Section A-Research paper
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An Examination of Recent Techniques for Iris and Retinal Identification in High as well as Low Resolution Pictures

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Abstract. The biometric techniques that identify eye characteristics in a picture include ocular and iris recognition systems. To get a high gratitude performance, such ocular and iris areas need to have a certain picture resolution; otherwise, there is a danger of performance deterioration. These are even more important when using intricate patterns for iris gratitude. The performance of recognition can be improved by acquiring picture of more resolution pictures using techniques like super-resolution reconstruction in scenarios where the acquisition equipment and surroundings cannot be changed and such picture of poor resolution photos are obtained. Previous survey publications, on the other hand, mostly included extensive precises of research on picture of more resolution ocular and iris gratitude. However, they did not do the same for studies on picture of poor resolution ocular and iris gratitude. As a result, we looked at picture of more resolution ocular and iris recognition techniques then described in clarity picture of poor resolution techniques as well as ways to overcome the picture of poor resolution issue. This survey study also highlighted the most recent deep learning-based techniques in detail, while previous survey papers had only focused on and reviewed findings on conventional handmade based on features ocular and iris gratitude.

Keywords: Deep learning, handcrafted features, super-resolution reconstruction, high and images with poor resolution, ocular and iris gratitude.

1 Introduction

Utilising fingerprinting, more recent safety protocols that are based on distinctive physiognomic characteristics, to replace passwords and other older-generation security measures is currently being explored and developed. Older security methods, like passwords, are easily predictable since they are often made depending on the expertise of the user or recollection. Those are also less secure than the next generation's biometric techniques since they are susceptible to physical strength attacks and probabilistic intellectual techniques [1]. Contrarily, the difficulty of theft and hacking efforts is raised with the use of biometrics since they are implemented using people' distinctive bodily parts, and the security risks are smaller than with conventional security measures. Because it is considerably harder to replicate and fake body parts than it is to breach conventional security measures, security is increased even further. [2] A subject's physiognomy is used by biometrics as a safety ration; often, face, fingers, hands are used since they are practical. First, there is a wide range of applications for techniques that employ the palm or fingerprints [3]. A vein located between the hand's blood vessels, like those found in the fingers or palm, has been used in studies on the gratitude technique in recent years [4-6]. The systems using a hand utilise a contact-based strategy using a camera or sensor to do user recognition, but traces are left on the contract surface, making them vulnerable to monitoring or forging [7]. In order to capture distinctive area traits, these face-based gratitude techniques frequently record a specific part (the complete an eye, face etc.). These techniques consist of entire recognition of faces through every facial feature [8], ocular understanding using just the eye's characteristics [9, 10], recognition of the ears utilising different comprehensive, mathematical, and area techniques, deep neural networks based on the characteristics of the ear area [11], and recognition of the iris segmenting utilising just the iris [12]. Though, unlike hand-based approaches, there are intrinsic limitations, such as the user having to be positioned within a specific distance to capture the image, despite the fact that there is no risk of leaving traces because the images are taken and used with no touching anything. Furthermore, if facial characteristics are altered by injuries, cosmetic procedures, or age, face recognition ability suffers. To get a photo of their ears, the user must position their side view of their face such that it faces the camera, even though these conditions have less of an impact on ear recognition. Iris recognition, which makes use of an eye's iris area that is on the face, can be used to solve these problems. The iris nearly never changes as a person matures, and since the eyelid covers it, external stimuli seldom cause deformations.

Additionally, the iris has the benefit of being properly identifying the owner when employed in biometrics due to its distinctive and one-of-a-kind characteristics. Iris recognition does, however, have certain disadvantages. To capture the image, a near-infrared (NIR) camera is necessary in the event of a dark iris colour because effective segmentation of the iris area is required. Additionally, it needs to enable a high enough picture determination to capture a precise iris design in tiny iris diaphragm. In reply to these issues, optical gratitude—which identifies the full, somewhat larger eye area, includes the area around the eyelids —has been proposed. This technique employs without good segmentation, the retina is in location. The benefit of ocular recognition over iris recognition is that the acquisition environment may be built with less difficulty because the limitations are often smaller. Furthermore, without the need for further acquisition steps, recognition may be done right away with the face or eye picture when recognising irises or faces is incorporated. As a result, whether recognising irises or faces is employed, it may be used as a backup recognition system. For recognising irises or faces, information are typically obtained as pictures. A biometrics classification conducts gratitude depending on the information provided using the acquisition tool. Additionally, to reduce the hazards that might negatively impact recognition performance, safety schemes remain often used in measured situations and picture of more resolution photographs of the iris and eyes are taken. Therefore, the major goals of studies on superior resolution techniques have been to more accurately discern the characteristics of separate section and rigorously classify the individuals. On the other hand, how well the detection technique performs is drastically reduced when a picture of poor resolution is provided. Only a tiny volume of knowledge may be recovered from the picture of poor resolution due to its small pixel count, and it is challenging to recover the use easy picture interpolation to create original data.

That example, a picture of poor resolution is one that has been obtained using a camera lens with a small number of pixels, whereas a picture of more resolution denotes that it has been taken by a camera device with a significant number of pixels (typically in excess of a million pixels) (typically fewer than a million pixels). For instance, the collected iris image is commonly classified as a picture of more resolution one if the iris diameter is more than 200 pixels in the obtained picture [13,14]. Studies have been done on techniques like super-resolution reconstruction (SR) to rebuild a picture of more resolution from a picture of poor resolution in order to tackle the picture of poor resolution problem. The development of (GPGPU) general-purpose computing on graphics processing units' expertise is also depends on the fact that graphic cards can now handle parallel data more efficiently and are utilised for general-purpose computing as opposed to only graphics processing. In the current survey papers, research on excellent quality based on pictures ocular and iris gratitude has been described, while studies on picture of poor resolution based ocular and iris gratitude have not been thoroughly documented. In order to explore the methods already in use, this study will first investigate picture of more resolution based ocular and iris gratitude before introducing picture of poor resolution based ocular and iris gratitude in depth to address the picture of poor resolution issue. Additionally, while previous studies have concentrated on and summarised manual, feature-based techniques for ocular and iris gratitude, this overview study will discuss the most recent deep learning-based developments. We examine the following issues in this study and provide a novel method for ocular and iris gratitude in picture of poor resolution.

1. The advantages then disadvantages of employing picture of more resolution photos for traditional ocular and iris gratitude are categorised according to the method used, and the issues that arise when a picture of poor resolution is entered are explored.
2. Studies on ocular and iris gratitude that used the SR technique to address the picture of poor resolution issue are grouped according to the strategy used, and the benefits and drawbacks of each approach are examined.
3. Techniques for ocular and iris gratitude that used cutting-edge deep learning SR algorithms did well.

In Section 2, we evaluate the benefits and drawbacks of ocular and iris gratitude in a picture of high resolution, both of which have been examined. The analysis of ocular and iris gratitude techniques that have addressed the picture of poor resolution issue by implementing SR approaches is then presented in Section 3 along with a summary of their benefits and drawbacks. The survey paper's conclusion is presented in Section 4.

2. Methods for Recognizing Ocular and iris Features from Picture of more resolution Images

The two main kinds of recognition techniques for the eye area are those that use the iris area and those that use the ocular area. Picture of more resolution, good-quality photos are frequently used in iris recognition applications. Ocular and iris gratitude use picture of more resolution produced with NIR illumination and cameras like those in Figure 1 from the Institute of Automation, (CASIA) Chinese Academy of Science database to recognise the whole eye area. Figure 1 demonstrates how either the full face, or only the iris area, may be instantly collected and used in the recognition system. Depending on the implementation context, this could change. As illustrated in Figure 1a, a picture of more resolution of the entire face area is obtained, in which the iris area, Figure 1b, is recognised. In general, a costly picture of more resolution camera is needed for recognition. In addition to this, there is a technique for obtaining only the iris area, Figure 1c, employing a camera with a small field of view and a zoom feature.

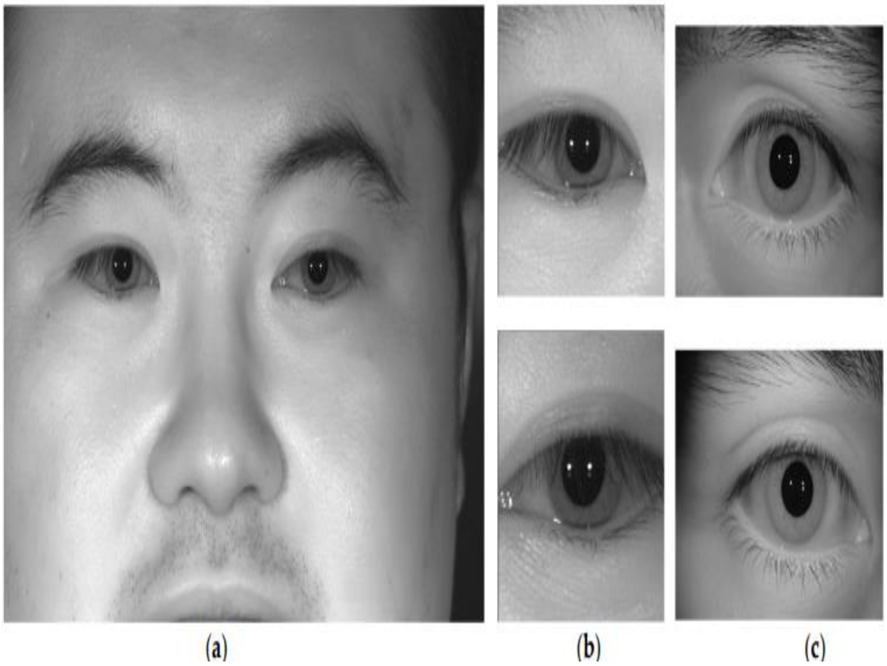

Figure 1. A sample of a CASIA database that contains pictures of the face or eyes. (a) The whole of the face as seen in the CASIA-iris-Distance v4 database; (b) the iris as detected in (a); and (c) the iris as seen in the CASIA-iris-Lamp v4 database.

Because a picture of more resolution already has many distinguishable characteristics, iris gratitude from that image concentrates on precise iris segmentation. The techniques for recognition are then chosen based on the outcome. The usual picture of more resolution image-based iris recognition experiments are introduced in the next subsection to describe this procedure.

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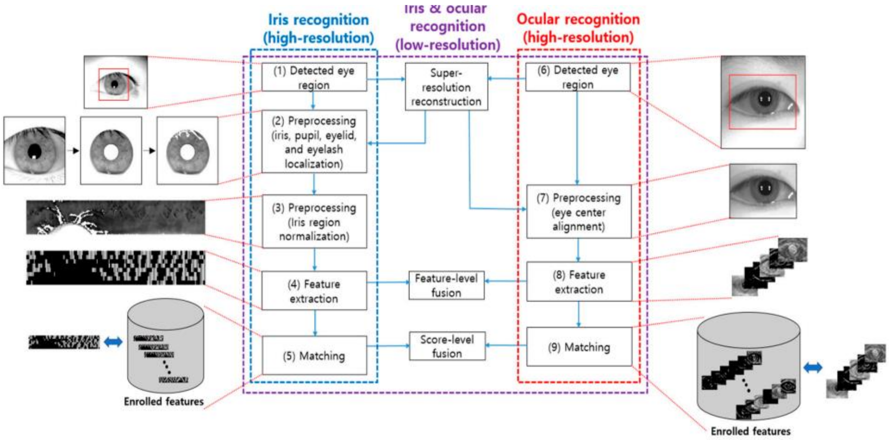

Figure 2. An overview of the gratitude of the iris and the eyes in high- and picture of poor resolution photos.

The effectiveness of iris gratitude using the conventional picture processing technique based on how precisely the iris characteristics are retrieved. The error equal rate (EER), a commonly used biometrics measure, is used to assess performance. The EER displays the error rate at a point when the false acceptance rate (FAR) matches the false rejection rate when genuine recognition is carried out (FRR). The FRR is the likelihood that a user will be mistakenly rejected as someone else, while the FAR is the likelihood that a topic will be approved wrongly. The research on iris detection in picture of more resolution may be divided into three categories: expert systems, computer vision, and image analysis.

2.1 Method of Image Processing

First, using iris segmentation for image processing, Thomas et al. [20] recognised the iris using a random sample consensus (RANSAC). The iris area is then transformed using a rubber-sheet model, which is frequently used in most algorithms for iris gratitude, to complete the preprocessing for iris recognition. The final recognition technique then uses the peak side-lobe ratio (PSLR), a performance assessment based on signals. For this, the rapid Fourier transform is used to convert the rubber-sheet picture of the iris into a frequency signal area (FFT). The suggested technique then performs recognition by template matching with the PSLR value serving as the similarity metric for the photos that were enrolled and used for gratitude. A morphological filter is used in the proposed technique to detect the iris area in order to eliminate the pupil-reflected light, using a template in the form of a circle for the vertical and horizontal preliminary directions to locate the iris area. Next, image-improving techniques, like such as the Hough transform, the Gaussian filter, the clever edge sensor, and histogram equalisation are used to detect the iris area. The eyelid area is then noticed using the refine-connect-extend smooth (R-C-E-S) approach, and a mask is made to protect the eye.

The iris area so discovered is converted into a rubbersheet form to establish an iris code, which is then used as th e basis for template matching with the Hamming distance or cosine dissimilarity to identify the iris. In comparison to the discrete wavelet transform (DWT)-based iris gratitude, Singh et al[23] .'s presented integer wavelet transform (IWT)-based iris gratitude.

The performances are superior than those of the DWT. An approach for dynamic radius matching for iris gratitude was put out by Thumwarin et al. [24]. Due to the pupil, the iris area's size might change. If the light is excessively strong, the iris area expands and the pupil area shrinks, and vice versa. The recognition performance might suffer, which is a drawback, if a specific level of input image quality is not assured. The complexity of the implementation approach for the recognition method is another drawback. When unexpected picture of poor resolution photographs are utilised in such a system, the recognition concert may suffer noticeably, necessitating the implementation of an appropriate method.

2.2 Machine Learning-Based Method

Machine learning techniques have been presented in light of the above-mentioned shortcomings of the picture processing techniques. A an (ANN) artificial neural network and (SVM) support vector machine are used in Salve et al[25] .'s suggested recognition approach for iris recognition. First, typical image processing techniques are essentially the same for picture preprocessing. The Hough transformation and canny edge detector

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techniques are used to segment the iris area, and the 1D log-Gabor wavelet transform is then used to removes the iris code from the segmented area after it has been converted into a rubber-sheet form. In order to accomplish iris recognition, the retrieved iris code is fed into the (ANN) artificial neural network and (SVM) support vector machine -based classifier.

Applying a domain adaptation (DA) method, Nalla et al. [26] developed an iris gratitude technique that employs NIR and visible pictures concurrently in order to provide a solution that demonstrates an accurate performance regardless of the image acquisition environment (sensor-specific or illuminator wavelength-specific). The input picture is preprocessed into a rubber-sheet form, and the log-Gabor filter is used to create real-value features. Then, using the DA-naveBayes nearest neighbour (DA-NBNN) technique, which incorporates the NBNN classifier into the DA method utilising the features, cross-spectral iris gratitude is carried out. Additionally, they suggested an enhanced DA-NBNN (EDA-NBNN) approach that incorporates spatial pyramid matching (SPM) to boost performance.

The concept of stylometric features-based iris gratitude with machine learning methods was put out by Adamovi'c et al. [27]. Instead of using the standard Daugman's techniques, such as 2-D or 1-D Gabor filters, they created iris templates using a Base64 encoder.

2.3 Deep Learning Method

Machine learning techniques offer the benefit of allowing for finer control over the recognition process, and in many situations, training can result in a high recognition rate. To correctly preprocess and turn a picture into a rubber-sheet model, which is a distinctive feature of iris recognition schemes, the picture has to have an acceptable quality or greater. In other words, the performance may suffer if a picture of poor resolution image is entered. The low gratitude ability for photos from unlearned environments from other environments is another issue. Given the aforementioned flaws in machine learning methods, research on iris gratitude using deep learning has been conducted.

The use of a CNN for iris gratitude was suggested by Gangwar et al. [28]. The technique of segmenting the iris area during preprocessing and then converting it intoa rubbersheet shape after that is comparable to classic mach ine learning and picture processing approaches. To create a squareshaped input picture for CNN, the extended rectangular rubber sheet is first cut in half, and the two pieces are then joined vertically to one another. The pict ure is inputted into the CNN asis rather than being converted into an iris code, and the weighted filters of the CN N are utilised o excerpt the features, The characteristics of the fully-connected (FC) layer prior to the SoftMax [29] layer, which is the last output layer, are utilised to compute the similarity score between the CNN architecture suggested in their work, which is named DeepIrisNet. Based on a (FCN) fully convolutional network model, Zhao et alteam .'s [30] developed a descriptor that generates spatially equivalent iris features and suggested an extended triplet loss (ETL) to train it. Additionally, a sub-network has been put in place to get the right data needed to recognise the iris area. The primary network utilised is FeatNet, while the secondary network is MaskNet. Wang et al. [31] presented DRFNet, which applies residual connections and dilated convolution, to further enhance performance over the approach suggested by Zhao et al. [30]. MaskNet is utilised to compute the ETL and carry out the training, as was previously demonstrated. The segmented iris area picture is sent into the appropriate MaskNet and DRFNet to accomplish iris recognition. The (VGG) visual geometry group 16 model developed by Simonyan et al. [16] was utilised by Minaee et al. [32] to perform iris identification utilising the ocular picture covering the iris as-is.

(PCA) Principal component analysis is performed for dimension lessening on the iris picture features recovered by means of the VGG-16 model without further adjusting the iris picture, and then the multiclass SVM be employed for iris gratitude. In order to improve performance, Zhao et al. [33] suggested a deep learning-based iris gratitude approach that makes use of a capsule network design. The iris gratitude capsule network exhibits great recognition accuracy while learning part-whole connections and boosting model resilience. Lee et al. [34] suggest using three CNN approaches and generative model-based data augmentation to improve the accuracy of iris detection on noisy photos recorded from visible wavelengths. In their study, Wang et al. [35] used CNN to execute an iris recognition approach. They employed a straightforward shallow CNN model with only three convolutional layers, although the shallow network may result in performance deterioration. In order to solve this, they implemented the supervised discrete hashing technique.

When it comes to deep learning iris recognition, there are numerous techniques that excerpt features and carry out identification by building a rubber-sheet model with adequate pre-processing or by giving more weight to the self-trained sorting abilities and the deep learning model with no segmentation. If in this case, a deep learning model is appropriate, it can show strong recognition performance for a wider range of picture variants. The masses of the model trained on picture of more resolution pictures might, however, be incorrectly determined if a picture of poor resolution image is supplied. As a result, it must also be ready to use picture of poor resolution photos.

Approach	Deep learning-based
Reference	[35]
Segmentation Methods	Handcrafted segmentation algorithm
Illum	Visible +NIR
Database	PolyU cross-spectral iris
performance	EER of 5.39%
Recognition Technique	CNN and SDH
Advantages	Supervised discrete hashing reduces the size of the iris template while improving speed utilising CNN.
Disadvantages	It is necessary to preprocess the input photos and to further train the supervised discrete hashing parameters.

Approach	Deep learning-based
Reference	[34]
Segmentation Methods	Handcrafted segmentation algorithm
Illum	Visible
Database	NICE-II, MICHE, CASIA-iris-v4 Distance
performance	EER of 2.96%, EER of 8.58% (NICE-II), EER of 16.41% (MICHE), (CASIA-iris-v4 Distance)
Recognition Technique	Three CNNs
Advantages	Demonstrates improved results when employing deep generative models to enhance data for noisy photos.
Disadvantages	Costs more to compute since it requires three CNNs, data augmentation, and preprocessing.

Approach	Deep learning-based
Reference	[33]
Segmentation Methods	Handcrafted segmentation algorithm
Illum	NIR
Database	luV3.1, JluV4, CASIA-iris-v4 Lamp
performance	The CASIA-iris-V4 Lamp has an accuracy of 93.87% and an EER of 1.17%, JluV4 has an accuracy of 98.88 and an EER of 0.295%; JluV3.1 has an accuracy of 99.37% and an EER of 0.039%.
Recognition Technique	Network architectures for capsules
Advantages	Excellent performances have been displayed.
Disadvantages	Preprocessing and the use of complex algorithms are required.

Approach	Deep learning-based
Reference	[32]
Segmentation Methods	No segmentation
Illum	NIR
Database	IITD iris, CASIA-iris-v4, Thousand.
performance	Accuracy of 99.4%
Recognition Technique	iris identification based on VGG feature extraction
Advantages	Does not need iris segmentation
Disadvantages	Uses the standard VGG-16 model to extract features.

Approach	Deep learning-based
Reference	[31]
Segmentation Methods	Haar cascade eye detector
Illum	NIR
Database	CASIA-iris-v4 Distance, WVU, ND-iris-0405
performance	EER of 1.91% (WVU Non-ideal), 4.91% (CASIA-iris-v4 distance), and 1.30% (ND-iris-0405)
Recognition Technique	DRFNet with ETL
Advantages	By using dilated convolution, additional spatial information are used.
Disadvantages	Requires preprocessing the iris picture to adapt it to Daugman's rubber-sheet model.

Approach	Deep learning-based
Reference	[30]
Segmentation Methods	RTV-L (Relative Total Variation-L) [37]
Illum	NIR
Database	CASIA-iris-v4 Distance, WVU, ND-iris-0405
performance	EER of 0.64% (IITD), 2.28% (WVU Non-ideal), 3.85% (CASIA-iris-v4 distance), 0.99% (ND-iris-0405), and 2.28% (WVU)
Recognition Technique	Loss of three with two FCN
Advantages	Uses two CNNs to extract more advanced characteristics
Disadvantages	The rubber-sheet model of Daugman has an impact on performance.

Approach	Deep learning-based
Reference	[28]
Segmentation Methods	Osiris
Illum	NIR

Database	ND-iris-0405, ND-CrossSensorIris-2013
performance	EER of 1.82% on two combined datasets
Recognition Technique	DeepIrisNet
Advantages	High accuracy based on deep features is displayed.
Disadvantages	Requires prior processing of the supplied picture

Approach	Machine learning-based
Reference	[27]
Segmentation Methods	Handcrafted segmentation algorithm
Illum	NIR
Database	IITD, CASIA-iris-v4 MMU
performance	0.9926–0.9997 (CASIA-iris-v4) Accuracy
Recognition Technique	Random Forest, OneR, J48, SMO, MultiboostAB, Support Vector Classification, and Gradient Boosting
Advantages	By employing the Base64 encoder for feature extraction, lowers the cost of computation and improves discriminating
Disadvantages	Uses the Base64 encoder for feature extraction to save computing costs and improve discriminating

Approach	Machine learning-based
Reference	[26]
Segmentation Methods	Handcrafted segmentation algorithm
Illum	Visible + NIR
Database	PolyU cross-spectral iris, ND Cross sensor 2012 iris, and IIIT-D CLI
performance	Bi-spectral iris recognition (EER) of 3.97% in the near-infrared and 6.56% in the visible
Recognition Technique	EDA-NBNN
Advantages	May employ cross-spectral photos from a feature that is learning-based.
Disadvantages	Performance does not much improve over single spectrum recognition.

Approach	Machine learning-based
Reference	[25]
Segmentation Methods	Edge detection using Canny and Hough transform
Illum	NIR
Database	Interval, Lamp, Syn, Thousand, and Twins in CASIA-iris-v4
Performance	SVM has a classification precision of 95.9% (RBF kernel) and 94.6% (polynomial kernel)

Recognition Technique	SVM or ANN
Advantages	Test data have less of an impact on performance than image processing techniques.
Disadvantages	There are only a few test photos, and the test is run in a closed-world environment.

Approach	Image processing-based
Reference	[24]
Segmentation Methods	Handcrafted segmentation algorithm
Illum	NIR
Database	CASIA v1.0
Performance	Accuracy of 94.89%
Recognition Technique	Dynamic radius matching
Advantages	Can be applied when the iris area's size varies.
Disadvantages	Since this approach relies on grayscale pixel values, preprocessing the picture (such as reducing specular reflection) is necessary.Since this approach relies on grayscale pixel values, preprocessing the picture (such as reducing specular reflection) is necessary.

Approach	Image processing-based
Reference	[23]
Segmentation Methods	Handcrafted segmentation algorithm
Illum	NIR
Database	UBIRIS v2
Performance	EER of 0.12%
Recognition Technique	Integer wavelet transform (IWT)
Advantages	Not require extra computing apparatus (such as a GPU).
Disadvantages	It is necessary for iris segmentation to operate well.

Approach	Image processing-based
Reference	[22]
Segmentation Methods	Watershed
Illum	Visible
Database	Subset of UBIRIS v2: UBIRIS v1 session 2
Performance	Decidability was measured at 2.0335 (UBIRISv1) and 1.3850 (UBIRISv2).
Recognition Technique	Cosine and Hamming distances
Advantages	Even in a loud, visible environment, may determine the iris ROI area.

Disadvantages	High accuracy in recognition for precise iris ROI in noisy pictures is inconclusive, and implementation is challenging.

Approach	Image processing-based
Reference	[21]
Segmentation Methods	R-C-E-S
Illum	Visible
Database	SDUMLA-HMT, CASIA (v1, v4 Lamp),
Performance	EER of 93.6% and 3.2% (SDMULA), 95.1% and 2.45% (CASIA v4), and 96.48% and 1.76% (CASIA v1) respectively.
Recognition Technique	Hamming distance
Advantages	Using morphological filtering, one may precisely identify the pupil region that is unaffected by specular reflection and define the iris ROI using a clever edge detector and the Hough transform.
Disadvantages	Needs a higher resolution image with discernible borders.

Approach	Image processing-based
Reference	[20]
Segmentation techniques	RANSAC
Illum	Visible
Database	WVU
Performance	There are only graphs and no stated accuracy.
Recognition Technique	PSLR
Advantages	RANSAC's ellipse fitting technique provides precise pupil identification.
Disadvantages	A precise performance table is not supplied, and the next steps are comparable to the currently used procedures.

Approach	Deep learning-based
Reference	[45]
Database	UBIRIS-II, UBIPr, MICHE, VISOB
Performance	EER of 0.49 (PolyU), 1.4 (Cross-Eyed) on cross-spectral and iris-periocular fusion by Resnet-50
Recognition Technique	Cosine distance matching

Feature Extraction	CNN, feature fusion
Areas	Periocular, Iris
Illum.	NIR, visible
Advantages	Numerous cross-spectral studies are conducted, and they show high accuracy.
Disadvantages	Inadequate evaluation of the outcomes of the experiment

Approach	Deep learning-based
Reference	[44]
Database	UBIPr
Performance	3.18% (SVM), 12.74% (cosine distance), and 15.25% (Euclidean distance) EER
Recognition Technique	Euclidean distance matching or cosine distance
Feature Extraction	CNN (ResNet50, VGG16, VGG19, etc.)
Areas	Ocular
Illum.	Visible
Advantages	High reliability and accuracy of identification when employing the paired method
Disadvantages	Performance improvement is constrained by traditional CNNs.

Approach	Deep learning-based
Reference	[43]
Database	UBIRIS-II, UBIPr, MICHE, VISOB
Performance	EER of 14.46% Resnet-50 has been fine-tuned on UBIRIS-II, UBIPr, and MICHE in the VISOB database.
Recognition Technique	Compares to Hamming distance or cosine similarity
Feature Extraction	EFL and KL diverging autoencoder
Areas	Ocular
Illum.	Visible
Advantages	Demonstrates good accuracy with a modified autoencoder and EFL loss.
Disadvantages	The input size is limited, and grayscale conversion is necessary.

Approach	Deep learning-based
Reference	[42]
Database	Cross-Eyed, UBIRIS-I, and UBIRIS-II
Performance	Cross-Eyed had an EER of 16.04%, UBIRIS I and II had 10.22% and 10.41%, respectively.

Recognition Technique	Euclidean distance matching
Feature Extraction	PatchNet based on landmark points
Areas	Ocular
Illum.	NIR
Advantages	Uses area patches and CNNs to divide different ocular characteristics
Disadvantages	A CNN is needed for each patch, which raises memory and computational expenses.

Approach	Deep learning-based
Reference	[41]
Database	Distance, Lamp, Thousand CASIA-iris-v4
Performance	EER of 2.1625 percent (CASIA-irisDistance), 1.595 percent (CASIA-iris-Lamp), and 1.331 percent (CASIA-iris-Thousand)
Recognition Technique	Euclidean distance matching and CNN feature extraction
Feature Extraction	Deep residual CNN
Areas	Ocular
Illum.	NIR
Advantages	Achieve high accuracy using deep residual without proper segmentation CNN
Disadvantages	For model training, a large dataset and input image with higher resolution are needed.

Approach	Machine learning-based
Reference	[40]
Database	CMU PIE, Yale Face, MBGC, and FRGC 2.0's "lights" subset
Performance	F1 score of 0.9969 (for the "lights" subset), 0.868 (for the "Yale face database"), 0.8694 (for the MBGC database), and 0.8108 (for the FRGC 2.0 database).
Recognition Technique	SVM
Feature Extraction	ULBP, WT-LBP, geometrical characteristics, the likelihoods that eyelids will close one or both ways, and combinations of these techniques
Areas	Ocular, skin texture, eyelids
Illum.	Visible Ocular, skin texture, e
Advantages	Offers good performance with various feature extraction and SVM combinations.
Disadvantages	Provides good performance by combining feature extraction with SVM in various ways.

Approach	Image processing based

Reference	[39]
Database	Cross-Eyed
Performance	4.87% EER for visible to visible matches, 6.36% EER for NIR to NIR matches, and 16.92% EER for visible to NIR matches
Recognition Technique	Same or crossspectral matching
Feature Extraction	Statistical or transformbased feature descriptor
Areas	Periocular, iris, ocular
Illum.	NIR, visible
Advantages	Cross-spectral periocular, iris, and ocular recognition is used.
Disadvantages	Due to handmade features, great performance cannot be achieved.

2.3 Utilizing Elevated Pictures for Ocular Gratitude

The ocular gratitude procedure using picture of more resolution photos. Ocular recognition may generally be used as a second layer of protection, as a supplement to iris recognition, or as a workaround in situations when it is challenging to take picture of more resolution pictures. The maintenance and design expenses are a little bit cheaper than iris recognition schemes used by other systems, which is a benefit in terms of deployment. The ocular ROI may be directly retrieved from the facial picture or the general eye area, making it simpler to produce the gratitude image than with traditional approaches.
Additionally, several aspects of the ocular area, including the eyelid, sclera, iris, pupil, and eyelash, have an impact on performance based on how much they are paid in order to be recognised. Another benefit is that, unlike iris gratitude methods, these techniques do not need precise iris area segmentation. To put it another way, ocular recognition algorithms have the benefit that their processing time and algorithm complexity are lower than those for iris gratitude since they identify the approximate ocular area through preprocessing [38]. Ocular recognition in higher-resolution photos: current research may be divided into three categories: deep learning, machine learning, and image processing.

2.4 Method Based on Image Processing

A method for ocular gratitude has been put out by Vyas et al. [39] that makes use of eye pictures concurrently captured in the visible and NIR spectrums. This technique divides the iris area independently, utilises the periocular area for the ocular area instead of the eye area, and uses the feature descriptor to extract structures from both the periocular area and the iris area. The characteristics are then combined for successful recognition. The periocular and iris areas produced under cross-spectral illumination are used for recognition based on the local image description approach. The benefit of using these conventional image processing techniques is that extra hardware, such GPUs, is not necessary. However, there is a drawback in that if a set level of input picture quality is not ensured when deployed, the recognition performance may suffer. Additionally, when a picture of poor resolution image is utilised as input, the recognition performance may suffer significantly, necessitating the implementation of a new, more suitable system.

2.5 Using Machine Learning

In this technique, the ocular area is located from the picture by detecting landmark points after taking frontal photographs of the subject's face. The characteristics of the surrounding ocular area are extracted using the landmark points identified for the left and right eyes. Here, features are retrieved using the local binary pattern (LBP) approach and the weighted LBP, as well as the histogram of gradient (HOG) method for geometric features. Finally, utilising the collected characteristics, recognition is carried out based on the SVM. In comparison to image processing approaches, the machine learning techniques offer the benefit of being able to attain a greater recognition rate by training on a variety of situations.

3. Techniques for Recognizing iris and Ocular Features from Picture of poor resolution Pictures

Picture of poor resolution photos can be input for iris and Ocular recognition in a number of circumstances, including from a distance, with a picture of poor resolution camera, and with lax subject limitations. When this

occurs, recognition is accomplished by creating a super-resolution image from a picture of poor resolution image, as seen in Figure 2's top box in the dashed purple box. The majority of studies have, however, used an image processing technique to create a picture of poor resolution image based on the picture of more resolution image, as shown in Figure 3, and performed super-resolution reconstruction using the pair. This is because it is challenging to obtain a pair of picture of more resolution and picture of poor resolution iris images in a real-world setting.
In other words, Figure 3 provides instances of pairs of picture of poor resolution iris pictures from the second and fourth columns that were created from equivalent picture of more resolution iris photos from the first and third columns using a conventional image processing technique [46]. These picture pairings serve as the experimental data used to build and evaluate the super-resolution reconstruction technique.

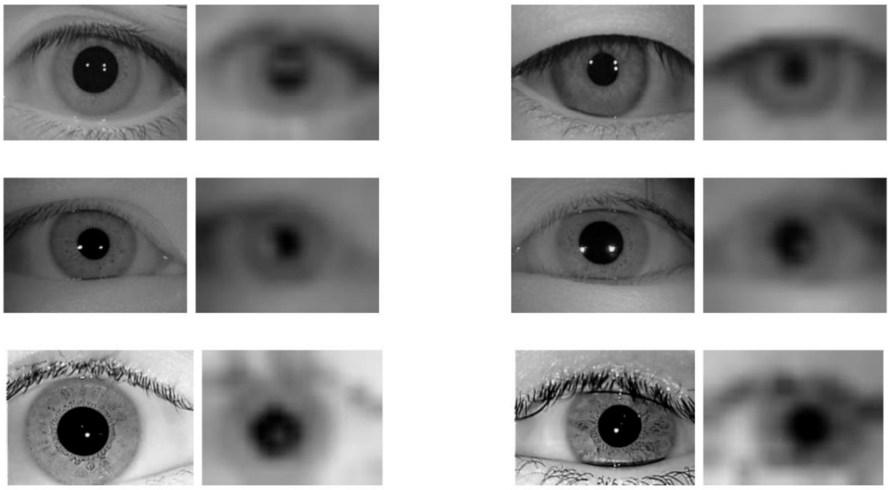

Figure 3 shows two samples of photographs with different resolutions (1/16). From the CASIA-iris-Lamp, Thousand, and IITD databases, respectively, come the first, second, and third rows.

A library of picture of more resolution and picture of poor resolution pairings is used to train either standard image processing techniques or cutting-edge deep learning algorithms to rebuild picture of poor resolution pictures.

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I_o(i,\ j) - I_r(i,\ j)]^2 \quad (1)$$

$$\mathrm{SNR} = 10log_{10}\left(\frac{\frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I_o(i,\ j)]^2}{mn}}{\mathrm{MSE}}\right) \quad (2)$$

$$\mathrm{PSNR} = 10log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right) \quad (3)$$

Ir is the picture of poor resolution reconstruction, whereas Io is the original picture of more resolution picture. The width and height of the picture are indicated, respectively, by m and n. The SSIM mathematical formula is displayed in Equation (4).

$$\mathrm{SSIM} = \frac{(2\mu_r\mu_o + S1)(2\sigma_{ro} + S2)}{(\mu_r{}^2 + \mu_o{}^2 + S1)(\sigma_r{}^2 + \sigma_o{}^2 + S2)} \quad (4)$$

The symbols μo and σo represent, respectively, the mean and standard deviation of the pixel values of an original picture of more resolution picture. The pixel values of the picture that was recreated from the picture of poor resolution image are represented by r and r, which show the mean and standard deviation of those values, respectively. ro is the covariance between the two images. Positive constant values S1 and S2 cause the denominator to be non-zero.

3.1 Method of Image Processing

A code-level strategy was used by Liu et al. [50] to accomplish heterogeneous iris recognition. When the enrolled and the obtained pictures have different quality or condition issues, this is referred to as heterogeneous iris recognition. The performance deteriorates when recognition is attempted utilising a picture of more resolution picture versus a picture of poor resolution image or when images are taken in various surroundings in cross-condition circumstances. Therefore, in this study, we extract the iris's characteristics using a Markov network-applied model and recognise the iris by code-level matching.

Using multi-frame pictures, Deshpande et al. [51] suggested iris super-resolution and recognition algorithms. They employ a manual labor-based methodology. In the multi-frame photos, they first choose the best frame, and only then do they execute the alignment. Then, patches are chosen, and they offer improved iterated back projection (EIBP) and Gaussian process regression (GPR) for super-resolution. Finally, a neural network classifier is used to categorise these rebuilt picture of more resolution iris pictures. Using eigen-patch, Alonso-Fernandez et al. [52] introduced PCA-based iris super-resolution techniques.

Iris feature super-resolution based on Papoulis-Gerchberg (PG) and projection onto convex sets (POCS) approaches was developed by Deshpande et al. [54]. With this approach, picture characteristics are analysed, and improvements are made to provide more accurate iris features. Principal component transform (PCT)-based information fusion was used by Jillela et al. [55] to conduct iris recognition studies on the picture of poor resolution iris movies. When compared to related image processing-based approaches, this method, which makes use of eigenvectors from PCT, performs better in terms of recognition.

3.2 Deep Learning Technique

Optimized ordinal measures (OMs) characteristics and a CNN-based approach were suggested by Zhang et al. [58]. First, procedures for detecting and cropping the ROI area are used for iris gratitude on mobile devices. The suggested CNN model receives these preprocessed pictures. Although the design is straightforward, they make use of the paired CNN model. It offers a comparison of the two irises. Additionally, pairwise features are combined with generated image features, which are computed via ordinal feature selection. This approach exhibits good performance on mobile devices, to sum up. In order to avoid a loss in recognition performance when a picture of poor resolution image is entered for iris recognition, Ribeiro et al. [59] utilised an SR approach to rebuild the image. They employ a stacked autoencoder and a CNN with three convolutional layers, comparable to the SRCNN model, which was previously investigated for SR, to reconstruct a picture of more resolution picture from the input picture of poor resolution iris image. The performance of iris recognition is then compared. The results revealed that the tweaked CNN performed best among the other learning techniques.

3.3 Discussions and Analysis

Whatever the implementation strategy, higher quality photographs are utilised to identify people's eyes and irises. Therefore, exhibiting excellent recognition performance requires the capacity to apply the method of collecting characteristics from the significant amount of information included in the image.

First, studies on iris gratitude using traditional image processing put a lot of emphasis on fine-grained iris area segmentation. This is because fine-grained segmentation can deliver rich, high-quality iris properties. The iris region is then preprocessed into a polar coordinate area using Daugman's rubber-sheet model in order to create an iris code for recognition.

Then, it is converted into an iris code using the appropriate kernel and a measurement such the Hamming distance [20–22]. The segmentation and identification processes are also being replaced by methods for iris gratitude that employ machine learning or deep learning [25,26,28,30-32]. Ocular identification in higher-resolution pictures, in contrast, does not need the extremely accurate segmentation of the eye region, unlike iris gratitude. In order to perform ocular recognition, conventional image processing methods either statistically analyse the distribution of the features [39] or extract data (such as edges) [40]. Although there are several advantages of using higher resolution images based on the ocular and iris features, the analysis's findings suggest that the following problems might arise.

When the system is implemented, a computer with significant computational capability is needed since picture

of more resolution photographs are employed. Picture of more resolution images collect more data than picture of poor resolution images and demand more processing power.
This raises the likelihood of performance reduction in embedded and mobile devices with low resolution. Ocular image recognition systems reduce the complexity of traditional iris gratitude systems since they don't need to accurately segment the eye area. However, in a different sense, this means that significant iris characteristics cannot be fully used, leading to a worse recognition presentation when compared to iris recognition schemes.

4 Conclusion

In this work, we compared studies that employed SR techniques to address issues that arise when picture of poor resolution pictures are used for recognition with picture of more resolution image-based ocular and iris recognition approaches. Additionally, we dissected each research and looked at its issues. Implementing iris recognition systems is more challenging due to major obstacles including I reliable extraction of the iris area segmentation and extraction of distinctive characteristics from the iris data to separate everyone. (ii) To address these issues, researchers looked at ocular recognition biometric techniques that make use of the complete eye area. (iii) In this case, photos were also taken and used for ocular gratitude. Depending on the surroundings, picture of poor resolution images will likely be obtained, which might affect the system's accuracy. In contexts where picture of poor resolution pictures are collected, deep learning-based SR techniques have been intensively investigated recently and can perform on par with picture of more resolution imaging systems. This can make it easier to establish a biometrics system when doing so in a secure setting, increasing the level of security in settings with mobile devices that are often used in daily life. As a result of these investigations, more and more practical applications are being made, such as remote driver gratitude in luxury vehicles and remote VIP member surveillance in hotels and resorts. Additionally, the elderly with dementia, criminals, and missing children may all be found using intelligent monitoring systems.

Algorithms that are resilient to occlusion, camera variety, and subject location should be explored in order to ensure system dependability in these applications. Additionally, a compact approach should be investigated for use in embedded devices with minimal computing power, such as those found in automobiles and security camera situations.

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