts simultaneously increaseaccuracy,**Wang *etal.*** [21]examineanewdeeplearning-basedstrategy for iris identification and made use of a more straightforward framework to retrieve the representative features. To streamline the learning process and gather contextual data from the iris pictures, we take into account residual network learning using dilated convolutional kernels. Along with simplifying the network and improving matching accuracy,such anapproachalsoeliminatesherequirementforthedown-samplingandup- sampling layers.

A deep learning technique based on the iris recognition capsule network architecture was suggested by **Zhao *et al.***[22]. To adapt this method to iris identification, the authors changed the network's fine-grained structure and offered a modified routing strategy based on dynamic routing between two capsule layers. Even with fewer examples, migration learning makes the deep learning approach possible. As a result, VGG16, InceptionV3, and ResNet50, three cutting-edge pre-trained models, are introduced. According to the number of their primaryconstituent blocks, we partition the three networks into some subnetwork architectures. Instead of using a single convolutional layer in the capsule network, they are employed as the convolutional portion to extract the main features.In addition to a strategy for enhancing recognition performance that makes use of this augmentation approach, **Lee *et al.*** [23] suggested iris image augmentation based on a conditional generative adversarial network (cGAN). The cGAN-based model is employed in this technique to generate normalized iris pictures, which are produced by arbitrary adjustments to the iris and pupil coordinates. Data augmentation that employs the particular area was shown to fail in terms of performance enhancement due to the constraints of the cGAN model. Based on this knowledge, the cGAN model's input was limited to the iris area.

With the use of deep convolution neural networks and supervised discrete hashing, Wang*et al*. [24] developed a novel framework for cross-spectral iris identification that offers not only significantly smaller iris templates but also more accurate performance. The most precise cross-spectral matching performance is achieved when supervised discrete hashing and softmax cross-entropy loss are applied to the features extracted from the trained CNN. In addition to performing better than earlier CNN designs, the recommended method also offered a substantially reduced template size when compared to existing iris recognition methods. To explore Super Resolution (SR) for iris identification by CNNs, Kashihara*etal*[25] suggested a modified Super Resolution (SR)method based on the SRGAN. This study examined how SRGANs influenced person identification by DCNNs under the assumptions of external image noise and a prefiltering technique in real-world iris recognition scenarios. A DCNN classifier identified the people from the restored photos after the SRGANs enhanced the degraded iris images. The accuracy of the DCNN classifier was superior to theSRGANs concentrating on perceptual loss in the SR pictures utilizing the Bicubic technique or squared mean errors. This finding implies that it may be simpler for the DCNN classifier to construct picture features basedon pixel-based differences than on perceptual image differences.

Machine learning techniques were used by Adamovi*et al* [26] to categorize biometric templates as numeric attributes. The biometric templates are created through stylometric feature extraction on a one-dimensional collection of fixed-length codes created from a normalized iris picture. The characteristics that were retrieved are then used for categorization. Additionally, the computing expenses are substantially lower compared to previous systems, which lessens the recognition system's total complexity.Mostofa*et al.* [27] developed cross-spectral iris matching using two unique new algorithms built on the conditional generative adversarial network (cGAN). Bytraining a cGAN that translates cross-resolution and cross-spectral tasks to the same resolution and within the same spectrum, the authors of the first method simultaneously solved the cross-resolution and cross-spectral matching issue. The authors created a coupled generative adversarial network (cpGAN) architecture consisting of a pair of cGAN modules that project the VIS and NIR iris images into a low-dimensional embedding domain to ensure the greatest possible pairwise similarity between the feature vectors from the two iris modalities of the same subject.

Table2: IrisRecognitionSystemBasedonArtificialIntelligenceMethods

Ref.No	Dataset	Recognition Method	Performance Analysis	Advantages	Limitation	Types of Illuminators
[14]	CASIA-iris-v4 Interval, Lamp,Syn, Thousand, and Twins	Segmentation using the Hough transform and the clever edge detector. The rubber sheet model developed by Daugmanusing SVMandANN isusedforirisrecognition.	Accuracy–94.6% for SVM polynomial kernel and 95.9% for RBFkernel	Performanceis less for ANN	Lessnumberoftest imageswhichleads to accurate results	NIR
[15]	IIIT-DCLI, ND Cross sensor2012 iris, PolyUcross-spectral iris	Handcrafted based segmentation algorithmand EDA-NBNN with Daugman'srubbersheetmodel	EER-3.97% ForNIRand 6.56% for Visible	Cross-spectral picturesfroma learning-based feature are used in this technique.	Performanceless	Visible +NIR
[16]	Newly composed databaseon the mobile device	PairwiseCNN-based feature extraction and recognition based on Ordinal measures features with pairwise Features	EER-0.56%	Better performance	Itdoesnotuseanypre-processing steps to detect the eye region which leads to degrade theperformanceof the model.	NIR
[17]	CASIA-iris-v4, Thousand, IITD iris	VGG-based feature extraction and iris recognition	Accuracy-99.4%	Noneedfora segmentation stage	Usedapre-trained model for feature extraction	NIR

[18]	CASIA-iris Interval v3	Feature extractionbased onMulti- layer Locality Constrained Iterative neighbor embedding and Log-Gabor filter, SIFT-based iris recognition	EER – under 4% for Log-Gabor filter Under 3.6% forLog-Gabor filter+ SIFT	Better performance	Onlylimitedsizes of images were used to verify the performance	NIR
[19]	ND-iris-0405, CASIA-iris-v4 Distance, IITDiris,	RTV-L-based segmentation and2FCNwith tripletloss were Usedforiris recognition	EER-0.99% for ND-iris-0405, 3.85% forCASIA-iris-v4 Distance,	Extractsmore important features by using2CNNs	Performance is affected by Daugman'srubber sheet model	NIR
	WVUNon-ideal	with Daugman'srubbersheet model	0.64% for IITDirisand 2.28% for WVU Non-ideal			
[20]	CASIA-iris-v3 Interval	3-layer CNN was used for feature extractionand normalized Hamming distance was used for iris recognition	EER-0.68%for downscalex one fourth, 1.41% for downscalex one eighth, 11.46% for downscale x one-sixteenth.	Higher Accuracy	Produces low accuracyforvery low-down sampling rates.	NIR

[21]	ND-iris-0405, CASIA-iris-v4 Distance, WVU	Haarcascadeeye detector- based segmentation and DRFNetwith Daugman'srubber sheet model	EER-1.30% for ND-iris-0405, 4.91% for CASIA-iris-v4 distanceand 1.91% for WVU Non-ideal	more spatial information maybedivided via dilated convolution	Needs to convert iris image to Daugman'srubber-sheet model in the pre-processing stage	NIR
[22]	JluV3.1, JluV4, CASIA-iris-v4 Lamp	Handcrafted-based segmentation algorithmand CapsNet	Accuracy-99.37%for JluV3.1, 98.88% for JluV4 and 93.87% for CASIA-iris-v4 Lamp EER-0.039% for JluV3.1, 0.295% for JluV4 and 1.17% for CASIA-iris-v4 Lamp	Good performance	Preprocessing and sophisticated algorithm implementationare needed for the reason of processing low-resolution images as input.	NIR

[23]	NICE-II, MICHE, CASIA-iris-v4 Distance	ThreeCNNs-based iris recognition	EER-8.58% for NICE-II, 16.41% for MICHE, and 2.96% for CASIA-iris-v4 Distance	improvedresults when usingthedeep generative model's data augmentation to noisy photos.	entails higher computational costs due to the necessityforthree CNNs, data augmentation,andpre-processing.	Visible
24]	PolyU cross-spectraliris	CNN and Supervised Discrete Hashing based iris recognition	EER -5.39%	Moreaccurate performance	It is necessary to trainthesupervised discrete hashing parameters further.	Visible+NIR
[25]	UBIRIS v1	Fast-SRGAN for Super-resolutionand feature extraction. DCNNutilized for iris recognition	ANOVA significant difference= 39.47forp<0.01).	Good accuracy	Restored images are not described andnoexperiments wereconductedfor very low-down scaling rates.	Visible
[26]	CASIA-iris-v4, MMU, IITD	Segmentation basedonhand-crafted algorithmsand OneR, J48, SMO, MultiboostAB, RandomForest, Support Vector Classification,	Accuracy–99.26 to 99.97% for CASIA-iris-v4	Less computation cost and increased the ability of discrimination for feature extraction	Pre-processingis not done and it producesasecurity problem	NIR

		Gradient Boosting based iris recognition				
[27]	PolyU, WVU databases	GAN-based super-resolution and Euclidean distance matching-based iris recognition	EER of 1.28%,1.31% (on the cross-resolutionandcross-spectral)	Thistechnique uses conditional GAN to provide iris identification on a cross-spectral and cross-resolution basis.	High computational costs	Visible, NIR
[28]	CASIA-IrisIntervalv4andIIT Delhi DB	FrDIrisNet-based CNN to iris recognition	**For Non- Augmented Database FAR-**0.008% for CASIA- IrisIntervalv4 and 0.006% for IIT Delhi DB **FRR-**1.62% for CASIA- IrisIntervalv4 and 2.42% for IIT Delhi DB **Accuracy** - 99.18% for CASIA-Iris Interval v4and 99.78% for IIT Delhi DB **CRR-**98.4%	Images transformedin the frequency domain	incorrect ordered data being presented which lowersthesystem's accuracy	NIR

			for CASIA-IrisIntervalv4 and97.73%for IIT Delhi DB			

Many AI-based iris recognition algorithms gather information and perform recognition by developing a rubber-sheet model with sufficient pre-processing or by providing more weight to the deep learning model without segmentation and utilizing the self-trained filtering capability.In this situation, a deep learning model can show strong identification performance for a wider range of picture variants if it is properly built. The weights ofthemodel trainedon low-resolution photos, however,can begeneratedas inaccurateresults ifalow-resolution image is supplied. As a result, it must also be ready to utilize photographs at full quality.

4. Discussion

The IRS has seen significant progress in the recent ten years. These accomplishments came about as a result of several iris recognition investigations in diverse domains. The performance efficiencyrate of both conventional and deep learning approaches in some of the IRS's earlier studies is shown in Tables 1 and 2. The performance effectiveness of the IRS has to be developed through a variety of research. The performance of low-resolution iris identification varies according to how effectively the original image's characteristics can be recreated. A group of experiments called Super Resolution focused on building high-resolution pictures from low-resolution ones. Depending on how effectively the original image's attributes can be recreated, different performances are obtained. Recent deep learning Super Resolution research has shown that it performs much better than Super Resolution techniques used in traditional image processing. Due to the lack of a database containing such low- resolution photos, several researchers have instead conducted tests by randomly downscaling high-resolution photographs. There is a critical need to increase accuracy in existing deep learning and conventional methods. Other difficulties were discovered in unrestricted situations. The cause of these performance discrepancies should be determined through accurate analysis. Some deep learning-based iris recognition algorithms do not employ segmentation and normalization methods. Deep learning technologies are excellent for usage through otherprominenttechnique enhancethe IRS's biometricperformance. Thesemethods maybeused separately or in conjunction with conventional CNNs to improve the capacity to extract features from pictures. Each method has its unique benefits. Deep learning techniques are seen to be the cutting edge of machine learning, capable of handling the aforementioned difficulties.

5. Conclusion

As a reliable biometric technology, IRS has attracted considerable attention on a global scale. Because of its accuracy,itisbeingused forscreeningand identifyingcriminals,runaways,andmigrants. IRSismoreaccurate than other biometric systems like face, periocular, and fingerprint recognition in terms of identification. However, when it comes to screenshots from films or photos of synthetic iris pictures, iris recognition algorithms become imperceptibly poor. This study presents several iris image identification system techniques based on two approaches, classical and deep learning, according to various phases. This survey article demonstrates that the IRS has a promising future and incites scientists to continue their research to find solutions to the problems.

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