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Article Advances in Feature Extraction and Selection for Iris Recognition Systems: A Review

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Abstract

The growing demand for security and reliable authentication methods has positioned biometric recognition systems at the forefront of modern security infrastructure. Among various biometric modalities, including facial and fingerprint, iris recognition has emerged as the most accurate and reliable, due to its rich texture, stability over time, and resistance to ageing and surgical alteration. However, existing iris recognition systems are primarily optimized for frontal, high-quality images and often fail to accurately process angular or partially captured iris images. To overcome these issues, techniques such as feature extraction, segmentation, and normalization need to be improved. Feature selection is essential in dimensionality reduction, and when combined with feature extraction techniques, the process will improve both time complexity and accuracy. This review explores the advancements in iris recognition, focusing on feature extraction and selection techniques that are crucial for improving system accuracy and efficiency. This study offers a comprehensive overview of various feature extraction and selection techniques, serving as a valuable reference for researchers.

1. Introduction

The demand for enhanced security measures is escalating daily, particularly in high-risk environments like airports, train stations, government facilities, and public transportation systems [1]. As the request for secure identification methods increases, particularly in critical applications such as police, financial services and security of mobile devices, the importance of implementing advanced iris recognition systems has never been more pronounced. The increase in cyber players and the growing need for robust authentication mechanisms have catalyzed research on improving the precision and efficiency of Iris recognition technologies [2], [3], [4].

Iris recognition systems have become a pivotal component of biometric security due to their distinct advantages compared to other biometric methods, such as digital imprint or facial recognition. The unique models found in human iris are very complex and stable throughout an individual’s life, making iris traits exceptionally adapted to personal identification [5], [6]. This characteristic, combined with the low probability of false correspondence resulting from the considerable variability of the textures of the iris, positions the biometric iris as one of the most reliable and secure identification methods available today [7].

Biometric is a unique physical or behavioural characteristic to identify individuals [8], [9]. The fingerprints, facial structure, iris, voice, retina, palm prints, and gait are the most common biometric traits, where iris recognition outperforms due to its distinctiveness, stability, and accuracy [10], [11], [12].

The iris is a delicate structure within the human eye, characterized by unique and highly distinctive features, making it an optimal choice for biometric identification and authentication. [13], [14]. In recent years, the iris has become a widely recognized biometric trait for identification. However, its performance is significantly affected when dealing with incomplete (partially captured) and off-angle iris images, which frequently occur in uncontrolled environments such as surveillance systems, mobile authentication, and remote identity verification. These challenges arise from factors like occlusions (eyelids, eyelashes, and spectacles), poor illumination, motion blur, and user non-cooperation, making it difficult to extract discriminative iris features and achieve accurate recognition [15], [16].

The iris recognition system (IRS) typically operates through four key stages: data collection, pre-processing, feature extraction, and matching or recognition [17], [18], [19]. Feature extraction is an essential phase in the iris recognition process, significantly contributing to the accuracy of the system [20], [21], [22].

Iris feature extraction involves capturing the distinctive texture of the iris that can be robust, highly discriminative, and computationally efficient [23], [24]. Iris features are the patterns and unique characters found in the human eye. It can be in different types, such as texture patterns (like rings, furrows, crypts), frequency components (LL, LH, HL, and HH sub bands), phase information (IrisCode), edge and contour features. Other features are extracted by various techniques, including statistical features (entropy, mean, variance, energy), keypoint descriptors, and zero-crossings [24]. In addition, feature selection can identify relevant and informative features from the set of extracted features, improving the accuracy, efficiency, and robustness of the IRS [25], [26]. It also helps eliminate irrelevant, redundant, or noisy data features that can otherwise lead to slower performance and affect accuracy [27], [28]. However, the iris features are frequently distorted, noisy, or obstructed, making feature extraction and matching difficult. This occurs as a result of poor resolution that is associated with distant imaging or low-quality sensors, which reduces the visibility of fine-grained iris textures such as crypts and radial furrows. Additionally, significant challenges arise from off-angle iris images, where the subject's gaze is not aligned directly with the camera. This misalignment distorts the iris geometry, resulting in warped texture patterns that adversely affect segmentation and normalization processes, which are critical for reliable feature extraction. The presence of occlusions, such as eyelids, eyelashes, or reflections from glasses and ambient lighting, introduces noise into the iris image. Furthermore, authentication of angular images, and incomplete where only a partial segment of the iris is visible remains a challenging area and needs improvement.

Therefore, this article aims to provide a novel way of addressing the above-mentioned problem of IRS. This paper addresses the challenges related to feature extraction and selection techniques in IRS while outlining potential future directions for improvement. It also highlights the various stages of the IRS where the extraction of features is given more attention due to its vital role played in improving the performance and accuracy of the system. The remainder of this article is Section 2 – Iris Recognition and Authentication Process, Section 3- Iris Feature Extraction and Selection Techniques, Section 4- Discussion and Feature Direction, and Section 5 - Conclusion.

2. Iris Recognition and Authentication

The iris recognition and authentication system (IRAS) is a multi-stage process designed to preprocess, extract, encode, and match distinctive features from iris images for identification and verification purposes [29], [30], [31], [32]. The iris features refer to the distinctive anatomical and textural characteristics embedded within the iris of the human eye. These features are central to the operation of IRAS, as they offer a high degree of uniqueness and stability, enabling accurate individual identification and authentication [33], [34]. Key iris features commonly utilized in recognition systems include:

1. Iris Texture: It comprises intricate patterns of ridges, furrows, and crypts that form the basis for high-resolution biometric encoding.
2. Iris Pigmentation: This is the coloration and distribution of melanin within the iris, and its contribution to individual variability, mainly under visible light imaging.
3. Crypts, Freckles, and Other Markings: These are Distinctive micro-patterns and pigment spots within the iris that remain stable over time, enhancing the discriminative capability of IRAS.
4. Pupillary Boundary: This is the circular demarcation that separates the pupil from the iris, essential for accurate segmentation and normalization.
5. Iris Geometry: It is the shape, radius, and relative positioning of the iris within the eye, offering structural cues for biometric localization [35].

Table 1 provides a summary of iris features used for IRAS.

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Table 1 *Iris feature extraction*

Feature Category	Instances	Extraction Role	Selection Role
Phase Features	Gabor phase bits	Illumination, invariant representation	Retain stable, distinct phase bits
Textural Features	Crypts, rings, freckles	Encode unique iris patterns	Select those with high inter-class variation
Edge/Contour Features	Iris boundaries, gradients	Structure delineation	Select consistent boundary descriptors
Local Keypoints	SIFT, SURF, ORB	Capture invariant interest points	Filter stable keypoints across samples
Statistical Features	Mean, variance, entropy	Global texture descriptors	Use thresholds or statistical significance
Frequency Features	Wavelet coefficients, Gabor responses	Capture multi-resolution textures	Select discriminative scales/orientations

Fig. 1 also shows the step-by-step process of IRAS, where the details of each stage are discussed in the subsection below.

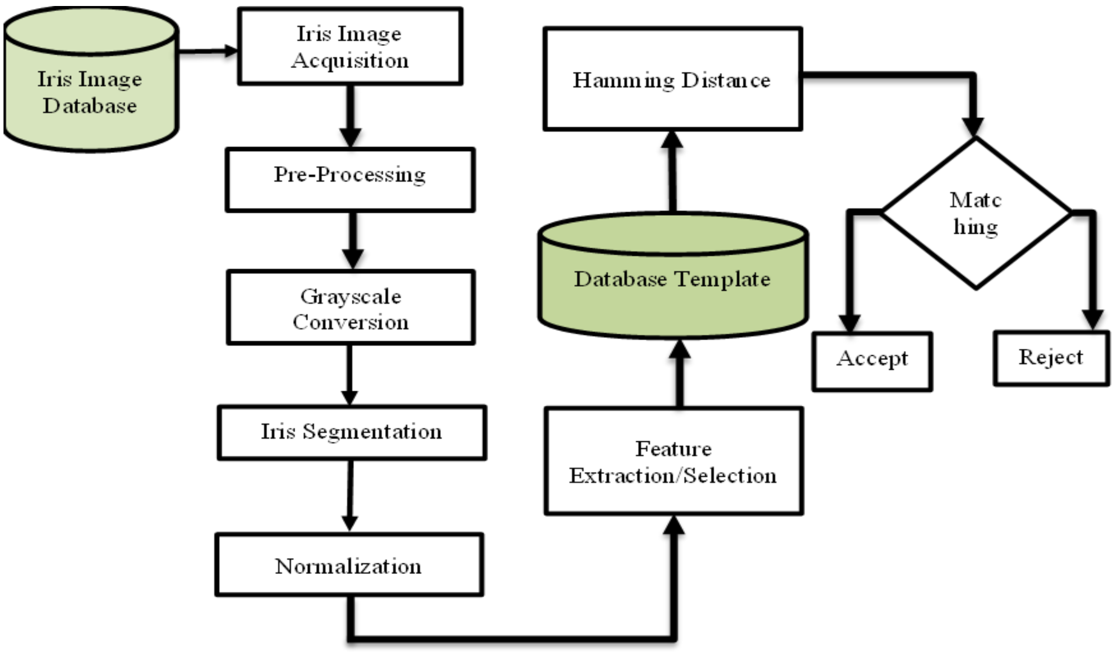

Fig. 1 *General process of IRAS*

2.1 Iris Image Acquisition

This is capturing an individual's iris image using a specialized imaging system such as a camera. It is an important stage in the IRAS where the precision of subsequent processes depends deeply on the clarity of the captured iris image [36], [37]. The visible wavelength (VW) and near-infrared (NIR) spectra represent categories of light that can be used for capturing and analyzing iris patterns [38]. NIR is the most widely used approach that captures the complex textures within the iris and minimizes reflections and distortions from the cornea, as it makes the process more robust to lighting variations. The VW is a visible light-based iris image that gains traction, especially in non-cooperative environments like remote or surveillance-based identification, but it gives additional challenges like occlusions from eyelashes, reflections, and noise [39]. There are captured iris datasets compiled by some organizations (MMU, IIT Delhi, UBIRIS, and CASIA) to provide databases as iris image reference points for preprocessing, feature extraction, and matching [38], [9], [39]. Fig. 2 shows the typical human eye captured under a cooperative environmental condition.

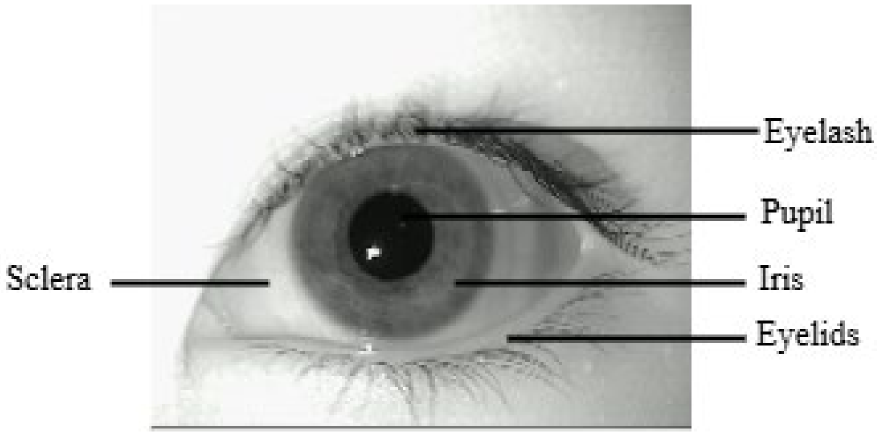

Fig. 2 *The human eye*

The CASIA iris database was developed by the "Institute of Automation at the Chinese Academy of Sciences" and is documented as the primary publicly accessible iris database. The early version of the CASIA databases was structured to emulate the ideal image acquisition conditions as defined by Daugman's foundational iris recognition model [40]. These conditions involved capturing iris images at a close distance, with the subjects pausing and looking directly into the camera.

The University Beira IRIS (UBIRIS) database is designed to provide a new instrument for assessing the viability of visible wavelength iris identification in imaging scenarios that are far from ideal. The diverse range of non-optimal image types, imaging distances, subject viewpoints, and lighting circumstances found in this collection may prove to be highly useful in defining the feasibility and restrictions of visible wavelength iris recognition [18], [39]. Table 2 summarizes some publicly available databases, detailing the number of subjects, images, resolution, and format associated with each dataset.

Table 2 *Iris image databases*

Reference	Database	Spectrum		Subjects	Images	Sizes	Features
		NIR	VL				
[41]	CASIA V1	✓		108	756	320×280	Early iris database with simple acquisition setup.
[42]	CASIA V2	✓		120	2,400	640×480	Second version of Casia.
[43]	CASIA V3	✓		1,614	22,548	640×480	Includes subsets for various environments like twins and lamp distortions.
[44]	CASIA V4	✓		3,284	32,537	640×480	Large-scale dataset with subsets for twins, lamp distortions, and occlusions.
[45]	UBIRIS V1		✓	241	1,249	800×600	Captured in visible light with noise (occlusions).
[46]	UBIRIS V2		✓	522	11,101	400×300	Focused on non-ideal conditions like motion blur and lighting variations.
[47]	IITD	✓		224	2,240	320×240	High-quality images taken in controlled conditions.
[48]	BATH	✓		400	16,000	1,280×960	High-resolution images for texture analysis.
[49]	MMU	✓		46	920	320×240	Multiple lighting conditions and occlusions for testing.
[50]	UPOL		✓	128	384	786×576	High-quality captured images in VL.

Reference	Database	Spectrum		Subjects	Images	Sizes	Features
		NIR	VL				
[51]	ICE	✓		244	3,953	640×480	Used in competitions like ICE 2005 and includes varying noise levels.
[52]	UTIRIS	✓	✓	79	1,540	2,048×1,360 (VIS)	Combines visible and NIR spectrum data for dual-spectrum analysis.
[53]	PolyU	✓		209	2,160	640×480	Contains high-quality iris images from constrained environments.

2.2 Preprocessing

Iris pre-processing is a process of separating the iris area from an eye image. It is applied to reduce noise, enhance the image, and eliminate unwanted artefacts (such as eyelids, eyelashes, reflections, or shadows) that affect the iris image [17]. The Gaussian filter, mean or median filter can be used to reduce noise and ensure good quality and reliability of the acquired iris image [54], [55]. The Gaussian filter G(x,y) is a low-pass filter used to reduce edge blur and Gaussian noise. It is mathematically expressed as:

$$G(\mathrm{x},\mathrm{y}) = \frac{1}{\sqrt{2\pi\sigma^2}} exp^{\left(-\frac{x^2+y^2}{2\sigma^2}\right)} \tag{1}$$

where σ is the SD of the Gaussian distribution, while x & y are image special coordinates.

The Recent advancements have incorporated advanced methodologies to mitigate diverse noise factors, including occlusions caused by eyelids and eyelashes, reflections, and image blurring. Table 3 shows the various modern iris noise removal methods that contribute to enhancing recognition performance

Table 3 *Advanced iris noise removal techniques*

Authors	Method	Findings
[56]	Wavelet-based denoising using Stationary Wavelet Transform (SWT)	Applies VisuShrink thresholding with the Golden Ratio for noise suppression, improving PSNR and reducing MSE.
[57]	Morphological operations	Converts images to binary and removes noise using thresholding and morphological operations. Effective for eyelid/eyelash occlusions.
[58]	Modified Whale Optimization Algorithm (MWOA) with Wavelet Transform	An improved image-denoising technique that utilizes MWOA to optimize wavelet transform parameters and achieving superior denoising performance compared to traditional methods.
[7]	This method applies the Wiener filter for deblurring iris images affected by motion or defocus blur.	The Wiener filter effectively enhances the quality of iris patterns in blurry images, improving recognition accuracy. It achieves faster execution times compared to other deblurring algorithms.
[59]	Denoising Convolutional Neural Network (DnCNN) and Contrast Limited Adaptive Histogram Equalization (CLAHE)	This work presents a framework for joint segmentation of ocular traits, employing DnCNN for denoising and CLAHE for image enhancement, resulting in improved segmentation accuracy.

2.3 Iris Segmentation

It isolates the iris region within the image, ensuring it is prepared for subsequent analysis [60], [61]. It is also a technique for detecting the actual iris region, where the accuracy of iris authentication is heavily dependent on it [62], [63].

Hsiao et al. [5] present a YOLO-based deep learning technique using a two-stage procedure for iris recognition. The iris and pupil area are extracted from the images, with the ROI identified and processed by the classifier. The segmentation of the iris ROI is performed, followed by the application of five distinct techniques to extract iris features, which are then classified using the EfficientNet deep learning model. They discovered that images without normalization yield a higher accuracy of 98%.

Hussein & Jasim [64] propose an iris segmentation technique that can handle occlusion from eye images. The ROI containing the iris is identified through the application of the entropy function and mathematical morphology techniques. The adaptive threshold was used to find the maximum entropy value for each image and applied dilation to extract the ROI for further analysis. The IITD database has been used for testing their proposed algorithm using the CNN classifier. The experimental result indicates the recognition accuracy of 93%, 98.8%, and 97.5% through the Segmentation stage, half IITD datasets and the complete datasets, respectively.

AlRifaee et al. [65] proposed an advanced segmentation technique designed to detect limbus boundaries and the pupil in iris images captured under unconstrained conditions. The method begins by converting RGB iris images into the HSV color space, followed by the application of histogram equalization to identify the sclera region. The images are then categorized into seven distinct classes. To enhance iris boundary detection, the study employs the Retinex filtering technique along with adaptive thresholding. The proposed approach was evaluated using the UBIRIS.v1 and UBIRIS.v2 datasets, achieving an accuracy of 99.32% with an EER of 1.59%. However, the author did not address the issues of occlusions and lighting conditions which may require further optimization for real-time processing.

Various techniques are employed for iris localization, including the Laplacian of Gaussian (LoG), "Canny Edge Detector, Hough Transform, and Integro-Differential Operator, Sobel Operator", among others [20], [66], [67], [68], [69]. Fig. 3 Shows an edge map of an iris area and pupil boundary using the HT technique, where the red and green circles represent the limbic boundary.

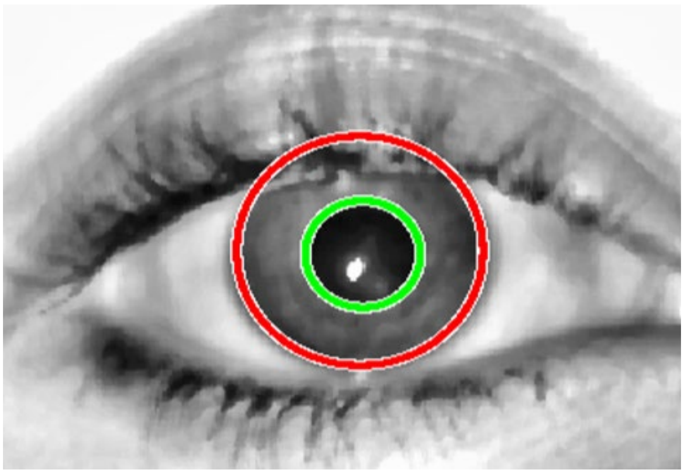

Fig. 3 *Iris segmentation using Hough transform*

2.4 Normalization

This process involves transforming an iris image into a standardized rectangular format to minimize variations caused by factors such as camera angle, pupil dilation, lighting conditions, and scaling, thereby improving the performance of the IRAS [55]. The normalization techniques include the Rubber sheet model, the Fourier transform, and Wildes' normalization, among others [70], [14], [40]. Daugman's normalization method is widely used to transform a localized iris texture [8], [71], [72], as shown in Fig.4.

Fig. 4 *Iris normalization [8]*

2.5 Iris Feature Extraction

This is a process of selecting unique patterns and characteristics from iris images for identification and authentication [18]. Several feature extraction techniques exist in the literature to extract unique features like texture patterns, orientation and direction, phase, and frequency information. These techniques include wavelet transform [73], Gabor filter [40], [74], Local Binary Pattern (LBP) [75], [37], log-Gabor filters [76], discrete cosine transform (DCT) [71], Scale Invariant Feature Transform [77], [78], among others. A brief review of these techniques is detailed in Section 3.

2.6 Iris Feature Selection

Feature selection is a fundamental technique in data analysis and machine learning that aims to identify the most relevant and informative features within a large dataset while removing redundant or irrelevant ones [26]. It is a vital stage in the recent development of the IRAS that focuses on selecting the most distinctive and discriminative features for improving the accuracy and speed of the system [79]. Several feature selection techniques have been used in iris recognition, like Fuzzy Particle Swarm Optimization (FPSO) [80], Genetic Algorithm (GA) [81], particle swarm optimization (PSO) [60], and Black Hole Optimization (BHO) [25], among others. A discussion of some FS techniques is stated in Section 4.

2.7 Matching

The extracted and selected iris features are utilized for the matching process, where they are compared against stored templates in the database [82], [83]. This comparison is performed using various matching algorithms, including template matching and machine learning-based approaches, to assess the similarity or dissimilarity between iris patterns [84], [13]. The following bullet points discuss some of these approaches to template matching.

2.7.1 Euclidean Distance

This is a method used to measure the similarity or proximity between two iris feature templates [85]. It measures the difference between the spatial and extracted features of iris images and computes the distance between them. The smaller the distance, the closer the match, indicating a higher level of similarity between the iris features [86]. It is calculated between two template vectors by:

$$P_1\,(r_1, q_1)\ \&\ P_2(r_2, q_2) = \sqrt{[(r_2 - r_1)^2 + (q_2 - q_1)^2]} \tag{2}$$

where $P_1\,(r_1, q_1)$ represents the first iris feature containing the pixel's x and y coordinates, and $P_2\,(r_2, q_2)$ is the second iris image containing the same data [87].

2.7.2 Hamming Distance

This is a metric that quantifies the number of differing bits between two binary patterns [88]. The Hamming distance provides a quantitative measure of dissimilarity, where a higher distance suggests greater dissimilarity between the patterns, indicating the likelihood of different irises being compared [89]. The matching technique using the Hamming distance approach is defined by:

$$HD = \frac{1}{N}\sum_{j=1}^{N} X_j \oplus Y_j \tag{3}$$

where X_j represents the jth feature of the tested iris, Y_j denotes the jth feature of the iris template, and N is the total number of bits in the feature vector. $\oplus$ is the element-wise exclusive-or operator.

2.8 Evaluation Parameters

There are several metrics used to assess and evaluate the performance of a matching process in an iris recognition system. Among these are Genuine Acceptance Rate (GAR), False Rejection Rate (FRR), Equal Error Rate (EER), False Acceptance Rate (FAR), and accuracy. The FAR represents the rate of instances where an impostor is incorrectly accepted [90]. On the other hand, the FRR is the rate at which genuine candidates are falsely rejected. Meanwhile, a GAR refers to the instances where genuine candidates are accepted [22]. The FAR, FRR, and GAR can be expressed as:

$$FAR = \frac{wrongly\ accepted}{total\ impostor\ comparison} \times 100\% \tag{4}$$

$$FRR = \frac{wrongly\ rejected}{total\ genuine\ comparison} \times 100\% \tag{5}$$

$$GAR = \frac{genuine\ accepted}{total\ genuine\ comparison} \times 100\% \tag{6}$$

Or $$GAR = 1 - FRR \tag{7}$$

The EER is another key metric that balances FAR and FRR. It is the point at which the FAR and FRR are equal, representing an optimal trade-off between security and usability. EER is found by plotting the Receiver Operating Characteristic (ROC) curve, where FAR and FRR are plotted against the threshold value, where the lower the EER, the better the system's overall performance.

The overall classification accuracy of the IRAS evaluates how well the system correctly identifies users. It is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

where the meaning of each component and its significance in the IRAS are as follows:

- True Positive (TP): The system correctly identifies an iris image as belonging to a known subject.
- True Negative (TN): The system correctly rejects an iris image that does not belong to any enrolled subject.
- False Positive (FP): The system incorrectly accepts an unauthorized iris image as a valid subject (i.e., an imposter is accepted).
- False Negative (FN): The system incorrectly rejects a valid subject's iris image (i.e., fails to recognize an enrolled user).

3. Iris Feature Extraction and Selection

This section reviews various studies that employed one or more feature extraction techniques (FET), as well as the fusion of feature extraction and selection algorithms, to authenticate individuals. Fig. 5 depicts the evolution of previous FETs before 2010 to the current trend, which is 2025. The brief discussion of each period is presented in the following paragraph.

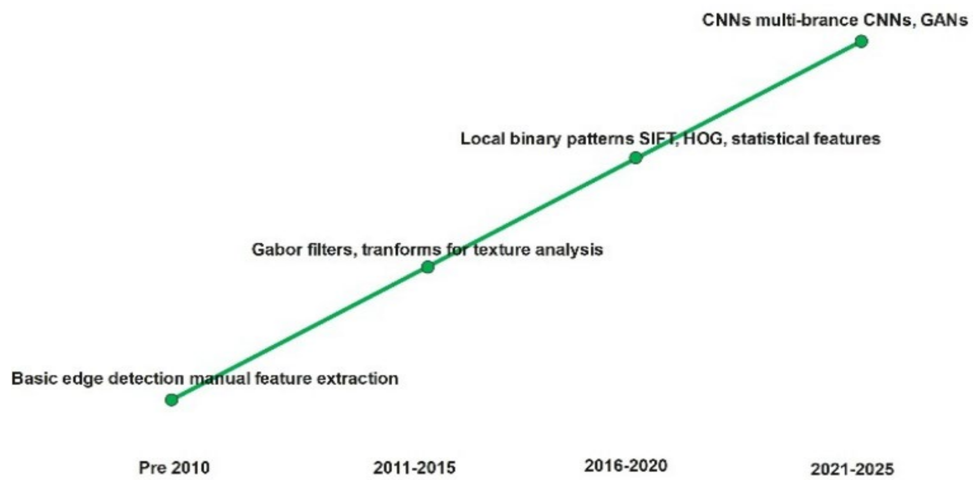

Fig. 5 *Evolutionary diagram of FET before 10 years to date*

In previous years (pre-2010), researchers have established the foundation for iris recognition, focusing on basic edge detection and hand-crafted feature extraction methods that extract simple structural signals are dominated [3], [40]. It then moves on to the robust texture, phase, and statistical feature extraction, often using Gabor filters [14], [32], [51]. The adoption of 2DGabor filters and wavelet transforms enabled more complex texture analysis of iris patterns, and it was witnessed during the period 2011–2015 [41], [71]. The transition from

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single-method algorithm to multi-algorithmic and hybrid feature extraction, with an emphasis on handling rotation and occlusion to increase computational efficiency and robustness [86], [88], [89]. The techniques are expanded to include LBP, SIFT, HOG, and various statistical features to enhance robustness and invariance [91], [55], [92]. The conversion of handcrafted feature extraction to deep learning approaches (CNNs) started in 2016–2020 for noisy, occluded, and incomplete or partially captured iris images [93], [94], [95]. It has gained significant attention from many researchers to enhance recognition performance. Hybrid approaches and the integration of machine learning for feature selection became increasingly common, reflecting the need for both accuracy and efficiency in real-world iris recognition systems [11], [16], [23] [36].

In this study, we focus on the most recent articles that highlight issues like distorted iris images, incomplete, off-angle, and occluded (eyelashes/eyelids) images. We also explored recent trends in iris feature extraction that have shifted toward deep learning approaches, particularly CNNs, which automatically learn hierarchical and discriminative features from raw iris images, enhancing robustness to noise, occlusion, and image quality variations. Fusion models combining texture, frequency, and spatial features using handcrafted FE techniques and transfer learning have gained prominence for recognition accuracy. To manage high-dimensional data, techniques like PCA, LDA, and weighted subregion fusion are commonly employed. In terms of feature selection, current methods emphasize discriminative and optimization strategies, including sparse learning, and metaheuristic algorithms such as PSO and Genetic Algorithms (GA). These are often integrated with feature extraction techniques and classified using machine learning classifiers (SVMs) or CNNs for efficiency and accurate recognition. The following subsection discusses recent methods used for FE/FS approaches.

3.1 Iris Feature Extraction Techniques

In 2004, Daugman proposed a two-dimensional (2D) Gabor filter, which integrates a sinusoidal plane wave modulated by a Gaussian envelope. This approach enhances the effectiveness of feature extraction and improves feature distinguishability, with the iris code generated using both real and imaginary components [96].

Huo *et al.* [92] introduced a feature descriptor for iris recognition by combining uniform local binary pattern (ULBP) transcoding and Gabor filters. The method involves pre-processing the iris images and extracting multi-orientation imaginary (MOI) features using a 2D-Gabor filter and then encoding the MOI features using uniform LBP. The use of blocked histogram statistics for MOI features and ULBP transcoding improved recognition accuracy, and the proposed method demonstrated outstanding performance. Despite the improved performance of the proposed method, there is a need for comparison with existing methods, as it was only compared with MOI and LBP [92].

A novel approach to enhancing iris recognition accuracy by combining Gabor filters with steerable pyramid decomposition (SPD) for feature extraction is proposed [97]. The methodology involves three main phases: preprocessing, feature extraction, and classification. In the preprocessing stage, the CHT is used for iris segmentation, while Daugman's rubber-sheet model is applied for normalization. Feature extraction is performed using Gabor filters to capture texture details, followed by steerable pyramid decomposition to extract multi-scale and multi-orientation features. High-frequency sub-bands are removed to minimize noise and enhance recognition accuracy. The approach is tested on three widely used iris databases: CASIA-v4, IITD, and UPOL. The proposed method achieves an impressive 99.99% accuracy on the CASIA-v4 database, outperforming other existing approaches. However, the real-time efficiency of the method is not extensively evaluated, which may affect its applicability in high-speed security environments.

Danlami *et al.* [98] developed a framework for recognizing incomplete iris images using a Legendre wavelet filter. This study addresses the limitations of existing systems, which often rely on frontal, high-quality images. The framework uses databases such as CASIA, MMU, and UBIRIS, focusing on segmentation, normalization, and feature extraction with Legendre wavelet filters. Experimental results demonstrate that partial iris recognition is feasible with a minimum of 12.5% of the iris region, although the optimal performance was observed at 16.5%. These findings establish thresholds for the minimum iris region size required for reliable identification. The introduction of partial iris recognition and the application of Legendre wavelet filters represent significant contributions to the field. Moreover, it suggests further exploration of additional techniques and creating a dedicated database for partial iris recognition [98].

Meanwhile, an iris feature extraction method based on the SIFT algorithm has been proposed for near-infrared (NIR) and visible spectrum (VS) iris images [77]. The results indicate that the method achieved 96.2% and 96.4% accuracy with the CASIA_v1 and ITTD_v1 databases, respectively. However, the accuracy decreased to 84.0% when using the UBIRIS_v1 database, attributed to challenges associated with visible spectrum images, such as image blur and occlusion.

Furthermore, Sun *et al.* [99] "introduced an iris recognition technique combining Local Circular Gabor Filters (LCGF) and Multi-Scale Convolution Feature Fusion Networks (MCFFN)." This approach leverages LCGF for data augmentation to address inaccuracies in iris registration caused by its annular structure. Experimental evaluations using the Sync and Lamp iris databases demonstrated that the method effectively enhances dataset quality and facilitates the construction of the MCFFN model. It also mitigates the impact of registration errors while preserving fine details such as small wrinkles and pigment spots within the iris texture. Despite the high recognition rate achieved, the study acknowledged a limitation in addressing the discrimination of unknown classes, highlighting this as a focus for future research to enable open-set identification [99].

Regencia *et al.* [100] investigated the integration of fuzzy logic into IRS, coupled with an enhanced Morlet wavelet transform for feature extraction. This approach addresses challenges associated with non-ideal iris images, including blurring, specular reflections, occlusions, and off-angle captures. The image is pre-processed using Gaussian Blur and Canny Edge detection. The feature extraction stage comprises two distinct processes: crucial information is obtained from the pre-processed iris image, and relevant details are extracted from the Gaussian-blurred image. The Morlet Wavelet is combined with a fuzzy logic model to enhance the system's understanding of the features extracted from the iris image, supporting the making of accurate decisions. The fuzzy logic model is then used to classify the input features. The researchers generated 700 image datasets that contained noises such as blurred images, off-angle, and occlusion. Table 4 indicates the summary of feature extraction techniques and the accuracy of the existing research work. The approach indicated that 85.43% overall accuracy was achieved. However, the system works on non-ideal datasets with poor recognition accuracy, and an additional technique is needed to improve the system's performance [100].

Table 4 *Feature extraction techniques and performance*

Author	Feature Extraction Technique	Database	Contribution/Strength
[55]	It integrated the Gabor filter with GRF, a DoG filter, a BSIF, and LBP descriptors.	The Poly U dataset	It attained a good performance at EER of 1.02% and accuracy of 98.97%.
[92]	MOI features are Extracted via a 2D-Gabor filter, then Block histogram statistics and ULBP transcoding.	CASIA-V1, CASIA-iris -Lamp and JLU Databases	The accuracy is achieved as CASIA-V1 98.34%, CASIA-iris -Lamp 98.09% and JLU 99.16 %.
[97]	Features are extracted using Gabor filters with SPD	CASIA-v4, IITD, and UPOL	The method achieves 99.99% accuracy on the CASIA.v4 database.
[98]	Legendre wavelet filter	CASIA, MMU, and UBIRIS	It demonstrates that partial iris recognition is achieved with a minimum of 12.5% of the iris region, but optimal performance was yielded at 16.5%.
[93]	The log-Gabor filter and RBFNN in a feed-forward architecture for extraction and classification.	CASIA iris Database	The system's accuracy in CASIA.v1 is 97%, while CASIA.V4 is 95% .
[91]	An optimized coarse-to-fine scheme and adaptive detection for eyelashes, then non-circular iris contours are regularized.	CASIA.v3-Interval, IITD.v1, and MMU.v1 database	It achieved accurate marking of iris contours of 99%, 98%, and 97.86% to the used database.
[94]	The CNN model is used to learn and extract features and classify them using softmax.	The IITD and CASIA datasets	The system exhibited a high accuracy of 96%.
[95]	The SURF technique generates key points. LBP and DTCWT for texture characterization.	The UPOL and UBIRS Iris database	The best result for the UPOL dataset is 97.14% using DTCWT, 88.80% using LBP and for the UBIRIS dataset is 97.43% for both LBP and DTCWT.
[77]	SIFT	The CASIA v1 and ITTD v1 databases	The CASIA_v1 and ITTD_v1 show good results of 96.2% and 96.4%, respectively. It dropped to 84.0% using UBIRIS_v1.

Author	Feature Extraction Technique	Database	Contribution/Strength
[99]	It uses LCGF and the MCFFN for feature extraction.	The CASIA.Iris Lamp and CASIA.Iris Sync Databases	The recognition rate of 99.7% and 98.62% is obtained for CASIA.Iris Lamp and CASIA.Iris Sync Databases, respectively.
[31]	It integrates segmentation and edge detection using CNN and is classified using HD.	IITDelhi, MMU, and CASIA.v4-Interval	It attained accuracies of 94.88% using CASIA, 96.56% for IITD, and 98.01% for MMU.
[100]	It combines Morlet Wavelet and fuzzy logic model to enhance features extracted and classification.	The 700 image datasets are generated	The approach indicated that 85.43% overall accuracy was achieved.

3.2 Iris Feature Extraction and Selection Techniques

Subban *et al.* [80] introduced an iris recognition framework that integrates "Haralick feature-based extraction with fuzzy particle swarm optimization (FPSO)" to enhance recognition accuracy. The approach employs weight-sampled geodesic active contours for precise iris edge segmentation, while Haralick features are utilized for feature extraction. FPSO is further applied to select the most significant features from the extracted dataset, and a relevance vector machine is used for model evaluation. Experimental findings indicate that the proposed method achieved a perfect accuracy rate of 100% on the CASIA-V3 database. However, the system needs to be tested with different databases to ascertain the claimed results.

Ahamed & Ali-Meerza, [60], proposed a low-complexity iris recognition system that utilizes Particle Swarm Optimization (PSO) to accurately locate the pupil and transform the image into the Curvelet (CV) domain. This approach significantly reduces computational time by employing a shorter feature length and was evaluated using the CASIA.Iris.v4 database. The PSO algorithm determines an optimal threshold value, resulting in a lower EER and a higher CRR. Experimental results indicate that the proposed method achieved an accuracy of 99.4% with a feature length of 472, demonstrating improved efficiency compared to other iris recognition systems [60]. However, the parameters and methodologies used for comparison with state-of-the-art systems are not adequately detailed, limiting the ability to fully validate the system's accuracy.

Meanwhile, Garg et al. [81] introduced an iris recognition approach that integrates "2-Dimensional Principal Component Analysis" (2DPCA) for feature extraction and GA for feature selection. This method reduces the dimensionality of iris features before classification to preserve essential information. A "Back Propagation Neural Network" (BPNN) utilizing Levenberg-Marquardt's learning algorithm is employed for the recognition process. Experimental results indicate that the 2DPCA-GA approach achieves a classification accuracy of 96.4%. The study also explores the potential of fusing iris biometrics with complementary biometric traits to further enhance recognition accuracy [81]. However, the proposed method exhibits high computational complexity, with a processing time of 7271 ms. The summary of feature Extraction/selection techniques with their performance is in Table 5.

Table 5 *Feature extraction/selection techniques and performance*

Author	Feature Extraction/Selection	Databases	Contribution/Strength
[101]	• 1D-`log-Gabor wavelet is used to extract features. • MOGA as feature selection and SVM for classification.	CASIA & ICE	The recognition rate of 99.81% on CASIA and 96.43% on ICE dataset are achieved.
[102]	• DCT and Garbo filter are used to extract features. • DBPSO for feature selection	IITD & MMU Database	96.46% is achieved for the IITD dataset, while 78.07% is in the MMU database.
[28]	• The 1st.order and 2nd.order statistical measures are used for textural feature descriptors. • Statistical dependency-based feature selection with BPNN is for classification.	CASIA_V1, CASIA_V3, and UBIRIS_ V1	The accuracy of 99.38%, 99.84%, 98.24% and 96.24% are achieved on four different datasets.

Author	Feature Extraction/Selection	Databases	Contribution/Strength
[80]	• Haralick is used to extract the key features. • FPSO for FS	CASIA-V3	100% accuracy is ascertained for all tested iris images but few failed due to noise.
[81]	It uses 2DPCA and GA for feature extraction and selection, and implements BPNN using Levenberg-Marquardt's learning algorithm	CASIA-V3 database	A high accuracy of 96.4% is achieved.
[60]	• Utilize the curvelet transform for feature extraction. • Apply PSO for accuracy optimization	CASIA-V4 database	It achieved a high recognition rate of 99.4% with a feature length 472.
[25]	• It uses Gabor Filter and LBP as feature extraction techniques. • VLBHO and SVM/ LR for feature selection and classification	The IITD and CASIA	The 95.982% accuracy is achieved for Gabor and LBP using the SVM classifier, while 99.107% for LBP using the LR classifier.
[103]	• The Gabor-based wavelets are used to extract key iris features (texture, color, and size). • GA for selecting the best feature	CASIA.v1	classification accuracy percentage is not stated
[104]	• It uses ScatT-Loop descriptor and LGP to extract features • It combined Chronological theory with the Monarch Butterfly Optimization (MBO).	UBIRIS.v1	It yields a maximum accuracy (k.fold) of 98.0571%
[105]	• 1st-order statistical features and 2nd-order features (GLCM) area used to extract features. • SDBFS for selecting most relevant features	CASIA.v1, VASIA.v3, and UBIRIS.v1	It achieved 94.04%, 98.11%, and 92.24% from different databases

4. Discussion and Future Direction

In the last 15 years, a lot of advancement has been achieved in the iris recognition domain by different researchers, especially in reliably authenticating individuals. Traditionally, the iris recognition system comprises four main stages. In modern implementations, feature selection is incorporated to enhance both the speed and accuracy of the system [25], [102]. The extraction of the iris feature is vital, as the precision/accuracy and efficiency of the system are deeply dependent. The researchers need to explore more feature extraction techniques apart from the Gabor filter, LBP, and wavelet transform, as shown in Table III and use either an AI-based or a conventional method for recognition/classification. A fusion of feature extraction and selection techniques can improve the system performance, as clearly indicated in Table 3. However, dealing with iris images acquired in unconstrained conditions with the VS (UBIRIS.V2) is challenging and needs further investigation.

The iris images with issues like off-angle, poor resolution, distance, noise (eyelids/eyelashes), incomplete capture, and poor illumination acquired under unconstrained conditions make it difficult to authenticate individuals. As a result of these challenges, the researcher needs to investigate good feature extraction/selection techniques that can handle noisy iris images differently from the existing methods to ensure the accuracy and efficiency of the system.

According to the literature, the fusion of feature extraction and selection for iris recognition yielded more accuracy, especially when properly choosing good feature selection, such as BHO, FPSO, and GA [80], [28], [60], [81]. The feature selection techniques: Whale Optimization Algorithm (WOA) [106] , Grey Wolf Optimizer (GWO) [107], Ant Colony Optimization (ACO) [108] are swarm intelligent with additional properties compare to PSO. These could help researchers when combined with feature extractors to improve the speed and accuracy of IRS.

The iris recognition system can be implemented on a phone device, even with challenges like noise, illumination, off-angle or uncooperative subjects, by using hybrid feature extraction/ selection techniques. Additionally, phone devices using an iris recognition system are mainly used to authenticate individuals or protect

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data. It is essential to unlock the mobile phone without partial contact (thumbprint) using an iris recognition system, even though it requires good computational time due to the low CPU in the phone device. For these reasons, researchers should strive to improve the computational time by fusing feature extraction/selection techniques at the feature extraction stage and machine learning (CNN) or conventional techniques for classification/ recognition.

5. Conclusion

This review paper examines feature extraction and selection techniques aimed at improving iris recognition systems. It explores the potential of various feature extraction methods and evaluates their impact on accuracy. Similarly, the fusion of iris feature extraction and selection was surveyed and performed better. The study also examines various challenges associated with iris recognition systems and explores potential solutions to mitigate these issues.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Muhammad Ghali Aliyu, Sapiee Jamel;* ***data collection:*** *Muhammad Ghali Aliyu, Muktar Danlami;* ***draft manuscript preparation:*** *Muhammad Ghali Aliyu. All authors reviewed the draft and approved the final version of the manuscript.*

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