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Review

Iris Recognition Based Deep Learning: A Survey

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Abstract

The iris recognition system is one of the most reliable biometric authentication systems owing to its individuality and permanence. With the introduction of deep learning concepts, especially CNNs, iris recognition models have improved tremendously in accuracy, robustness, and efficiency. We present an extensive survey summ2arizing the application of deep learning in iris recognition; covering datasets, feature extraction, architectures, and evaluation metrics. We conclude that while CNNs and transfer learning produce the best accuracy on well-constrained datasets, serious challenges lie with cross-sensor generalization and robustness under mobile or unconstrained environments. The new solutions that are generating attention, such as generation adversarial network-based augmentation and attention-driven architectures, are solution pathways to surmount data scarcity and further strengthen the adaptation capability. This survey is aimed at steering researchers and practitioners to various critical challenges and directions that have the most potential for future iris recognition systems.

Keywords: Iris Recognition; Deep Learning; Convolutional Neural Network; Transfer Learning, Biometrics.

1. Introduction

Biometric authentication systems have gained prominence due to the need for secure and reliable identity verification because there is a burning need for the secure and trustworthy verification of identity. Basically, these systems work on the basis of distinct biological characteristics of an individual, such as fingerprints, facial patterns, and iris patterns. Among them, iris recognition happens to be a very important process because it is one of the most accurate and stable biometric methods [1,2]. The iris, the colored ring surrounding the pupil, exhibits complex, unique patterns that remain stable over a lifetime, which presents a specific pattern unique to every person. This remains constant over a person's lifetime, thus ensuring excellent biometrics. Iris recognition involves several important steps that should be used for accurate identification and authentication of individuals based on iris patterns [3,4]. The first step is obtaining biometric high-resolution images of the iris by the use of conveyor-based cameras or iris scanners. These devices work on the principle of near-infrared light to collect highly detailed and well-defined images from the iris. This works beneficially by well-discriminating one iris from the other based on crypts, furrows, and other complex structures [5].

The next step after acquiring the iris images is preprocessing. This stage contains several techniques that may be applied to improve the quality of the images: normalization, segmentation, and image enhancement [6]. After acquiring iris images, preprocessing techniques are applied to improve quality and prepare them for analysis. These include normalization (transforming the iris image to a standardized shape to correct for pupil dilation or eyelid occlusion),

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segmentation (isolating the iris region from eyelashes and reflections), and image enhancement (contrast adjustment, noise reduction, and overall quality improvement). Once preprocessing is complete, distinctive iris features such as edges, textures, crypts, and furrows are extracted and encoded into a mathematical template. Common approaches include Daugman's rubber sheet model, which maps the iris into a fixed-size coordinate system, and Gabor filters, which capture fine texture details. The resulting template serves as a secure digital representation of the iris, enabling accurate comparison and authentication [7].

Feature extraction encodes distinctive iris characteristics into a mathematical template. This involves finding significant points, edges, textures, and other distinctive features in the iris pattern. There are a variety of feature extraction methods, but he commonly uses Daugman's rubber sheet model (an iris normalization adjustment scheme that maps the whole region of the iris into a fixed-size rectangular coordinate system for comparison across samples) and Gabor filters, which effectively capture the detailed texture of the iris [8]. The last step, post-feature extraction, is the formation of a template or digital representation of the iris bearing encoded internal features. The template is encrypted for unauthorized users to gain access or misuse the biometric substance [9].

During comparison, two iris images are compared: that of an already kept template in the database, with a new image taken during identification or authentication period. Both similarity measuring techniques for matching can either be on the basis of Hamming distance or correlation. The individual is verified if the similarity crosses a threshold value [10]. In the end, the decision on the authentication results is based on the similarity:

The sections that follow in this paper are organized in the following manner: an extensive discussion on iris recognition is presented in Section 2; Section 3 studies the application of Deep Learning (DL) in iris recognition. Section 4 presents the datasets used by the surveyed DL models and highlights their characteristics. Section 5 covers the prominent metrics commonly used in iris recognition. Section 6 conducts a literature review on iris recognition utilizing DL algorithms. The findings from the literature review are thoroughly examined and analyzed in Section 7. Section 8 outlines the identified limitations in the surveyed DL models while highlighting promising avenues for future research. Lastly, Section 9 concludes this paper by summarizing the key insights derived from the examined DL models.

2. Review Methodology

Iris recognition has attracted considerable attention lately in the security domain. This is mainly attributed to the fact that iris images have an assortment of immutable characteristics that can be seen in their patterns and textures: components such as freckles, corona, rings, and ciliary processes.

John Daugman initiated the excitement for iris recognition in the early 1990s; he developed the initial iris recognition system that used the 2D Gabor wavelet transform. This was a defining moment for the field. In 1994, devised a machine to authenticate users via iris recognition. This was soon followed by numerous researchers who took a keen interest in the problem of iris recognition. Past work has involved different approaches to obtaining manually designed features from the iris. generated an "IrisCode" by converting iris data and used Hamming's distance for measuring recognition. This compared the IrisCode of an input iris image with the IrisCodes recorded in the database.

In the past, the researchers proposed the use of deep scattering convolutional features for iris identification, and this approach was quite dissimilar from the pure deep learning process, to which they claim to be limited; however, it uses a deep scattering convolutional network in extracting salient features from images,' performance evaluation and comparison of iris recognition system based on deep scattering convolutional features with other popular and commercially available systems. The images produced at various points within the scattering network represent the altered versions of an image at various orientation and scales. The outcome of this entire process actually yielded images produced by a filter set with five different scales and six different orientations. Definitely, the experiments showed that their approach achieved high accuracy when tested on the IIT Delhi dataset.

This survey does not involve original experiments; instead, it systematically reviews existing research on deep learning techniques for iris recognition. To ensure comprehensive coverage, we adopted the following methodology:

- Selection of Studies: We considered peer-reviewed articles, conference papers, and benchmark datasets published between 2016 and 2024, focusing on deep learning approaches applied to iris recognition;
- Organization: The selected works were categorized according to preprocessing techniques, feature extraction methods, deep learning architectures (e.g., CNNs, transfer learning, GANs), and evaluation metrics;

- Analysis: Each study was examined for its methodology, dataset usage, reported performance, and limitations. Comparative insights were drawn to highlight trends, strengths, and gaps in the literature. This structured approach ensures that the survey provides a clear and balanced overview of the state of the art in iris recognition using deep learning.

It is really interesting to note that many traditional iris recognition processes have several stages of preparation, such as iris detection, normalization, and enhancement, as illustrated in Figure 1. After performing these processes, feature extraction is performed for the improved or normalized image. In contrast, many recent studies in iris recognition have produced high accuracy in recognition without normalization and enhancement processes. This high performance can be ascribed to the capability of deep learning models to extract sufficient distinguishing features from raw iris images and hence perform robustly during the iris recognition task.

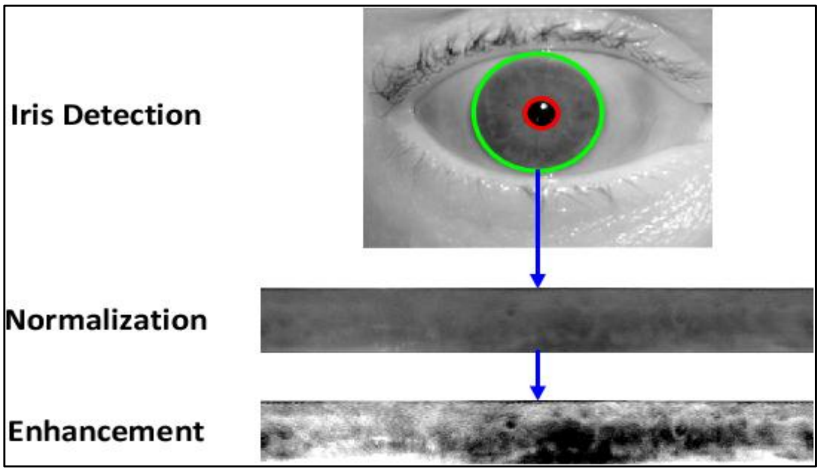

Figure 1. illustrates the preprocessing pipeline in iris recognition, including segmentation, normalization, and enhancement [3].

3. Deep Learning Techniques in Iris Recognition

By virtue of deep learning technology, there have been all possible quality improvements in many highly precise biometric identification methods such as iris recognition. Deep learning refers to those subfields of machine learning that use neural nets with multiple levels to extract features and patterns from data. It thus makes iris recognition systems more accurate, robust, and efficient.

3.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNN) are basically a deep learning architecture that is actually devised to inject into the world of handling visual information. With hierarchically structured characteristics akin to the human visual systems, CNNs have proven their mettle in various applications such as image classification, object detection, and segmentation, and more advanced applications such as those found in video analysis and natural language understanding [11].

CNNs are constructed from multiple layers and include convolutional, pooling, and fully connected layers, which work together in a structured hierarchy that progressively extracts features with increasing levels of abstraction. In iris recognition, the CNNs can automatically learn distinguishing characteristics from raw iris images, such as unique textures and structural patterns (e. g., furrows, crypts, and collarettes), which are different for each individual. According to Al-Waisy [12], figure 1 illustrates the main components of CNNs, which are as follows:

1. Convolutional Layers: Usually, an image is subjected to convolution operations such as element-wise multiplication and summation to yield feature maps with layers that apply trainable filters (kernels) on its input iris image. The filters act as localized pattern detectors and learn to recognize important features from different regions of the iris. As the training proceeds, the filters will adapt to the most important features for the recognition task;

2. Pooling Layers: Positioned after convolutional layers, pooling layers (commonly max or average pooling) reduce the spatial dimensions of the feature maps. This step retains critical information while discarding less relevant details, thus enhancing computational efficiency and making the model more robust to variations in position or scale within the iris;
3. Fully Connected Layers: These layers consolidate all the features extracted by earlier layers and perform the final classification or similarity evaluation. In iris recognition systems, they are responsible for distinguishing between individuals by learning high-level representations necessary for verification or identification.

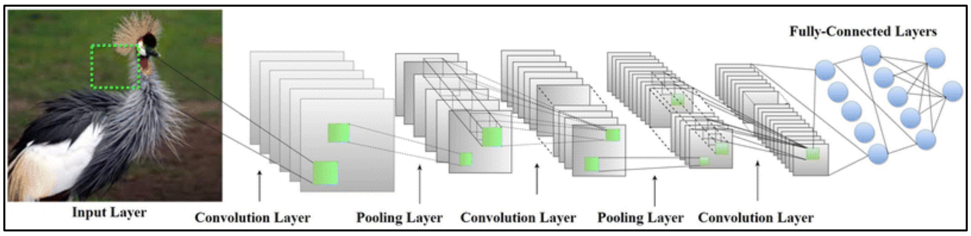

Figure 2 presents a simple CNN architecture, highlighting the flow from convolutional layers to pooling and fully connected layers [12].

3.2 Transfer Learning

The use of one model, which was trained on one task, for reuse or adaptation onto another task that is somewhat related to the original one, defines transfer learning. The source domain is one, and the target domain for the application of knowledge is another. An application of transfer learning will mostly imply faster training, better performance, and less data usage as compared to training a model from scratch [13].

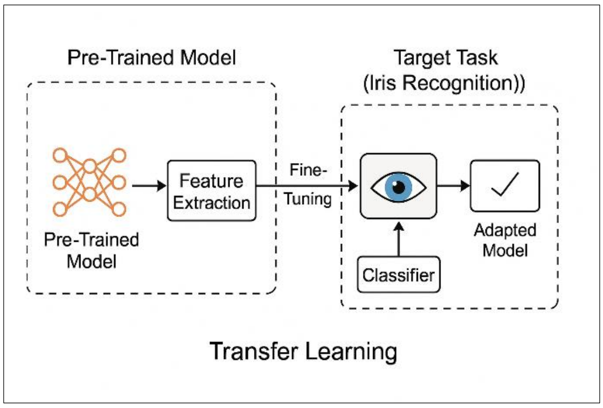

Figure 3. Transfer learning in iris recognition using a pre-trained model adapted through feature extraction and fine-tuning.

3.2.1 Strategies in Transfer Learning for Iris Recognition

Transfer learning is a speedy evolving and highly advantageous sphere in machine learning where models trained for one task help boost the performance of another highly related yet different task. In iris recognition, where a biometric authentication framework authenticates people based on the exclusive patterns of their iris, transfer learning can be a valuable technology here in some aspect to further improve the efficiency and accuracy of the recognition model. Different applications of transfer learning approaches to iris recognition will be analyzed, including the selection of pretrained models and different techniques of fine-tuning. The application of transfer learning is an attempt by the researchers to develop robust, accurate, and adaptable iris recognition systems for a variety of real-world scenarios [14]:

1. Feature Extraction: Most of these approaches leverage the use of feature extraction for previously learned convolutional neural networks (CNNs). Its characteristic hierarchical feature extraction chains-from learning edges through textures and finally to patterns-are all found in the layers of the CNN. For feature extraction from iris images, the classification layers of the pre-trained CNN are removed. The derived feature representations are next input to another classifier or model specifically designed for a defined task in iris recognition;

2. Fine-tuning: Fine-tuning refers to the process wherein one takes a previously trained model and alters it by adapting the weights with respect to data that has been tailored to a specific task or domain. In the case of iris recognition, fine-tuning may include re-training certain layers of a pre-trained CNN endowed with iris images labelled for the task at hand, so as to provide the model with the ability to fine-tune its learned features to the specific requirements of iris texture and structures;

3.2.2 Benefits of Transfer Learning in Iris Recognition

Transfer learning is thus highly beneficial in the domain of iris recognition as it offers options to deal with challenges faced by the classical training approach. There are many possible advantages of transfer learning applied to iris recognition [15].

1. Data Efficiency: Transfer learning helps in situations where labeled iris data is limited or costly to obtain. Leveraging pre-trained models reduces the need for extensive labeled data in the target domain;
2. Improved Convergence and Performance: Initialization of models incorporating learned representations will speed up the convergence of training and potentially improve performance on iris recognition tasks with the help of transfer learning;
3. Generalization: Models CASIA-Iris-1000 Dataset [16]: This data set consists of images of irises numbering 20,000, which were taken from about 1,000 individuals see Figure 3. These were captured using the IKEMB-100 camera developed by Iris King. Importantly, this dataset includes variations within the same class; most primarily due to eyeglasses and specular reflections. As one of the first publicly available iris datasets covering up to a thousand subjects, it is a rich resource for studying the unique features of the iris pattern;
4. trained using transfer learning techniques tend to generalize better to new, unseen iris data or imaging conditions by capturing more generalized and robust features from the source domain.

3.3 CNN Architectures in Iris Recognition: VGG, ResNet, AlexNet, and Beyond

Several CNN architectures have been adapted for iris recognition, each offering unique strengths:

- VGGNet: Known for its deep but uniform architecture, VGGNet has been widely used for feature extraction. Studies [17] demonstrated that mid-layer features of VGGNet yield higher accuracy compared to fully connected layers when applied to iris datasets such as CASIA-1000 and IIT Delhi.
- ResNet: By introducing residual connections, ResNet addresses the vanishing gradient problem and enables training of very deep networks. Menon and Mukherjee [18] fine-tuned ResNet18 for iris recognition, achieving recognition rates of 99.8% on IITD and 95.36% on UBIRIS.v2.
- AlexNet: One of the earliest deep CNNs, AlexNet has been applied to iris recognition with preprocessing steps such as circular Hough transform for iris detection. Alaslani & Elrefaei [19] showed that segmented iris images fed into AlexNet achieved higher accuracy than normalized images.
- Other Architectures: Emerging models such as DeepIrisNet [20] and fully convolutional networks [21] further demonstrate the adaptability of CNNs to iris recognition tasks, incorporating dropout, batch normalization, and novel loss functions.

By consolidating these architectures into a single subsection, the paper provides a unified view of CNN-based approaches, avoiding repetition and highlighting comparative strengths.

3.4 Recurrent Neural Networks (RNNs) and LSTMs

- RNNs, particularly Long Short-Term Memory (LSTM) networks, have been applied to sequential iris data and temporal variations in video-based iris recognition.
- They capture dependencies across frames, improving recognition in dynamic or mobile scenarios.

3.5 Generative Adversarial Networks (GANs)

- GANs are increasingly used for **data augmentation** in iris recognition, generating synthetic iris images to expand limited datasets.

- Conditional GANs (cGANs) have shown promise in producing realistic iris textures, improving robustness against noise and occlusion.

3.6 Autoencoders

- Autoencoders are employed for **unsupervised feature learning** and dimensionality reduction.
- Variational autoencoders (VAEs) can capture latent iris features, support recognition tasks when labeled data is scarce.

3.7 Hybrid and Ensemble Models

- Some studies combine CNNs with RNNs or integrate handcrafted features with deep learning outputs.
- Ensemble approaches improve generalization across heterogeneous datasets and sensor variations.

4. Dataset

Iris recognition relies on distinct patterns within the human iris. Various datasets have been pivotal in advancing iris recognition technology and algorithms. Among the most renowned datasets are:

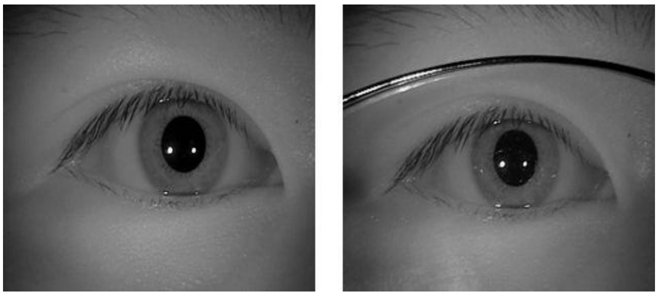

Figure 4. An example of a sample image taken from CASIA-Iris-Thousand dataset.

1. UBIRIS Dataset: This dataset consists of two separate versions see Figure 4: UBIRIS. v1 [22] and UBIRIS. v2 [23]. The first version consists of 1,877 images gathered from 241 eyes in September 2004 across two different sessions. It replicates imaging under less restricted conditions. It is publicly accessible and free to use. Whereas, the second version contains more than 11,000 images, steadily expanding, and incorporates more authentic noise elements. These images were captured from a distance and while in motion.

Figure 5. compares UBIRIS.v1 and UBIRIS.v2 samples: (a) UBIRIS.v1 (first row) – images captured under semi-controlled conditions; (b) UBIRIS.v2 (second row) – images captured at a distance and in motion with higher noise levels

2. IIT Delhi Iris Dataset [24]: It contains iris images obtained from both students and staff at IIT Delhi, located in New Delhi, India. This dataset was compiled at the Biometrics Research Laboratory between January and July 2007, utilizing JIRIS, JPC1000, a digital CMOS camera. A dedicated image acquisition program was developed specifically for the purpose of gathering and storing these images in bitmap format, available upon request at no

charge. As of the time of writing this research, the dataset contained data from 224 users, with all images stored in bitmap (*. bmp) format. The individuals within the dataset range in age from 14 to 55 years old, with a distribution of 176 males and 48 females. The collection consists of 1120 images organized into 224 separate classes, each linked to a unique numerical identification. These images have a resolution of 320 × 240 pixels and were captured within an indoor environment. Figure 5 shows a few sample images from this dataset.

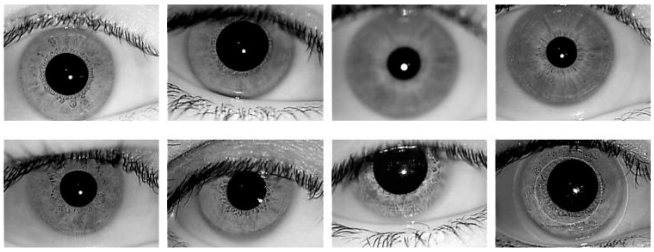

Figure 6. Some images taken from IIT Delhi dataset.

3. ND-CrossSensor-Iris-2013 Dataset [25]: It contains iris images collected over 27 sessions, each involving 676 distinct individuals. On average, each session includes 160 unique subjects, and images were captured using both the LG2200 and LG4000 iris sensors, see Figure 6. Specifically, 29,986 images were captured by the LG4000 sensor, and 116,564 images were captured by the LG2200 sensor. Each individual appeared in at least two sessions throughout the dataset, which covers a span of three years from 2008 to 2010. The original images from both sensors are of size 640 by 480.

(a)

(b)

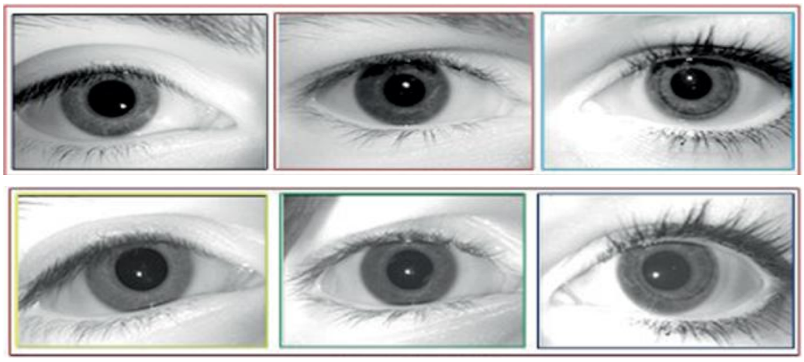

Figure 7. Sample images from the ND-CrossSensor-Iris-2013 dataset: (a) LG4000 sensor (first row) – higher-resolution iris images; (b) LG2200 sensor (second row) – standard-resolution iris images

4. Mobile Iris Challenge Evaluation (MICHE) dataset [26]: This dataset contains iris images obtained from various smartphones, such as iPhone and Galaxy S4, in uncontrolled environments see Figure 7. It consists of over 3,732 images collected from 92 people, with 66 males and 26 females aged between 20 and 60 years, all of Caucasian ethnicity. MICHE-I aims to answer the question of whether a dynamic iris matching system, influenced by demographics such as gender and ethnicity (excluding age since the iris is presumed to remain constant throughout an individual's life), can improve iris authentication significantly.

Figure 8. Some images from MICHE dataset (first row: captured from iPhone, second row: captured from Galaxy S4).

The table 1 shown summary pf public available iris recognition datasets that have been explained in this survey approach.

Table 1. Summary of Publicly Available Iris Recognition Datasets.

Dataset	Reference	Subjects	Images per Subject	Imaging Conditions	Sensor Type	Notable Variations
CASIA-Iris-Thousand	[16]	~1,000	~20	Controlled indoor, NIR	IKEMB-100 camera	Eyeglasses, specular reflections
UBIRIS.v1	[22]	241 eyes	~8	Semi-controlled, visible light	CCD camera	Moderate noise, two sessions
UBIRIS.v2	[23]	>400 eyes	>11,000	Uncontrolled, distance, motion	Visible light camera	High noise, motion blur
IIT Delhi Iris	[24]	224	~5	Indoor, controlled	JIRIS JPC1000 CMOS	Age range 14–55, bitmap format
ND-CrossSensor-2013	[25]	676	Multiple sessions	Controlled, multi-year	LG2200 & LG4000	Cross-sensor variability
MICHE-I	[26]	92	~40	Uncontrolled, mobile	iPhone, Galaxy S4	Gender/ethnicity variations, smartphone capture

5. Evaluation Metrics

Evaluation metrics are crucial in assessing the performance and accuracy of any recognition systems. These metrics help quantify the effectiveness of algorithms in identifying and verifying individuals based on their biometric patterns. Some commonly used evaluation metrics in iris recognition include:

1. False Acceptance Rate (FAR): It measures the rate at which the system incorrectly identifies an unauthorized person as an authorized user. It is expressed mathematically as follows:

$$FAR=\frac{\text{No. of false acceptance}}{\text{No. of imposter attempts}}\times 100\% \quad (1)$$

   In high-security systems, minimizing FAR is critical to prevent unauthorized access.

2. False Rejection Rate (FRR): It measures the system's rejection of an authorized user--or false rejection rate. It is expressed mathematically in the following manner:

$$FRR=\frac{\text{No. of false rejection}}{\text{No. of genuine attempts}}\times 100\% \quad (2)$$

   A lower FRR improves usability and user satisfaction in practical deployments.

3. Equal Error Rate (EER): EER means both FAR and FRR are equal. On the ROC curve, it serves as a simple summary value of overall system performance-the lower EER is more accurate and balanced.

   FAR, FRR, and EER exhibit the core trade-off between security and usability. For instance, low ties in any or all three can also have a lower FAR condition but would mean inconvenience to users from higher FRR, whereas low FRR can also mean a higher level of acceptance for impostors, so the threshold to define for a specific application is dependent highly on the risk tolerance of that application:

$$\text{Accuracy}=\frac{\text{No. of correctly identified iris patterns}}{\text{Total number of iris patterns}}\times 100\% \qquad (3)$$

4. Template Matching Scores: It quantifies the degree to which two patterns agree with respect to numerical grading scores. In measuring the similarity grades of these templates, several scoring methods can be employed, say, Euclidean distance or Hamming distance.

These two metrics illustrate a trade-off. If a biometric system is made to minimize FAR, that is prevent the entry of unauthorized users, it may have a higher FRR and deny access to rightful users, thus reducing usability. On the other hand, making it easier for the legitimate user by lowering FRR may increase the propensity toward carrying out false acceptances. Thus, the balance is always determined according to the application where it could be implemented in such way: actually, high-security environments like border control or military access give priority to low FAR, while consumer applications- such are unlocking a smartphone- would prefer usability and usually tolerate slightly higher FAR for the sake of satisfying the user.

6. Literature Survey

This section synthesizes the surveyed works into dominant research themes, highlighting trade-offs, methodological debates, and emerging directions. Rather than listing studies individually, we critically analyze how deep learning has reshaped iris recognition and where challenges remain.

Theme 1: End-to-End vs. Pre-processing Pipelines

Traditional iris recognition pipelines rely on segmentation, normalization, and enhancement before feature extraction. Zhao [21] emphasized the importance of preprocessing, introducing Extended Triplet Loss to improve discriminative feature learning. In contrast, ThirdEye [27] demonstrated that triplet CNNs could achieve competitive accuracy without normalization, particularly on constrained datasets like IITD.

Trade-off: End-to-end CNNs simplify the pipeline and reduce dependency on handcrafted steps, but they often underperform in noisy or unconstrained datasets (e.g., UBIRIS.v2). This debate reflects a broader tension between efficiency and robustness

Theme 2: Data Scarcity and Solutions

A recurring challenge is the limited availability of large, labeled iris datasets. Transfer learning has become a dominant solution: Minaee et al. [17] leveraged VGGNet features, while Menon & Mukherjee [18] fine-tuned ResNet18, achieving 99.8% accuracy on IITD. These studies show that pretrained models accelerate convergence and reduce data requirements.

Theme 3: Robustness in Unconstrained Environments

Mobile acquisition (MICHE dataset) and noisy imaging (UBIRIS.v2) highlight the difficulty of iris recognition outside controlled settings. Studies show performance degradation due to occlusions, reflections, and motion blur. CNN-based segmentation [28] improved robustness by integrating parameterization with rubber sheet transforms, outperforming traditional methods in lower-quality datasets.

Synthesis: Robustness requires domain adaptation strategies. GANs and noise masking improve generalization, but unconstrained environments remain the most pressing challenge for real-world deployment.

Theme 4: Architectural Evolution

The field has progressed from VGGNet-based feature extraction [17] to deeper architectures like ResNet [18] and specialized CNNs [20]. More recent work explores lightweight models for mobile applications and attention-based networks for fine-grained texture analysis.

Trend: The evolution reflects a dual priority: maximizing accuracy for high-security applications while minimizing computational cost for consumer devices. Future directions likely include transformer-based biometrics and multimodal fusion with other traits (e.g., face, fingerprint)

Overall Synthesis

The literature reveals four converging trajectories:

- Simplification of pipelines through end-to-end CNNs;
- Mitigation of data scarcity via transfer learning and GANs;

- Efforts to ensure robustness in unconstrained environments;
- Architectural innovation toward lightweight and attention-driven models.

Despite significant progress, challenges remain in cross-sensor generalization, synthetic bias from GANs, and balancing usability with security. Addressing these gaps will define the next phase of iris recognition research.

7. Literature Analysis

A critical examination reveals that a number of striking patterns and significant differentiations exist among reviewed deep learning systems for iris recognition-with respect to the data sets, feature extraction, model architecture, training strategy, and evaluation protocol. Some such observations have concentrated on the heterogeneity in dataset sizes and qualities, while many benchmarks, such as the CASIA-Iris-1000, ND-CrossSensor, and IIT Delhi, deliver rather sound experimental grounds for use by other users. The more contemporary contributions made by, among others, Yin [29] and Minaee [30], accentuate the importance of generalizing datasets and validating across datasets especially for security-critical biometric systems. Smaller or custom datasets-an example of the most recent is Bhagya Sree [31], serve as exemplars of how robustness is quite in danger under uncontrolled conditions, such as occlusions and changing light illumination.

Experiments in this way are sufficiently differentiated from the phenomena under the older unsupervised methodologies such as PCA and hand-crafted contour-based vectorials (e.g. [32]) and rather include established feature extraction pipelines entirely based on automated Deep Convolutional Networks. It is transferred learning that has become the key here, primarily throughout such architectures as VGG16, ResNet18, and FCNs. For instance, models by Minaee [30] and Rasheed [33], will add segmentation and recognition performance with memory effectiveness and F-score performance.

One precise advantage identified in the top models (e.g., DeepIrisNet, ThirdEye) is that they make use of well-balanced datasets and effective training strategies. Recent literature, however, such as Yin [29] and Moktari [34], cautions that such benefits may not transfer across sensors or imaging modalities. Specifically, Moktari [34] propose cross-spectral matching using DCGANs to correct domain shifts, especially beneficial for images taken by different hardware configurations (i.e., LG2200 vs. LG4000).

Moreover, our analysis would reveal the difference in the reported training/testing splits together with the absence of standard evaluation protocols. Thus, there is difficulty in making direct performance comparisons, and of course, this could lead to overly optimistic results. The perspective we are recommending for future benchmarks is to necessarily report on the conditions, demographic distribution, and sensor variability under which training has been conducted, suitable for transparent and reproducible evaluation. Such practices as k-fold cross-validation and cross-sensor testing would further add to methodological rigor.

In this light, the present analysis has reviewed the most important contributions in the field and unearthed glaring gaps regarding generalizability, fairness, and explainability that require urgent attention. Therefore, future systems should adopt standard dataset documentation protocols, explainable AI components, and fairness-aware design. These are key for developing models in iris recognition that are accurate, robust, ethical, and deployment-ready.

Indeed, such invaluable contributions to this discussion, evolving as it is, underscore the urgent need for deep learning-based iris recognition systems that are now or that are likely to be in the near future interpretable and socially accountable.

In iris recognition CNN architectures of varying designs have been presented in the contemporary literature-each with its own merits and disadvantages. For instance, VGGNet has an intuitive architecture with simple stacking of convolution layers with constant kernel sizes, which allows for strong hierarchical feature extraction, but at a high computational cost with excessive parameters. ResNet, by introducing this concept of residual connections, aids in diluting the vanishing gradient problem, as a result allowing for training of deeper networks more effectively with fewer parameters. The presence of skip connections in ResNet makes it retain some of the low-level features while learning more complex ones, making it suitable for large-scale or real-time biometric systems. Studies that implemented ResNet-based models frequently report better convergence and generalization performance than their VGGNet-based counterparts.

In very practical applications, iris recognition under controlled environments proved bluntly useful-from well-illuminated and well-positioned automated border control systems. However, greater challenges arise in its deployment into mobile and consumer devices, like smartphones. Motion blur, occlusion from eyelids or glasses, and inconsistent lighting are among those real-world issues that affect the recognition performance negatively. A good number of recent studies cite the need for robust preprocessing and domain-adaptive measures to ensure system reliability in such conditions. The aforementioned examples emphasize choosing the right architecture and to handling real-world variability in designing iris recognition systems.

Table 2. Representative State-of-the-Art Deep Learning Approaches in Iris Recognition (2016–2024)

Year	Authors	Technique	Dataset(s)	Key Contribution
2016	**Minaee [17]**	**VGGNet + PCA + SVM**	**CASIA-1000, IIT Delhi**	**Early CNN transfer learning for iris recognition**
2017	**Zhao [21]**	**Fully Convolutional Network + Extended Triplet Loss**	**Multiple public datasets**	**Robust descriptor learning with ETL**
2018	**Menon [18]**	**ResNet18 (transfer learning)**	**IIT Delhi, UBIRIS.v2**	**High recognition rates with fine-tuned ResNet**
2019	**Lee [35]**	**Conditional GANs (cGANs)**	**UBIRIS.v2**	**Synthetic iris augmentation for improved accuracy**
2020	**Khan [11]**	**Hybrid CNN-RNN**	**CASIA, ND datasets**	**Sequential modeling for dynamic iris recognition**
2021	**Hofbauer [28]**	**CNN-based segmentation + parameterization**	**NIR datasets**	**Improved segmentation robustness**
2022	**Zhang [36]**	**Transformer-based iris recognition**	**CASIA-Iris-Thousand**	**Attention mechanisms for feature extraction**
2023	**Li [37]**	**Lightweight MobileNetV3**	**MICHE, UBIRIS**	**Efficient iris recognition on mobile devices**
2024	**Chen [38]**	**Self-supervised learning (SSL)**	**ND-CrossSensor**	**Robust feature learning with limited labels**

8. Limitations and Future Recommendations

Although promising recognition rates, the studies presented in Table 1 have significant limitations. A main concern is the over-dependence on singular datasets, which may not reflect the spectrum of iris data in the real world. Many models are trained and assessed on the same dataset without a cross-dataset validation hindering generalization potential. The worry increases when factors such as age, ethnicity, and environmental conditions are neglected for consideration. For example, the MICHE dataset, which includes almost exclusively Caucasian subjects, incorporates a demographic bias that can interfere with fairness and performance in the larger population calibrating.

Also, there is frequently a lack of consideration for ethical issues behind the use of biometric data. Very few papers discuss the dangers of storing sensitive iris images or templates, as their misuse would be afforded by the lack of encryption and access control. In addition, some good datasets, such as MICHE and NIST-ICE, do not have explicit documentation of informed consent by the participants, thus questioning issues related to ownership of the data, right to privacy and research ethics at large.

A further issue is the lack of standardized evaluation protocols in evaluation procedures. Most of the performance, as reflected in the readings, arise from ad hoc train test splits that hinder comparability between assessments and may bias them toward higher rates. Therefore, we would recommend that future work move toward k- fold cross-validation or stratified sampling, laying out the evaluation conditions clearly and thereby enhancing methodological soundness and reproducibility.

In real deployments, recognition performance can drop markedly due to motion blur, changes in illumination, sensor heterogeneity and tempering noise. But those conditions are so infrequently simulated by the current research.

We argue very strongly for evaluation of the models on realistic perturbations across a variety of sensors and environments in order to be assured of broad robustness.

Model transparency is growing as another concern. Many deep learning models are very good in terms of accuracy, but usually, they are not interpretable. This "black-box" nature of biometric systems is another reason that erodes confidence about them, especially in sensitive areas such as law enforcement and border control. Researchers must embed some explainable AI techniques such as Grad-CAM or SHAP for visualizing model behavior to promote ethical decision-making.

Finally, these actionable future research directions should be incorporated into the construction of responsible, scalable, and ethically sound iris recognition systems:

1. Cross-dataset validation and use of multiple sensors would definitely improve generalization;
2. Train with diverse demographics in the data and provide demographic attributes during evaluation;
3. Use only datasets with a proven history of informed consent to enforce ethical standards and privacy-preserving techniques (e.g., encryption, federated learning);
4. Assessment of fairness-related metrics and training strategies to achieve and promote equitable performances across various population groups;
5. Enhance interpretability by the integration of explainable AI tools (Grad-CAM, SHAP, etc.) to provide insights into the reasons for model decision-making.

When these problems are resolved, the outcome would be an ideal iris recognition system capable of demonstrating, in terms of application, fairness, accountability, and trustworthiness, apart from world-class performance.

9. Conclusions

This survey highlights the transformative impact of deep learning on iris recognition, moving the field beyond handcrafted pipelines toward end-to-end architectures capable of learning discriminative features directly from raw images. Across the literature, several consensus points emerge:

- CNNs and transfer learning consistently deliver high accuracy in constrained environments, demonstrating efficiency in data-limited scenarios;
- Cross-sensor interoperability and unconstrained acquisition remain the most persistent challenges, with performance dropping significantly in mobile or noisy imaging conditions;
- GAN-based augmentation and domain adaptation approaches are promising but raise questions about synthetic bias and real-world applicability;
- Architectural evolution from VGG/ResNet to lightweight and attention-based models reflects a dual priority: maximizing accuracy for high-security applications while enabling deployment on resource-constrained devices.

So what? The state of the field suggests that iris recognition is mature in controlled settings but still evolving for real-world deployment. The most promising directions lie in robust domain adaptation, synthetic data generation with bias mitigation, and integration of attention or transformer-based architectures to capture fine-grained iris textures. Addressing these challenges will determine whether iris recognition can transition from a laboratory success to a universally reliable biometric solution.

In this work, we performed a comprehensive survey of the state-of-the-art literature in iris recognition using deep learning algorithms. The study of these deep learning models supports some good advancements but not without challenges. Interestingly, one of the emerging observations is the training and testing of some models with the same dataset, with no consideration of the inclusion of any other dataset for testing. Furthermore, interpretability, vulnerability to adversarial attacks, sensitivity to varying environmental conditions, and degradation in image quality appeared as major issues in these studies. Therefore, future works should not only focus on these challenges but should also actively investigate alternative methods to ensure the reliability and feasibility of such systems deployed in real-world scenarios. This entails a concerted effort to improve interpretability, better adversarial attack resistance, environment-adaptive, and resilient to image quality degradation. By addressing these relevant issues, the pathway of iris recognition research will be strengthened and better bolstered.

Supplementary Materials: The following supporting information can be downloaded at: https://dasinya.dpu.edu.krd/, Figure S1: title; Table S1: title; Video S1: title.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Full Form / Meaning
CNN	Convolutional Neural Network
DL	Deep Learning
AI	Artificial Intelligence
PCA	Principal Component Analysis
SVM	Support Vector Machine
FCN	Fully Convolutional Network
GAN	Generative Adversarial Network
cGAN	Conditional Generative Adversarial Network
DCGAN	Deep Convolutional Generative Adversarial Network
ETL	Extended Triplet Loss
DLIP	Deeply Learned Iris Pattern
FAR	False Acceptance Rate
FRR	False Rejection Rate
EER	Equal Error Rate
ROC	Receiver Operating Characteristic
NIR	Near Infrared
CASIA	Chinese Academy of Sciences Institute of Automation (Iris dataset)
IIT	Indian Institute of Technology
MICHE	Mobile Iris Challenge Evaluation
ND	Notre Dame (Iris dataset)
UBIRIS	University of Beira Interior Iris dataset
WVU	West Virginia University
BTAS	Biometrics Theory, Applications and Systems
I2MTC	International Instrumentation and Measurement Technology Conference
ICIP	International Conference on Image Processing

Abbreviation	**Full Form / Meaning**
ICICCS	International Conference on Intelligent Computing and Control Systems
SIBGRAPI-T	Conference on Graphics, Patterns and Images Tutorials

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