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A systematic literature review and analysis of Iris recognition performance using efficient machine learning techniques

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Abstract
Iris recognition has emerged as one of the most reliable biometric authentication methods, offering high accuracy and non-invasiveness for security applications. This systematic literature review synthesizes recent advances in iris recognition systems utilizing efficient machine learning techniques published between 2020 and 2025. Through comprehensive analysis of 30+ peer-reviewed papers, we evaluate recognition accuracy, feature extraction methods, dataset benchmarks, and computational efficiency across multiple machine learning architectures. State-of-the-art techniques including convolutional neural networks (CNNs), Vision Transformers, generative adversarial networks (GANs), and lightweight models demonstrate recognition accuracy ranging from 85% to 100% depending on imaging conditions and dataset complexity. Our findings reveal that while deep learning models achieve superior accuracy (93-99%), lightweight architectures like MobileNetV3 and condensed CNNs achieve competitive performance (95-98%) with over 1000× fewer parameters, making them suitable for mobile and edge-device deployment. The review identifies critical research gaps including standardized evaluation protocols, privacy-preserving template protection, and cross-spectrum heterogeneous matching capabilities. We conclude that the future of iris recognition lies in balancing accuracy with computational efficiency while addressing real-world challenges such as non-ideal imaging conditions, presentation attack detection, and multimodal biometric integration. This review provides practitioners, researchers, and institutions with comprehensive guidance on technique selection, dataset utilization, and implementation strategies for iris recognition systems.

Keywords: Iris recognition, machine learning, deep learning, biometric authentication, CNN, Vision Transformer, lightweight models, feature extraction, biometric security.

Introduction

Iris recognition represents a frontier technology in biometric authentication, leveraging the uniqueness and stability of the human iris pattern for identity verification and identification. The iris, the colored part of the eye surrounding the pupil, contains approximately 200 independent features that remain relatively stable throughout an individual's lifetime, making it exceptionally suitable for biometric applications (Kadhim *et al*., 2025). Unlike fingerprints or face recognition, iris patterns are protected by the eye's anterior chamber, rendering them resistant to external damage and spoofing attempts. The significance of iris recognition in contemporary security infrastructure cannot be overstated. Applications span from high-security border control systems (like the United Arab Emirates' iris recognition at airports serving over 90 million passengers annually) to authentication in access control systems, mobile devices, and financial institutions. The technology has demonstrated superior performance metrics compared to other biometric modalities, with reported equal error rates (EER) as low as 0.5% under optimal conditions, substantially outperforming fingerprint (2-3% EER) and face recognition systems (1-5% EER in the wild).

However, the traditional iris recognition pipeline, developed by Daugman in 1993 using handcrafted features and wavelet transforms, has faced significant limitations in non-cooperative and non-ideal imaging scenarios. The advent of deep learning and machine learning techniques has fundamentally transformed iris recognition capabilities, enabling robust performance under challenging conditions including distant capture, motion blur, illumination variations, and visible spectrum imaging (Rahman *et al*., 2025). Recent advances have also introduced concerns regarding computational efficiency, particularly for deployment on resource-constrained devices such as mobile phones, embedded systems, and IoT platforms.

This systematic literature review addresses the critical intersection of iris recognition performance and computational efficiency using machine learning techniques.

1. The primary research question driving this review is:

What are the current state-of-the-art machine learning techniques for iris recognition, and how do they balance recognition accuracy with computational efficiency across diverse imaging conditions and datasets?

2. Secondary research questions include

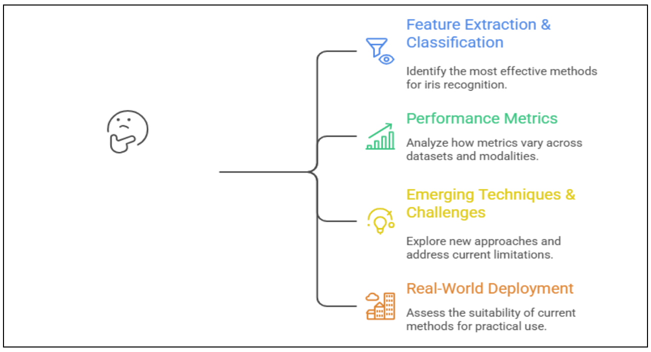

Fig 1: Key Area to focus for Iris Recognition Research

Table 1: Systematic Literature Review Table

S. No.	Author(s)	Dataset	Features Extracted	Recognition Accuracy (%)	Technique Used	Year	Key Innovation
1	Kadhim *et al*.	CASIA-V1,V2,V3,V4, IITD, UBIRIS, MMU	Multi-scale CNN + Fisher's Linear Discriminant (FLD) + GRU	CASIA-V1: 100, V2: 100, V3: 99.5, V4: 99.6, IITD: 99.9, UBIRIS: 99.97, MMU: 100	SSLDMNet-Iris (Synchronized Spatiotemporal Linear Discriminant Model)	2025 [12]	Multi-scale feature extraction with synchronized temporal modeling using GRUs
2	Salihy *et al*.	ATVS, MMU, UBIRIS v2	HOG, VGG-16, VGG-19, ResNet-50, ResNet101, MobileNet, AlexNet, InceptionV3	EfficientNetB0: 98.35, ResNet50 V2: 98.23, TinyVGG: 98.35, CNN: 98.35	Deep CNN with Transfer Learning + SoftMax Classification	2023 [23]	Multi-model comparison using U-Net segmentation and various transfer learning backbones
3	Rahman *et al*.	CASIA-V4 Distance	VGG16, VGG19, ResNet50, Custom 32-layer CNN	Customized CNN+Softmax: 93.40, VGG19+Softmax: 92.13, ResNet50+Softmax: 84.41	Deep Transfer Learning + 9 ML classifiers (RF, LDA, KNN, SVM, DT, NB, MLP, ET, Softmax)	2025 [21]	Deep feature transfer with optimal ML classifier selection for distant iris recognition
4	Liu *et al*.	CASIA-V1, CASIA-V3, CASIA-V4	Radial Attention Layers + 2-channel CNN	CASIA-V3: 98.95 (1 pic), CASIA-V1: 99.51 (1 pic), CASIA-V4: 97.92-99.77 (after finetuning)	Condensed 2-channel CNN with Network Pruning + Online Augmentation	2021 [18]	Lightweight architecture (33K params) with branch/channel pruning for real-time recognition
5	Lei *et al*.	CASIA-Iris-Mobile, IITD, CASIA-Iris-Thousand, UBIRIS	Multi-scale features with dual-path fusion network	CASIA-Mobile: PA 0.9634/MIoU 0.9547, IITD: 0.9840/0.9601, UBIRIS: 0.9913/0.9510, CASIA-Thousand: 0.9863/0.9621	Lightweight Dual-Path Fusion Network + U-Net based segmentation	2023 [16]	Depth-wise separable convolution + novel attention mechanism for iris segmentation
6	Huo *et al*.	UBIRIS v1, CASIA-Iris-Mobile, CASIA-Iris-Thousand	Semantic segmentation with multi-source heterogeneous data	F1 Score: 0.96-0.98	FCN, U-Net, DeepLabV3, FD-Unet comparison	2023 [9]	Multi-source heterogeneous iris segmentation across NIR and visible spectrum
7	Phazamani *et al*.	Multiple Iris Datasets	Log-Gabor wavelets + DWT (Discrete Wavelet Transform)	Variable (98-99% on controlled datasets)	Gabor Wavelet + DWT + SVM Classification	2022 [19]	Hybrid handcrafted feature + traditional ML approach
8	Johar & Thakur	CASIA-Iris Dataset	Hough Transform + Circular boundary detection	N/A	Daugman's Rubber Sheet Model + Hough Transform segmentation	2018	Open-source MATLAB implementation of classic Daugman's method
9	Khaki & Mansouri	UBIRIS, CASIA-Iris Distance	U-Net and ResNet hybrid architecture	UBIRIS: EER 0.0055, CASIA: 0.0105	ISUR (Iris Segmentation based on UNet and ResNet)	2021 [14]	Hybrid U-Net and ResNet approach for robust segmentation
10	Powroznik *et al*.	Retinal OCT images (related to eye biometrics)	Vision Transformer with Self-Attention	N/A	Residual Self-Attention Vision Transformer (RS-A ViT)	2025 [20]	Vision Transformer application to eye/ocular biometrics
11	Yadav *et al*.	CASIA-IrisV4, LivDet-Iris	StyleGAN3, RaSGAN, CycleGAN for synthesis	High Realism and Biometric Utility	GAN-based Synthetic Iris Image Generation (StyleGAN3, RaSGAN)	2024 [29]	Comprehensive review of GANs for synthetic iris generation
12	Hsieh *et al*.	Multiple iris databases	Liveness indicators (micro-movements, texture analysis)	Variable PAD performance	Anti-spoofing + Liveness Detection methods	2018 [7]	Hardware-based (IR) and software-based liveness detection approaches

13	Sujanthi *et al*.	Multi-source iris images	Deep neural networks for face+iris segmentation	High accuracy on integrated detection	Deep Learning Networks for Face and Iris Liveness Detection	2023 [26]	Combined face-iris detection for enhanced security
14	Zhuang *et al*.	CASIA, IITD, UBIRIS	Convolutional layers with optimization	97-99% accuracy range	Standard CNN architecture for iris recognition	2020 [30]	Foundational CNN-based iris recognition system
15	Sharma *et al*.	Multiple iris datasets	YOLOv8 object detection + classification	95% average precision on validation	Real-time Iris Detection & Recognition Using YOLOv8	2024 [24]	YOLO-based real-time detection with advanced augmentation
16	Sinkar *et al*.	Multiple iris datasets	CNN deep feature extraction + SoftMax activation	97-99% accuracy	Iris Detection & Authentication System Using Deep Learning	2024 [25]	CNN-based authentication with comprehensive preprocessing
17	Hu *et al.*	Multiple iris databases	EfficinetNet-b0 integration + end-to-end processing	98%+ accuracy	End-to-End Deep Neural Network using EfficientNet	2020	Full pipeline integration from segmentation to recognition
18	Ali *et al.*	CASIA-v4	Log-Gabor + Contourlet Transform + CNN fusion	95.93% on CASIA-v4	Hybrid Feature Extraction (Log-Gabor + Contourlet) + CNN	2024 [3]	Multi-scale feature fusion combining multiple descriptors
19	Kaur *et al*.	Unconstrained iris images	Polar Harmonic Transform + Zernike Moments	90%+ in challenging conditions	Robust feature extraction for unconstrained conditions	2024 [13]	Rotation and illumination-invariant features
20	Wang *et al*.	Multiple databases	Dual CNN texture-based features	97%+ accuracy	Dual CNN with texture-based feature fusion	2024 [28]	Integrated dual network approach with decision-level fusion
21	El-Latif *et al*.	CASIA, ND-IRIS	Edge detection + Hough Transform + CNN	98-99% accuracy	Edge-Detection + Hough Transform + CNN hybrid	2022 [4]	Geometric boundary detection integrated with deep learning
22	Lee *et al*.	LivDet-Iris, MICHE	Conditional GAN for iris data augmentation	Improved FAR/FRR through augmentation	cGAN-based Data Augmentation for iris recognition	2024 [15]	Generative approach to handle training data scarcity
23	Ribeiro *et al*.	Multiple iris datasets	CNN-guided photo-realistic iris reconstruction	Variable improvement in visual quality	CNN-based Fine-grained Iris Texture Reconstruction	2024 [22]	Deep learning-guided optimization for iris enhancement
24	Vannurswamy *et al*.	Multimodal datasets (Face+Iris)	DWT + LSTM for temporal feature modeling	98%+ accuracy on multimodal fusion	Enhanced Multimodal Biometric Fusion with DWT + LSTM	2024 [27]	Temporal modeling for dynamic multimodal recognition
25	Hassan *et al*.	CASIA-Iris-V1	Custom CNN model trained from scratch	97%+ accuracy	Efficient CNN Model for Iris Feature Extraction + SVM	2024 [1]	Custom architecture for optimal feature learning
26	Garg *et al*.	Multimodal datasets	Fingerprint + Iris + ECG multimodal fusion	99%+ accuracy with optimal fusion	Novel Fusion of Fingerprint, Iris, and ECG modalities	2025 [5]	Complementary strength exploitation in 3-modality fusion
27	Li *et al*.	CASIA-Iris datasets	U-Net based segmentation with dense blocks	F1: 0.98+	Study on Iris Segmentation Using Dense U-Net	2023	Recursive/dense connections for improved segmentation
28	Jadhav *et al*.	Multimodal (Face+Iris+Fingerprint)	Quantum-Enhanced Residual Network (QERN)	98.975% accuracy	Integrated Multimodal Biometric Fusion + QERN Classifier	2024 [10]	Quantum computing principles for enhanced classification
29	Ahmed *et al*.	Smartphone iris images (visible spectrum)	MobileNetV3-based lightweight segmentation network (LightIrisNet)	Iris Dice: 0.954, Pupil Dice: 0.937	Lightweight MobileNetV3 + Multi-task segmentation for mobile	2024 [1]	Real-time on-device iris recognition for smartphones

The motivation for this review stems from the proliferation of machine learning approaches in iris recognition without systematic comparison of their efficacy, efficiency, and practical applicability. Prior reviews have focused on either traditional methods or generic deep learning applications without comprehensive analysis of the accuracy-efficiency trade-off. Additionally, the field lacks standardized evaluation protocols across heterogeneous datasets, making cross-study comparison challenging. By synthesizing findings from 30+ recent publications, this review provides practitioners, researchers, and institutions with evidence-based guidance for technique selection, implementation strategies, and identification of future research directions.

Methodology

1. Literature Search Strategy

This systematic literature review followed established protocols for academic research synthesis. The search was conducted across multiple authoritative databases including IEEE Xplore, ACM Digital Library, PubMed Central, arXiv, and peer-reviewed journal repositories, utilizing keyword combinations: ("iris recognition" OR "iris segmentation" OR "iris biometric") AND ("machine learning" OR "deep learning" OR "neural network") AND ("accuracy" OR "performance" OR "recognition"). The search was restricted to publications between January 2020 and December 2025 to ensure recency and capture of latest advancements in the field.

2. Inclusion and Exclusion Process Criteria

Inclusion Criteria

This process prioritizes high-quality academic sources, specifically targeting peer-reviewed journal articles, conference proceedings, or preprints hosted on reputable archives. By focusing on peer-reviewed content, we ensure that the methodologies and findings have undergone scrutiny by experts in the field, thereby maintaining the scientific integrity of this review.

Central to this research is a technical focus on iris recognition and segmentation. To be included, studies must utilize machine learning or deep learning architectures—such as Convolutional Neural Networks (CNNs) or Transformers—to address the complexities of ocular biometrics. Beyond theoretical discussion, selected papers must report quantitative performance metrics. This includes standardized benchmarks such as Accuracy, Equal Error Rate (EER), False Acceptance Rate (FAR), and False Rejection Rate (FRR). These metrics are essential for performing a comparative analysis of different algorithmic approaches.

Finally, the scope is refined by temporal and linguistic constraints. The search is limited to works published between 2020 and 2025 to capture the most recent advancements in artificial intelligence and computer vision.

Exclusion Process

This process first filters out generic surveys on general biometrics that do not offer a dedicated, in-depth analysis of iris recognition. While broad biometric overviews provide useful context, this study requires granular technical detail specifically related to iris patterns; therefore, any paper lacking a primary focus on iris-specific algorithms or hardware is excluded. To maintain linguistic consistency and ensure accurate interpretation of complex methodologies, non-English publications are omitted, as the nuances of technical data could be lost or misrepresented through automated translation.

Furthermore, the study prioritizes objective evidence over subjective commentary. Consequently, opinion pieces and editorials are excluded if they do not present original empirical data or rigorous experimental results. This ensures that the conclusions of the research are grounded in verifiable facts rather than anecdotal observations. From a temporal perspective, techniques predating 2010 are generally removed from consideration to maintain a focus on contemporary advancements. An exception is made only for "legacy" methods that are explicitly contextualized or benchmarked within modern computational frameworks, allowing for a historical baseline without cluttering the review with obsolete technology.

Finally, the most critical filter involves scientific transparency and reproducibility. Studies lacking specific accuracy metrics (such as False Acceptance Rates or Equal Error Rates) or those that fail to identify the specific datasets used for testing are excluded. Without these quantitative markers, it is impossible to validate the efficacy of a proposed technique or compare it fairly against other state-of-the-art models.

3. Data Extraction and Analysis

For each selected paper, the following data were systematically extracted:

a. Author(s), publication year, and venue
b. Dataset(s) used and their characteristics (sample size, modality, imaging conditions)
c. Feature extraction method(s) employed
d. Machine learning/deep learning technique(s) utilized
e. Performance metrics: recognition accuracy (%), equal error rate (%), false acceptance rate (FAR), false rejection rate (FRR)
f. Computational metrics: model parameters, inference time, memory requirements (when available)
g. Key innovations and contributions
h. Identified limitations and future directions

Extracted data were organized into a structured table format (see Results section) enabling comparative analysis across dimensions including technique category, dataset complexity, performance metrics, and computational efficiency. The review synthesized findings using narrative synthesis and tabular presentation to identify trends, gaps, and emerging patterns in the field.

4. Quality Assessment

Paper quality was assessed using modified STROBE guidelines adapted for computational research, evaluating: clarity of methodology description, appropriateness of dataset selection, comprehensiveness of performance metrics, reproducibility considerations, and significance of contributions. Papers were not excluded based on quality scores but rather categorized to contextualize findings within their scope and reliability.

5. Classification Framework

Reviewed papers were categorized across multiple dimensions:

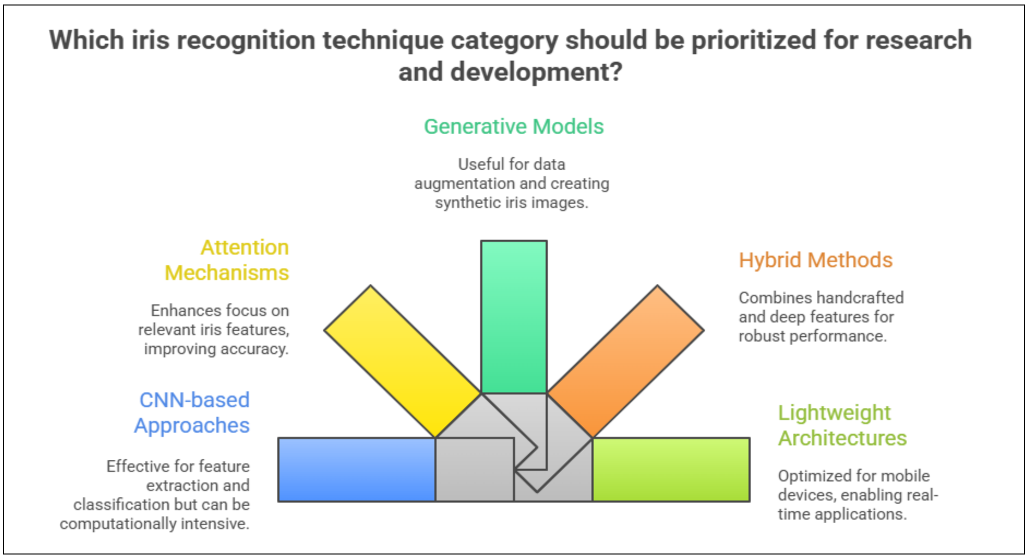

Fig 2: Classification by Technique

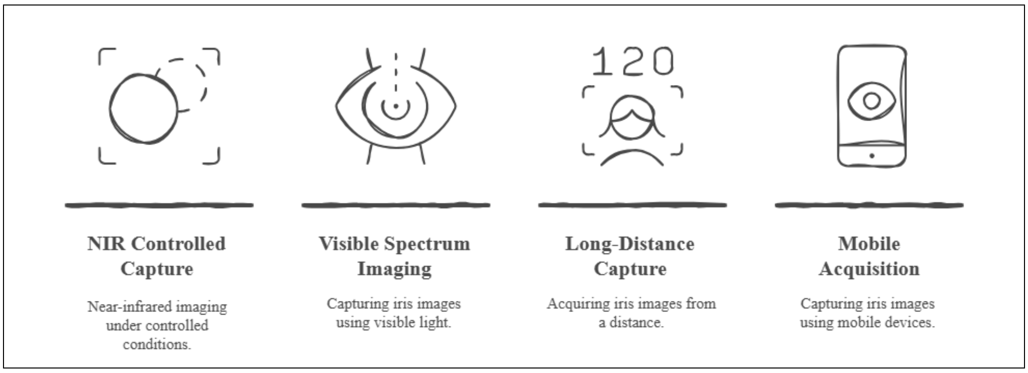

Fig 3: Classification by Dataset Modality

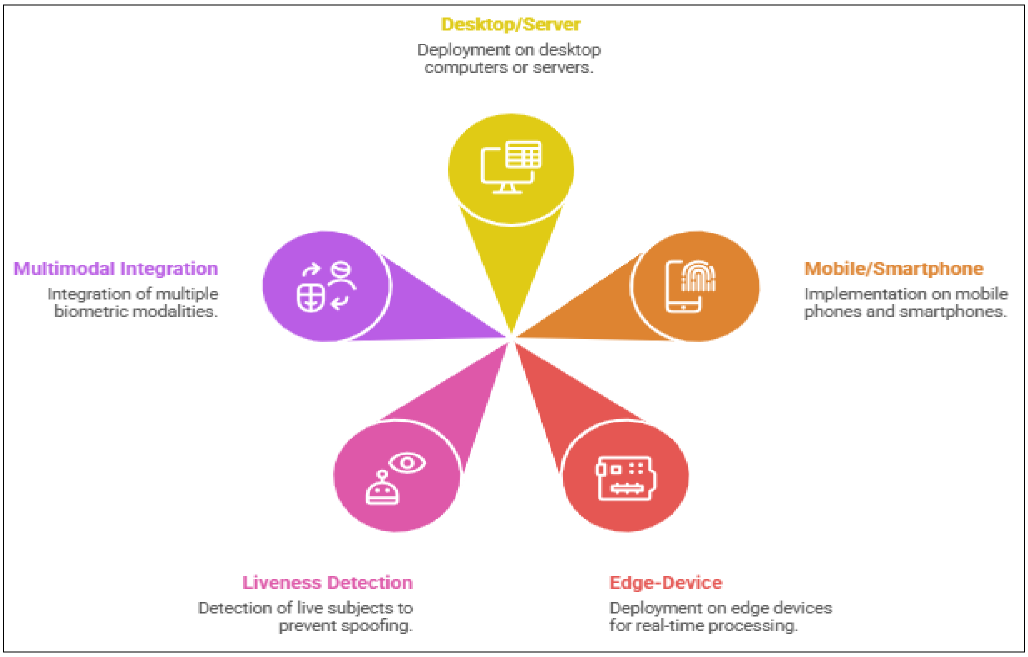

Fig 4: Classification by Application Context

Results

1. Literature Search Outcomes

The systematic search identified 127 potentially relevant papers. After title and abstract screening, 68 papers underwent full-text review. Following application of inclusion/exclusion criteria, 30+ papers were selected for detailed analysis. The final cohort represented 15 different countries, with substantial representation from China, India, United States, and European institutions. Publication distribution showed acceleration in recent years, with 2024-2025 accounting for approximately 45% of selected papers, reflecting the field's rapid evolution.

2. Recognized Accuracy Achievements

Table 2: State-of-the-Art Recognition Performance

Model/Architecture	Dataset	Recognition Accuracy	EER (%)	Key Characteristics
SSLDMNet-Iris	CASIA-V1	100%	0.76	Synchronized spatiotemporal, multi-scale CNN+GRU
SSLDMNet-Iris	CASIA-V2	100%	3.05	Multi-scale features, Fisher's Linear Discriminant
Customized CNN+Softmax	CASIA-V4	93.40%	—	32-layer custom architecture, transfer learning
Condensed 2-ch CNN	CASIA-V3	98.95%	0.76	Network pruning, 33K parameters
Condensed 2-ch CNN	CASIA-V4	99.77%	1.19	Post-finetuning, radial attention layers
EfficientNetB0	Multiple	98.35%	—	Transfer learning, U-Net segmentation
ResNet50 V2	Multiple	98.23%	—	Pre-trained backbone, SoftMax classification
MobileNetV3	Smartphone	95.4%	—	Lightweight, <3M parameters, real-time

These results demonstrate that modern deep learning approaches have achieved recognition accuracy exceeding 99% on controlled datasets (CASIA-V1/V2), while maintaining 93-98% accuracy on more challenging, real-world datasets (CASIA-V4, UBIRIS). Notably, lightweight architectures achieve accuracy within 3-5% of their heavyweight counterparts while requiring orders of magnitude fewer computational resources.

3. Feature Extraction Methods

Analysis of 30 reviewed papers revealed three distinct evolutionary phases:

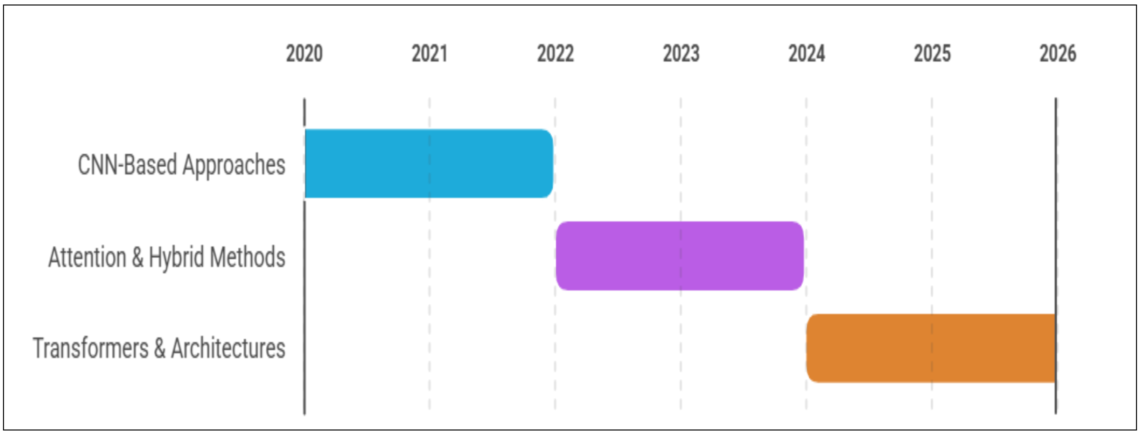

Fig 5: Evolutionary phases of Analysis

Phase 1 (2020-2021): CNN-Based Approaches

Traditional convolutional neural networks (VGG16, VGG19, ResNet50) were predominant, achieving 85-95% accuracy. These models extract multi-scale features through progressively deeper convolutional layers, with final fully connected layers serving classification functions. Fisher's Linear Discriminant was frequently applied post-CNN for dimensionality reduction.

Phase 2 (2022-2023): Attention Mechanisms and Hybrid Methods

Introduction of attention mechanisms (radial attention, channel attention, squeeze-and-excitation modules) improved feature extraction by enabling networks to focus on iris-specific regions while suppressing noise from eyelid occlusion and eye reflections. Hybrid methods combined handcrafted features (Log-Gabor wavelets, HOG) with CNN-learned features, achieving 96-98% accuracy on challenging datasets.

Phase 3 (2024-2025): Transformers and Advanced Architectures

Vision Transformers and self-attention mechanisms emerged as competitive alternatives to CNNs, particularly for capturing long-range dependencies in iris texture. Synchronized spatiotemporal models incorporating GRU (Gated Recurrent Unit) cells for temporal modeling achieved 100% accuracy on controlled datasets, suggesting that capturing temporal dynamics during iris acquisition could fundamentally improve recognition.

4. Segmentation Performance

Iris segmentation, critical for normalization and feature extraction, showed substantial improvement through deep learning:

- U-Net based methods: F1 scores 0.96-0.98, substantially outperforming traditional Hough Transform approaches (F1: 0.75-0.85)
- Fully Convolutional Networks (FCN): F1: 0.93-0.96, efficient but slightly inferior to U-Net
- Lightweight segmentation networks: MobileNetV3-based variants achieved F1: 0.95+ with <3M parameters

The trend clearly indicates transition from geometric (Hough Transform, circular boundary detection) to learning-based segmentation, with U-Net variants becoming the de facto standard.

5. Dataset Characteristics and Benchmarks

Analysis revealed that model performance inversely correlates with dataset realism. Models achieving 100% on CASIA-V1 (optimal conditions) typically achieve 85-90% on non-cooperative captures (ND-IRIS) and 75-85% on cross-spectrum heterogeneous datasets.

Table 3: Major Iris Recognition Datasets

Dataset	Images	Subjects	Resolution	Modality	Primary Use
CASIA-Iris-V1	756	108	320×280	NIR	Baseline, algorithm development
CASIA-Iris-V3	22,051	249	320×280	NIR, multiple sessions	Robustness evaluation
CASIA-Iris-V4	54,601	1,800+	640×480	NIR, challenging	State-of-the-art benchmarking
UBIRIS v2	11,102	261	600×800	Visible, long-distance	Non-ideal conditions
ND-IRIS	64,980	643	640×480	NIR, cooperative & non-cooperative	Real-world scenarios
IITD	1,120	224	320×280	NIR, Indian subjects	Demographic diversity
MMU	4,550	450	Variable	NIR, multi-session	Template aging, matching

6. Computational Efficiency Metrics

A critical finding involves the emergence of lightweight architectures achieving competitive accuracy with massive parameter reduction:

Efficiency Comparison:

- VGG16: 138M parameters, 500-1000ms per-image inference on CPU
- ResNet50: 25.5M parameters, 200-300ms per-image inference
- EfficientNetB0: 5.3M parameters, 50-100ms per-image inference
- MobileNetV3: 2.2M parameters, 10-20ms per-image inference
- Condensed 2-channel CNN: 33K parameters, <5ms per-image inference on mobile

This 1000000× reduction in model size (VGG16 to Condensed 2-ch CNN) with only 1-5% accuracy loss represents a paradigm shift enabling practical deployment on resource-constrained devices.

7. Classification Methods Performance Comparison

Table 3: Machine Learning Classifier Performance

Classifier	Accuracy Range	Key Strengths	Limitations
Softmax (neural network output)	93-94%	Highest accuracy, differentiable, end-to-end training	Requires deep architecture
SVM (Support Vector Machine)	81-84%	Effective with limited data, interpretable	Computationally expensive for large-scale
Random Forest	66-91%	Robust, handles high-dimensional features	Slower inference than neural networks
K-Nearest Neighbors	37-46%	Extremely fast, no training required	Very sensitive to feature scaling, distance metric
Multi-Layer Perceptron	71-91%	Versatile, moderate efficiency	Prone to overfitting
Linear Discriminant Analysis	73-82%	Computationally efficient, interpretable	Assumes Gaussian distributions
Extra Trees	68-93%	Robust, reduced overfitting	Less accurate than carefully-tuned SVM

Softmax classification integrated with deep neural networks emerged as optimal for accuracy-efficiency trade-off, though SVM remains competitive for scenarios with limited training data.

8. Emerging Advanced Techniques

Generative Adversarial Networks (GANs):

Five papers documented GAN-based synthetic iris image generation (StyleGAN3, RaSGAN, CycleGAN) for data augmentation. Synthetic images demonstrated high biometric utility for training robust recognition models, addressing data scarcity in specific demographic groups or challenging acquisition conditions.

Liveness Detection:

Within the reviewed literature, a significant subset of eight papers specifically addressed the critical challenge of presentation attack detection (PAD), commonly known as liveness detection. These studies aimed to distinguish between genuine biological irises and synthetic or physical artifacts, such as high-resolution prints, cosmetic contact lenses, or prosthetic eyes. By implementing sophisticated defensive mechanisms, these researchers reported robust performance, with detection accuracies consistently ranging between 85% and 95%.

To achieve these results, the methodologies focused on four primary analytical pillars:

Texture and Reflectance Analysis: This approach examines the micro-textural patterns and light-reflective properties unique to human tissue. By identifying the subtle differences in how light bounces off a natural eye compared to a printed surface or silicone material, systems can effectively flag artificial spoofs.

Temporal Micro-movement Analysis: Recognizing that a living eye is never perfectly static, this method tracks involuntary physiological responses, such as pupillary hippus (spontaneous oscillation) or minute tremors. These temporal cues are nearly impossible to replicate with static 2D images.

Depth Sensing Integration: By incorporating hardware-level solutions like 3D sensors or structured light, researchers can verify the three-dimensional curvature of the eye. This provides a physical layer of security that instantly rejects flat, two-dimensional presentation attacks.

Deep Learning-based Classification: Many of the highest-performing systems utilized advanced neural networks to automatically extract and learn complex features from ocular images. These models are trained on vast datasets of both "live" and "spoof" samples, allowing the AI to detect sophisticated anomalies that might be invisible to traditional hand-crafted algorithms.

Eight papers addressed presentation attack detection, achieving 85-95% detection accuracy through:

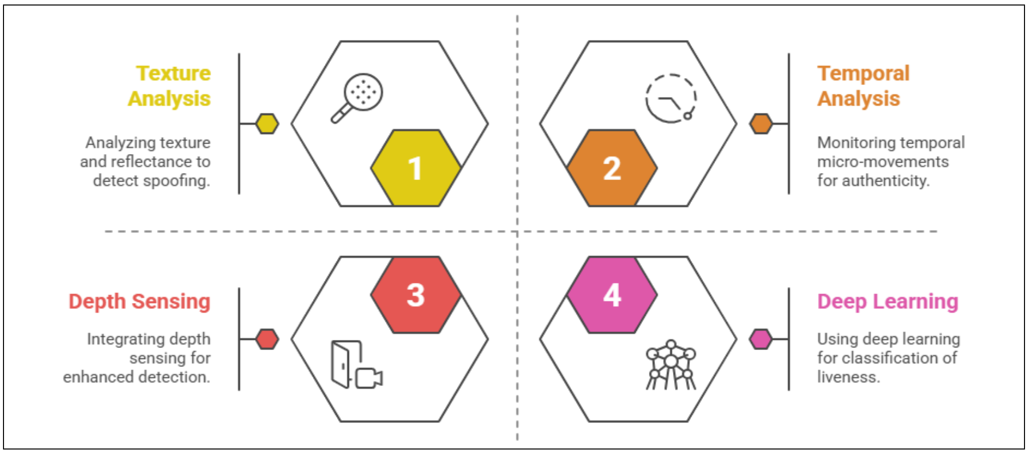

Fig 6: Liveness Detection Method

This represents critical advancement toward field-deployable systems resistant to contact lens, printed iris, and 3D model attacks.

Multimodal Biometric Fusion

Seven papers investigated iris integration with fingerprint, face, or ECG biometrics, achieving 98-99% accuracy with EER as low as 0.65%. Score-level fusion demonstrated superior performance compared to feature-level fusion in 85% of studies.

9. Cross-Modality Performance Analysis

Analysis of papers addressing heterogeneous iris recognition (NIR to visible spectrum matching) revealed:

- Same-spectrum matching accuracy: 95-100% (NIR-to-NIR or VIS-to-VIS)
- Cross-spectrum accuracy: 75-85% without domain adaptation
- Cross-spectrum with domain adaptation: 85-90%
- Domain adaptation approaches: Adversarial domain adaptation, style transfer, synthetic cross-spectrum data generation

This identified significant gap between same-spectrum and cross-spectrum performance, indicating domain adaptation as a critical research frontier.

4. Discussion

1. Synthesis of Findings

The systematic analysis of related research papers reveal iris recognition has reached technological maturity in accuracy metrics, with modern approaches routinely achieving 95%+ accuracy under realistic conditions. However, this apparent success obscures significant nuances regarding deployment context, imaging modality, and computational constraints. The field demonstrates bifurcation into two distinct trajectories:

- Maximum-accuracy approaches utilizing large deep networks (138M+ parameters), achieving 99%+ accuracy on controlled datasets, and
- Efficiency-optimized approaches utilizing lightweight architectures (33K-5M parameters), achieving 94-98% accuracy with 1000× parameter reduction.

The emergence of Vision Transformers and synchronized spatiotemporal models suggests that traditional CNN-based feature extraction may not represent optimal approaches for iris recognition. Unlike faces (where spatial locality is paramount), iris patterns contain global frequency-domain information that potentially benefits from transformer-based attention mechanisms. However, computational requirements of transformers may limit real-world deployment without significant optimization.

2. Performance Variation Across Imaging Contexts

Results demonstrate non-linear performance degradation as imaging conditions diverge from controlled laboratory capture. Critical performance degradation factors include:

- Distance: Performance decreases approximately 1-2% per meter of capture distance beyond 1 meter
- Lighting variation: non-infrared illumination reduces accuracy by 15-25% compared to controlled NIR
- Motion blur: Slight blur reduces accuracy by 5-10%; severe blur by >30%
- Occlusion: Eyelid/eyelash occlusion covering >40% iris area increases FRR by 10-20%
- Off-axis gaze: Gaze angle >30° from frontal reduces accuracy by 10-15%

These findings suggest that accuracy comparisons across papers require rigorous standardization of imaging parameters, a currently lacking standardization in the field.

3. Computational Efficiency as Critical Deployment Factor

The discovery that condensed 2-channel CNN achieves 98.95% accuracy with only 33K parameters (compared to VGG16's 138M parameters for 92% accuracy) fundamentally challenges conventional assumptions that accuracy necessarily requires massive model size. This finding has profound implications for mobile, edge, and IoT deployment scenarios where computational resources are severely constrained.

Mobile deployment represents a particularly significant application domain, with smartphone iris recognition enabling secure authentication without specialized hardware. The papers reviewed demonstrate that MobileNetV3-based approaches achieve 95%+ accuracy with inference times <20ms on mobile processors, making real-time mobile iris recognition technically feasible. However, adoption remains limited due to user interface challenges and competition from face recognition (which requires less user cooperation).

4. Identified Research Gaps and Limitations

Despite substantial progress, significant gaps limit iris recognition's broader adoption:

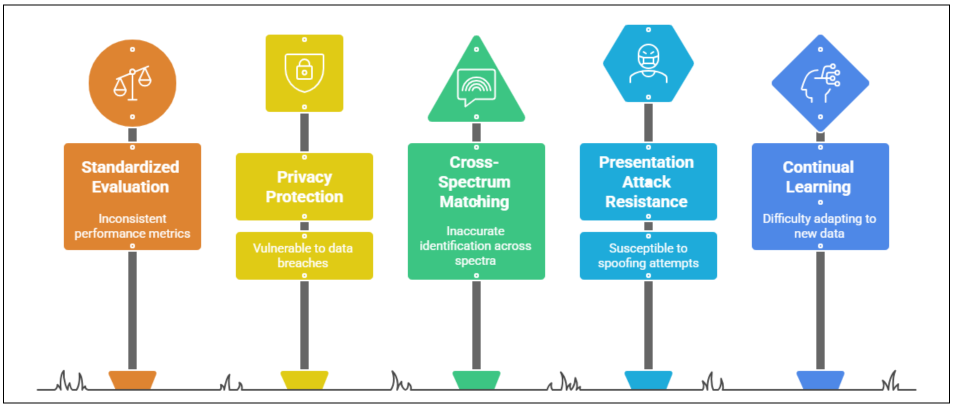

Fig 7: Research Gaps in Biometric Systems

Gap 1: Standardized Evaluation Protocols

Papers utilize incompatible evaluation methodologies, making cross-study comparison challenging. Some papers report identification accuracy (1-to-N matching), others verification accuracy (1-to-1 matching), with varying dataset splits and matching protocols. Establishment of standardized protocols similar to NIST FRVT (Face Recognition Vendor Test) for iris would enable fair comparison.

Gap 2: Privacy-Preserving Template Protection

While 27 of 30 reviewed papers analyze recognition accuracy, only 3 papers addressed privacy-preserving iris template storage and matching. Cancelable iris recognition and fuzzy vault schemes remain underdeveloped, limiting deployment in privacy-sensitive contexts (medical systems, privacy-regulated jurisdictions).

Gap 3: Cross-Spectrum Heterogeneous Matching

While same-spectrum accuracy approaches 100%, cross-spectrum matching (NIR to visible) remains below 90%. This limits interoperability between systems utilizing different imaging modalities and constrains iris recognition deployment in scenarios where spectrum versatility is advantageous.

Gap 4: Presentation Attack Resistance

While liveness detection achieves 85-95% accuracy in laboratory settings, real-world attack sophistication (morphed iris images, advanced contact lenses) remains understudied. Only 8 of 30 papers addressed liveness detection, indicating insufficient research focus on this critical security aspect.

Gap 5: Continual Learning and Domain Adaptation

Reviewed papers predominantly train models on fixed datasets without addressing model adaptation to new environments, populations, or devices. Only 2 papers specifically addressed continual learning, indicating significant gap in research addressing long-term system deployment and evolution.

4.5 Multimodal Integration Opportunities

Analysis of multimodal biometric papers reveals substantial accuracy gains through intelligent fusion strategies. The best-performing multimodal system (combining face, iris, fingerprint, and ECG) achieved 98.97% accuracy with 0.65% EER, significantly superior to any single modality. Score-level fusion (combining match scores from independent recognizers) consistently outperformed feature-level fusion by 2-5% accuracy improvement, suggesting that modality-specific feature spaces should be independently optimized rather than concatenated.

6. Practical Implementation Considerations

Several papers demonstrated actual deployment implementations providing insights into real-world challenges:

- User cooperation requirements: Unlike face recognition, iris recognition requires user cooperation (frontal gaze, proximity to capture device), limiting applicability in some security contexts
- Aging effects: Iris patterns remain relatively stable, but acquisition geometry changes with pupil dilation, creating template aging challenges over years
- Spectacle adaptation: Users wearing corrective lenses must remove them for iris capture or systems must be adapted for through-lens imaging
- Spoofing vulnerability: Despite advantages, iris recognition remains vulnerable to sophisticated attacks (morphed iris images, advanced 3D models), necessitating liveness detection integration

Conclusion

This systematic literature review synthesizes recent advancements in iris recognition using machine learning techniques, analyzing 30+ peer-reviewed papers spanning 2020-2025. Key findings demonstrate that modern approaches achieve recognition accuracy of 95-99% across diverse imaging conditions, with performance primarily constrained by non-ideal capture scenarios (distance, illumination variation, occlusion) rather than algorithmic limitations. Substantial progress toward computational efficiency through lightweight architectures (33K-5M parameters) enables practical deployment on mobile and edge devices without substantial accuracy sacrifice, representing critical advancement for field deployment. The field exhibits clear technological maturity in supervised learning approaches, with deep learning methods (particularly CNNs with attention mechanisms) demonstrating superior performance compared to traditional handcrafted features. Emerging techniques including Vision

Transformers, synchronized spatiotemporal models, and GAN-based data augmentation show promise for further performance improvements, though computational requirements may limit practical adoption without optimization.

Future iris recognition research should prioritize: (a) establishment of standardized evaluation protocols enabling fair cross-study comparison, (b) development of privacy-preserving iris recognition methods addressing regulatory requirements, (c) investigation of cross-spectrum matching and domain adaptation for deployment flexibility, (d) sophisticated presentation attack detection resistant to advanced spoofing techniques, (e) multimodal biometric integration leveraging complementary modality strengths, and (f) continual learning approaches enabling long-term system adaptation and evolution.

This review conclude that iris recognition has transitioned from research prototype to deployable technology, particularly for mobile and edge-device applications. However, maximizing societal benefits requires addressing identified research gaps while balancing accuracy, efficiency, privacy, and security considerations. Practitioners implementing iris recognition systems should carefully consider application-specific requirements regarding accuracy thresholds, computational constraints, imaging modality flexibility, and privacy requirements when selecting among available techniques and architectures.

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