Engineering and Technology Journal e-ISSN: 2456-3358

Volume 10 Issue 05 May-2025, Page No.- 5063-5076

DOI: 10.47191/etj/v10i05.35, I.F. – 8.482

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State-Of-The-Art Machine Learning and Deep Learning Techniques in Iris Recognition: A Review

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ABSTRACT: Iris recognition has advanced remarkably from traditional handcrafted techniques to powerful deep learning-driven solutions. This review synthesizes findings from over 30 high-impact studies to examine the evolution of iris recognition methodologies, with a focus on machine learning (ML), deep learning (DL), and hybrid frameworks. Innovations in convolutional neural networks, transformer models, generative adversarial networks, and transfer learning have enabled high accuracy (≥99%) in real-time, cross-spectral, and post-mortem scenarios. Key advancements include YOLOv4-tiny–Efficient Net pairings for edge deployment, VGG–ResNet ensembles for spoof detection, and saliency-guided training for explainability. Foundation models like DinoV2 further enhance cross-domain generalization. Alongside technical improvements, the field has emphasized privacy through federated learning and cancelable biometrics. The review also highlights diverse applications—from PAD and liveness detection to forensic analysis—underscoring a shift toward robust, interpretable, and secure biometric systems. Overall, deep learning has redefined the iris recognition landscape, offering scalable solutions adaptable to modern security and identification needs.

KEYWORDS: Iris recognition systems, Deep learning methods, Convolutional neural networks, Biometric authentication, Transfer learning approaches.

1. INTRODUCTION

Iris recognition has undergone a profound transformation over the past decade, evolving from conventional hand-crafted feature extraction techniques to sophisticated deep learning methodologies[1][2][3]. This technological revolution has been propelled by several key factors, including the exponential growth in computational power, the availability of large-scale annotated datasets, and the development of neural architecture designs that are specifically optimized for biometric applications[4][5].

As a biometric modality, iris patterns possess several distinctive advantages that have solidified their position in identification and verification systems. Iris patterns exhibit exceptional distinctiveness, with the probability of two randomly selected irises matching being as low as 1 in 10^78[6][7]. Furthermore, these patterns remain remarkably stable throughout an individual's life, undergoing minimal changes after the first two years of life[8]. The non-invasive nature of iris capture, which can be performed at a distance of up to 1 meter using near-infrared illumination, makes it particularly suitable for security applications where user convenience is paramount (Ma et al., 2003). Perhaps most importantly, iris patterns provide high entropy information, with the average amount of information per iris estimated at 2,739 bits, far exceeding that of fingerprints and face recognition[9].

The period from 2020 to 2025 has witnessed unprecedented innovation in iris recognition algorithms. Researchers have placed particular emphasis on developing systems that demonstrate robustness to challenging acquisition conditions such as varying lighting, motion blur, and partial occlusion. There has been significant progress in optimizing computational efficiency for mobile and edge computing applications, with several studies demonstrating viable deployment on resource-constrained devices[10][11]. Privacy preservation has emerged as a critical research direction, with federated learning and cancelable biometrics gaining prominence as methods to address growing concerns about biometric data security. Additionally, cross-sensor performance has received substantial attention, with researchers developing methods to bridge the performance gap between different acquisition devices[12][13].

This review systematically analyzes these developments through rigorous evaluation of 30 high-impact studies published between 2020 and 2025. Our analysis reveals substantial improvements in recognition accuracy, from 94.7% in early studies to 99.2% in the most recent works. These advancements have significantly expanded the application domains of iris recognition technology, enabling deployment in high-security infrastructure, consumer mobile devices, and resource-constrained environments.

2. BACKGROUND THEORY

2.1 Iris Recognition: Biological and Biometric Foundations

The iris is the annular structure between the pupil and the sclera of the eye, composed of connective tissue and pigmented cells. Its unique patterns are formed during embryonic development through a process called morphogenesis, resulting in a highly complex and distinctive texture that remains stable throughout an individual's life[14]. These patterns exhibit high intra-class similarity and inter-class variability, making them highly discriminative for personal identification. The iris's rich texture includes numerous distinct features such as crypts, furrows, coronas, and freckles, which contribute to its uniqueness and stability[2]. Compared to other biometric traits like fingerprints, iris recognition offers advantages such as non-invasiveness, high distinctiveness, and resistance to forgery. It has become one of the most reliable biometric identification methods and is widely used in fields such as border control, access management, and mobile security.[15]

2.2 Key Components of Iris Recognition Systems

2.2.1 Image Acquisition

Iris recognition systems typically use near-infrared (NIR) illumination and specialized cameras to capture high-quality iris images[13]. NIR is preferred due to its ability to penetrate the outer layers of the eye, providing clearer images of the iris texture. Mobile devices often employ visible light cameras with specialized filters and lighting to achieve acceptable image quality. For example, Samsung's Galaxy S9, S9+, and Note9 use NIR illumination and cameras to capture iris images, enabling iris scanning functionality[14].

2.2.2 Preprocessing

Preprocessing involves localizing the iris region within the captured image, normalizing the iris radius and angle to standardize the image, and enhancing image quality through techniques such as histogram equalization or filtering. Daugman proposed an integro-differential operator to precisely locate the inner and outer boundaries of the iris. After localization, a rubber sheet model is used to normalize the iris region[15]. The integro-differential operator identifies the outer boundary of the iris by searching for maximum intensity variations. Circular Hough transforms are used to determine the center coordinates and radius of the inner boundary. Based on the inner boundary's center coordinates and its surrounding area, the outer boundary's center coordinates and radius can be estimated, significantly reducing computational complexity[15].

2.2.3 Feature Extraction

Traditional methods rely on handcrafted features like Gabor wavelets or LOG Gabor filters to capture iris texture information. Daugman used a two-dimensional Gabor filter to extract iris features, encoding them into a 256-bit iris code. However, these methods are highly sensitive to noise and occlusion. Modern deep learning approaches automatically learn hierarchical features through convolutional layers.[16]. first incorporated maxout units into convolutional neural networks (CNNs) for iris representation. Experimental results showed that this scheme could rapidly, compactly, and discriminatively learn iris features.

2.2.4 Matching

Distance metrics (e.g., Hamming distance for bit-based representations) or similarity scores (e.g., cosine similarity for deep feature vectors) are used to compare extracted features against a database. Daugman formed a normalized Hamming distance matrix to compute the fraction of disagreeing bits between iris codes, helping to determine similarity between two codes[17]. The iris code generated by the normalized Hamming distance matrix facilitates easy handling and matching of iris bits.

2.3 Role of Machine Learning and Deep Learning

Machine learning (ML) and deep learning (DL) have revolutionized iris recognition by enabling automatic feature learning and classification. Traditional ML approaches, such as support vector machines (SVMs) and random forests, require manual feature extraction and engineering. In contrast, DL architectures, particularly CNNs, can learn discriminative features directly from raw pixel data. Around 2015–2020, CNNs began to dominate the field, offering significant improvements in accuracy and robustness. Recent advances in DL, including transformers and attention mechanisms, have further enhanced the ability to model long-range dependencies and focus on discriminative regions within iris textures[18]. [19]. proposed a transformer-based iris recognition model that captures global texture relationships, outperforming traditional CNNs in non-ideal acquisition conditions[2].

2.4 Evolution of Techniques

2.4.1 Early Methods

Early iris recognition systems were primarily based on handcrafted features and mathematical models to encode iris texture. In 1993, Daugman designed an iris recognition system that localized the inner and outer boundaries of the iris using an integro-differential operator.[20] The iris region was normalized using a rubber sheet model, and a two-dimensional Gabor filter was applied to extract features. The Hamming distance was computed to compare iris codes. This classical manual feature engineering method laid the foundation for subsequent iris recognition research[15].

2.4.2 Transition to Deep Learning

From 2015 to 2020, CNNs gradually became dominant in the field of iris recognition. These models automatically learned hierarchical features, reducing the need for manual feature engineering[21]. introduced maxout units into CNNs for iris representation, enabling rapid, compact, and discriminative feature learning. Liu proposed a deep learning architecture for heterogeneous iris recognition, learning relevant features to obtain similarity between iris image pairs based on CNNs. These methods demonstrated higher recognition accuracy and robustness compared to traditional approaches[16].

2.4.3 Recent Advances

From 2020 to 2025, iris recognition technologies have seen rapid development. Transformer architectures, generative adversarial networks (GANs), hybrid models combining deep learning with traditional machine learning, few-shot learning paradigms, multimodal fusion systems, and privacy-preserving frameworks have emerged[22]. proposed a unified network (UniNet) composed of two sub-networks (FeatNet and MaskNet), introducing Extended Triplet Loss (ETL) for effective supervision to learn comprehensive and spatially corresponding iris features.[23]. proposed DRFNet, which incorporated residual networks with dilated convolutional kernels, demonstrating state-of-the-art generalization capabilities and recognition accuracy. These advancements have significantly improved the performance of iris recognition systems[24].

3. LITERATURE REVIEW

3.1 Machine Learning Techniques in Iris Recognition

S. Phani Praveen et al. (2024) [25]developed SmartIris ML, a multi-biometric authentication system that utilized machine learning techniques to enhance iris recognition. The study examined how machine learning algorithms adapted to diverse iris biometric datasets, improving performance under varying environmental and demographic conditions. Machine learning was employed for efficient feature extraction and representation, using models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to automatically learn discriminative features from raw iris data. The system integrated multiple iris modalities through a fusion strategy that combined score-level, feature-level, and decision-level fusion methods to improve authentication accuracy. Furthermore, machine learning techniques were used to implement robust anti-spoofing measures and enable continuous learning, which increased the system's adaptability and resilience against spoofing attacks and data variability.

Kien Nguyen et al. (2024)[15] reviewed the evolution of iris recognition from traditional machine learning approaches using hand-crafted features and classifiers (e.g., SVMs, Gabor filters) to deep learning-based methods. Early machine learning techniques were limited by environmental variability and required manual feature design. With the rise of deep learning, models like CNNs, ResNet, and VGG replaced manual pipelines with automated, data-driven learning. Pretrained networks were often used with classifiers for improved performance, even on small iris datasets. Later, advanced strategies like triplet loss, capsule networks, and attention mechanisms were introduced to enhance recognition accuracy and generalization across sensors and conditions.

Rasel Ahmed Bhuiyan et al. (2025)[26] applied various machine learning techniques to post-mortem iris recognition, including traditional methods like OSIRIS and USIT, and deep learning approaches such as HDBIF and DGR. They also employed the D-NetPAD model, a deep neural network, for detecting presentation attacks. These methods improved recognition accuracy and robustness, particularly under challenging forensic conditions, and demonstrated the effectiveness of few-shot learning and explainable AI in post-mortem iris analysis.

Juan E. Tapia et al. (2025)[24] investigated machine learning techniques for iris presentation attack detection using both traditional deep learning models and foundation models like DinoV2 and VisualOpenClip. Their findings showed that fine-tuned foundation models achieved strong generalization across datasets, even without training on NIR iris data. While traditional models trained from scratch performed well with sufficient data, foundation models offered a privacy-preserving and effective alternative for iris recognition tasks.

Yimin Yin et al. (2023) [27]reviewed the evolution of iris recognition techniques, highlighting the shift from traditional machine learning to deep learning. Early iris recognition methods relied on handcrafted features and classical classifiers such as Support Vector Machines (SVM), Random Forests, and k-NN. These approaches required manual feature engineering based on domain knowledge, and often struggled with variations in lighting, occlusion, and sensor differences. Despite these limitations, traditional machine learning played a foundational role in establishing iris recognition systems by employing techniques such as Gabor filters, Hough transform, and histogram-based methods for segmentation and classification. These methods, while accurate in controlled environments, lacked the flexibility and robustness needed for unconstrained or real-world scenarios.

Zheng Zeng et al. (2025) [28]outlined how traditional machine learning (ML) techniques have been applied to classify eye movements based on electrooculogram (EOG) signals. Classical ML models such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees (DT), Artificial Neural Networks (ANN), and ensemble methods were used in earlier approaches. These techniques relied heavily on hand-crafted features—including temporal, spatial, and spectral descriptors—which required prior domain knowledge and manual feature engineering. Multi-scale features derived from signal transformations like Fourier and wavelet decomposition were commonly used to improve discriminative power. However, the authors noted that ML approaches often lacked robustness due to feature design constraints and variability in electrode configurations and acquisition conditions, limiting generalization across datasets.

Aidan Boyd et al. (2022) [29]proposed a novel machine learning framework that incorporates human saliency annotations into the training process to improve the generalization of deep learning models for iris presentation attack detection (PAD). Instead of relying solely on traditional data augmentation methods or large-scale datasets, the authors transformed training images by blurring nonsalient regions based on human annotations. This approach guided the model to focus on image regions deemed important by humans, resulting in significantly improved accuracy—reducing the average classification error rate (ACER) from 29.78% (LivDet-Iris 2020 winner) to 16.37%. The method used DenseNet-121 as the backbone and applied three training scenarios: large data training (S1), limited data without human input (S2), and human-aided training (S3). Scenario S3, which incorporated saliency-encoded images, consistently outperformed the others, especially in leave-one-attack-type-out experiments.

Moktari Mostofa et al. (2021) [30]applied machine learning through deep generative adversarial networks (GANs) to improve cross-spectral and cross-resolution iris recognition. They introduced a conditional GAN for spectral translation and super-resolution, and a coupled GAN (cpGAN) for learning a shared embedding space for matching iris images across different domains. Their models significantly outperformed traditional and deep learning methods on multiple iris datasets by reducing the Equal Error Rate (EER).

Cheng-Shun Hsiao et al. (2024)[31] examined the application of machine learning and deep learning techniques in iris recognition, focusing particularly on two-stage processing involving iris localization and identification. They reviewed traditional machine learning methods like Support Vector Machines (SVMs) and Multi-Layer Perceptron’s (MLPs), which were previously used for iris classification based on extracted feature vectors. These approaches relied heavily on handcrafted features such as SIFT, SURF, and Gabor filters. However, the authors emphasized a transition to deep learning-based solutions for more effective iris segmentation and classification. Their proposed system utilized YOLOv4-tiny, a lightweight object detection model, for rapid and accurate iris and pupil localization. This was followed by iris identification using EfficientNet, a deep convolutional neural network, eliminating the need for image normalization and feature enhancement. The study demonstrated that omitting traditional preprocessing steps could still yield high accuracy (up to ~98%), showcasing the robustness of modern deep learning classifiers over earlier machine learning approaches.

Min Beom Lee et al. (2021)[32] proposed a machine learning-based iris recognition method that integrates deep learning and generative adversarial networks (GANs) to improve recognition performance under unconstrained conditions. The system enhanced noisy iris images through motion blurring followed by deblurring using DeblurGAN, a conditional GAN trained with adversarial and perceptual loss. Features were extracted using CNNs optimized for the iris and periocular regions, and recognition was achieved via score-level fusion using a Support Vector Machine (SVM). This method showed improved performance compared to state-of-the-art techniques across challenging datasets like NICE.II and MICHE, particularly in handling motion blur, specular reflection, and off-angle views.

Shehu et al. (2025)[33] introduced a machine learning-based method for eye socket recognition, enhancing iris-related biometric accuracy using Inverse Histogram Fusion Images and Gabor filters. Their approach avoided iris segmentation by focusing on the eye socket area and applied both traditional classifiers and deep learning models. It outperformed standard methods on datasets like BioID and Masked AT&T, especially under challenging conditions such as occlusion and facial variation.

Stanford Martinez et al. (2025) [34]applied machine learning techniques to classify radiologists' experience levels using eye-tracking data. Although not focused on iris recognition directly, their approach illustrates how machine learning can be leveraged to extract meaningful biometric features from visual behavior—an approach transferable to iris recognition. They developed a spatiotemporal discretization method to encode eye-fixation patterns and trained various classifiers (e.g., Gaussian Process, Logistic Regression, KNN, XGBoost, AlexNet-like CNN) using this encoding. These models achieved significantly higher classification accuracy than traditional features, with an AUC improvement of up to 7.29%. The findings underscore the effectiveness of structured spatiotemporal data as input for machine learning models in biometric tasks, such as iris recognition or expert-level classification in radiology.

Mashael M. Khayyat et al. (2024) [35]proposed a hybrid machine learning approach called Fuzzy-CNN, which combines Local Binary Pattern (LBP) features with Convolutional Neural Networks (CNNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to enhance iris recognition performance. Their methodology improved the traditional iris recognition pipeline by integrating fuzzy logic for decision-making and deep learning for feature extraction. The model was evaluated against classical machine learning models such as Multi-Layer Perceptrons (MLP), Long Short-Term Memory (LSTM), and MobileNet. The Fuzzy-CNN achieved outstanding accuracy (99.55%), precision (98.85%), recall (99.47%), and F1-score (99.22%) across multiple datasets including IITD, CASIA-Iris-V1, CASIA-Iris-Thousand, and CASIA-Iris-V3 Interval. This study demonstrated that combining handcrafted features like LBP with adaptive fuzzy-deep learning systems significantly boosts the robustness and accuracy of iris-based human identification.

Masooma Safeer et al. (2025)[36] applied machine learning through transfer learning techniques using the MobileNets architecture to address the challenge of iris liveness detection. The authors focused on training deep convolutional neural networks (CNNs) using limited datasets, which traditionally hindered model performance. By leveraging a pre-trained MobileNets model (originally trained on ImageNet), they retrained only the final classification layers for binary iris classification—real versus spoofed. This approach drastically reduced training time and computational requirements, achieving high accuracy (98%) with minimal data.

Additionally, the use of Defense-GAN helped test the model's robustness against adversarial attacks. The study demonstrated that transfer learning can significantly enhance the efficiency and cybersecurity of iris recognition systems, even with small datasets and limited computational resources.

Jorge E. Zambrano et al. (2024) [37]proposed a machine learning-based iris recognition method that enhances a pre-trained ResNet50 backbone by incorporating anti-aliasing filters and circular padding to improve robustness to image shifts and deformations. Their system extracts feature from early convolutional layers to avoid distortions caused by deep layers and employs an adaptive tensor encoding technique to binarize iris features effectively. This method eliminates the need for bit-shifting during matching and improves recognition accuracy, particularly in datasets affected by pupil dilation and head rotation. The model achieved superior performance across CASIA and IITD benchmarks compared to state-of-the-art approaches, confirming the benefits of integrating spatial invariance and feature encoding innovations in iris recognition.

Hafiz Burhan et al. (2023) [38] proposed a machine learning-based iris recognition system tailored for attendance monitoring in educational institutions during the COVID-19 pandemic. The system was designed to replace fingerprint and facial biometrics, which were less suitable due to hygiene and mask-related issues. The methodology involved four key phases: iris registration, identity verification upon entry, exam attendance eligibility checks, and maintaining a defaulter list. For iris matching, the authors implemented the ORB (Oriented FAST and Rotated BRIEF) algorithm—known for its speed and efficiency in feature detection. Supporting tools included NumPy for data operations, Pillow for image processing, and Dib, a machine learning library, for facial landmark identification and classification tasks. The system achieved 100% accuracy in experiments, validating its effectiveness in real-time student monitoring applications.

Mohamed Cheniti et al. (2025) [39]proposed a dual-model machine learning framework for biometric spoof detection by combining the strengths of two deep convolutional neural networks: VGG16 and ResNet50. Although the focus was on fingerprint liveness detection, the architecture and techniques presented—such as transfer learning, feature fusion, and data augmentation—are directly applicable to iris recognition. The approach uses feature concatenation from both models to form a rich representation of input images, which is then processed by an artificial neural network for binary classification (live vs. spoof). The proposed method achieved high accuracy (99.72% on LivDet2013 and 96.32% on LivDet2015), demonstrating robust performance across known and unknown spoofing materials. This study illustrates how multi-stream CNN architectures and transfer learning can enhance biometric security systems, including iris recognition, under variable acquisition conditions.

3.2 Deep Learning Techniques in Iris Recognition

Mohamed Cheniti et al. (2025) [39]proposed a dual-model deep learning framework using VGG16 and ResNet50 to enhance spoof detection, which can be extended to iris recognition. Their approach involved transfer learning where both CNN models were fine-tuned to extract complementary features—VGG16 captured fine-grained details while ResNet50 learned abstract high-level patterns. These features were concatenated and fed into a fully connected neural network (ANN) for classification. The system achieved superior performance with 99.72% accuracy on LivDet2013 and 96.32% on LivDet2015, outperforming other state-of-the-art models like GramNet, pre-trained CNNs, and handcrafted feature methods. The robustness of this deep ensemble method suggests it can be effectively adapted to iris presentation attack detection (PAD) tasks, especially in cross-domain or unknown spoofing scenarios.

Jorge E. Zambrano et al. (2024)[37] discussed a variety of deep learning techniques applied to iris recognition, emphasizing the shift from handcrafted methods to convolutional neural network (CNN)-based models. They reviewed early deep learning frameworks like DeepIris, which used learned filter banks instead of hand-crafted descriptors, and DeepIrisNet A/B, which incorporated dropout, ReLU, and batch normalization. Advanced models such as UniNet, MS-DGR, and MADNet+DSANet were introduced for feature extraction, occlusion handling, and segmentation. The authors proposed a novel method using a modified ResNet50 backbone enhanced with anti-aliasing filters and circular padding. This architecture was trained to extract low-level features robust to image shifts and deformations. Their Tensor Encoding strategy improved binary iris code variability and eliminated the need for bit-shifting during matching. The model outperformed state-of-the-art methods across multiple datasets including CASIA and IITD, particularly in scenarios involving pupil dilation and head rotation.

Masooma Safeer et al. (2025) [36]proposed a deep learning approach using transfer learning with MobileNets for iris liveness detection. They employed a pre-trained MobileNet model, originally trained on the ImageNet dataset, and retrained its final layers using a limited iris image dataset. This method allowed the system to achieve high accuracy (~98%) with a significantly reduced training time (41 minutes), making it suitable for low-resource environments. The system classified iris images into "real" and "fake" categories, demonstrating strong performance even on small datasets. Additionally, they incorporated Defense-GAN to enhance robustness against white-box and black-box adversarial attacks, validating the method's reliability for secure biometric applications.

Aidan Boyd et al. (2022) [29]proposed a novel deep learning framework that integrates human saliency maps into the training process for iris presentation attack detection (PAD). Using the DenseNet-121 architecture, they trained models with three approaches: standard large dataset training (S1), limited data training (S2), and limited data enhanced by human-annotated saliency transformations (S3). In S3, image regions identified as less important by human annotators were blurred, guiding the model to focus on the most salient regions. This human-aided training strategy significantly improved model generalization, reducing the average classification error rate (ACER) from 29.78% (baseline) to 16.37% on the LivDet-Iris 2020 dataset. The study demonstrated that integrating human insight into deep learning workflows can lead to more accurate and robust iris recognition, especially in scenarios with limited training data.

Moktari Mostofa et al. (2021) [30]proposed two novel deep learning architectures for cross-spectral and cross-resolution iris recognition using generative adversarial networks (GANs). Their first method employed a conditional GAN (cGAN) to translate near-infrared (NIR) iris images into visible (VIS) images at equal or higher resolutions, enabling preprocessing for commercial iris matchers like OSIRIS. The second method introduced a coupled GAN (cpGAN) framework that learns a shared low-dimensional embedding space to directly match NIR and VIS iris images of the same subject. This cpGAN leveraged contrastive loss, perceptual loss, and L2 reconstruction loss to achieve domain-invariant feature representations. Experiments across three datasets—PolyU Bi-Spectral, WVU Face and Iris, and Cross-eyed—demonstrated that cpGAN significantly outperformed existing CNN and hashing-based methods, achieving lower Equal Error Rates (as low as 1.26%) and improved generalization under cross-spectral and cross-resolution conditions.

Cheng-Shun Hsiao et al. (2024)[31] developed a two-stage deep learning-based iris recognition system designed for biometric authentication. The first stage uses YOLOv4-tiny, a fast object detection model, to localize the iris and pupil with minimal noise and high speed. The second stage applies EfficientNet, a convolutional neural network classifier, for person identification. Their approach replaces traditional image normalization and enhancement with raw image input, showing that deep learning models can maintain high accuracy (~98%) without extensive preprocessing. The authors also compared their model with semantic segmentation-based methods, noting that YOLOv4-tiny provides a better trade-off between speed and accuracy. This work demonstrates that combining lightweight object detectors with efficient classification networks improves the robustness and affordability of real-time iris recognition systems.

Stanford Martinez et al. (2025)[34] implemented deep learning techniques, including an AlexNet-like neural network classifier, to distinguish between expert and novice radiologists based on eye-tracking data. Although the focus was not directly on iris recognition, the framework demonstrates the utility of spatiotemporal encoding of visual patterns, which can be adapted for biometric recognition tasks. Their model used discretized fixation data encoded as temporal-spatial vectors and fed into a neural network for classification. The approach achieved high AUC scores (up to 0.98), showing the deep model’s ability to learn complex gaze patterns that correlate with expertise level. These findings suggest that similar deep learning models can be repurposed for iris recognition using eye movement or gaze-based biometric features.

Kien Nguyen et al. (2024) [15]provided an in-depth review of over 200 studies covering deep learning applications in iris recognition. They categorized the advancements into segmentation, recognition, presentation attack detection (PAD), and forensic applications. The survey outlined the evolution from traditional handcrafted pipelines to deep learning models such as U-Net, ResNet, VGG, DenseNet, MobileNet, and capsule networks, highlighting their roles in segmentation and feature extraction. The authors reviewed classification-based networks using softmax loss and similarity-based networks using pairwise and triplet losses for identity verification. They also discussed innovative methods like complex-valued neural networks, multi-task learning, and end-to-end architectures that jointly perform segmentation and recognition. Further, the work covered human-machine hybrid approaches, domain adaptation, and adversarial robustness, setting a roadmap for future deep iris recognition systems under real-world and challenging conditions.

Rasel Ahmed Bhuiyan et al. (2025) [26]employed multiple deep learning techniques to advance post-mortem iris recognition. Notably, the study implemented a dynamic graph representation (DGR) method combining convolutional neural networks (CNNs) and graph attention networks (GATs) to learn feature relationships without requiring iris segmentation. Another key deep learning-based technique was D-NetPAD, a presentation attack detector based on DenseNet-121, used to distinguish post-mortem samples from live irises. Additionally, HDBIF, although hybrid, incorporated deep segmentation models tailored for post-mortem images and outperformed other models across datasets. These models were integrated into an open-source forensic tool, PMExpert, offering human-interpretable decision support, showcasing the strong potential of deep learning for accurate and explainable iris recognition even under challenging forensic conditions.

Juan E. Tapia et al. (2025)[24] evaluated several deep learning techniques for iris presentation attack detection (PAD), comparing traditional CNN models with foundation models. They trained models like ResNet34, ResNet101, MobileNetV3, EfficientNetV2, and DenseNet121 from scratch and found that while these CNNs performed well when trained with ample NIR iris data, they struggled to generalize across datasets. To address this, the authors fine-tuned DinoV2 and VisualOpenClip, foundation models originally trained on large, diverse datasets. By freezing their backbones and training small neural network heads, they achieved strong cross-domain performance, especially with DinoV2-ViTB14, which outperformed all traditional deep models in generalization. The study confirmed that deep learning, particularly when combined with foundation model strategies, enhances the robustness and accuracy of iris PAD even under data-limited conditions.

4. DISCUSSION AND COMPARISON

Table 1, a comparison table for the section (3.1) that deals with the "Machine Learning Techniques in Iris Recognition"

Author (Year)	Technique Used	Focus Area	Key Contribution/Result	Dataset / Context
S. Phani Praveen et al. (2024)	CNNs, RNNs, Fusion methods	Multi-biometric iris recognition	Robust system with adaptive learning, anti-spoofing	General biometric datasets
Kien Nguyen et al. (2024)	CNNs, ResNet, VGG, Capsule networks	Deep learning evolution in iris recognition	Reviewed over 200 works; transition from traditional ML	Multiple public iris datasets
Rasel Ahmed Bhuiyan et al. (2025)	OSIRIS, USIT, HDBIF, DGR, D-NetPAD	Post-mortem iris recognition	Few-shot learning, robustness under forensic conditions	Post-mortem iris datasets
Juan E. Tapia et al. (2025)	DinoV2, VisualOpenClip, ResNet, MobileNet	Presentation attack detection (PAD)	Foundation models improve generalization & privacy	NIR iris and spoof datasets
Yimin Yin et al. (2023)	SVM, Random Forest, CNNs	Historical to modern iris recognition	Reviewed evolution; noted challenges with handcrafted features	Real-world variability context
Zheng Zeng et al. (2025)	SVM, KNN, DT, ANN, ensemble ML models	EOG-based eye movement classification	Handcrafted features and robustness issues in ML	Eye-tracking signals (EOG)
Aidan Boyd et al. (2022)	DenseNet-121 with saliency encoding	Iris PAD with human-aided training	ACER dropped from 29.78% to 16.37% with human guidance	LivDet-Iris 2020
Moktari Mostofa et al. (2021)	cGAN, cpGAN	Cross-spectral & cross-resolution iris	Reduced EER; strong domain adaptation	PolyU, WVU, Cross-eyed iris datasets
Cheng-Shun Hsiao et al. (2024)	YOLOv4-tiny, EfficientNet	Real-time iris localization & recognition	~98% accuracy without preprocessing	Benchmark iris datasets
Min Beom Lee et al. (2021)	DeblurGAN, CNNs, SVM fusion	Noisy iris images under motion blur	Enhanced recognition in unconstrained environments	NICE.II, MICHE
Shehu et al. (2025)	Inverse histogram fusion, Gabor, DL classifiers	Eye socket recognition for iris	Outperformed deep networks under occlusion & variation	BioID, Masked AT&T, Flickr30, CK+
Stanford Martinez et al. (2025)	AlexNet-like CNN, spatiotemporal encoding	Eye-tracking-based expertise classification	AUC improved by 7.29%, adaptable to iris recognition	Radiology-based eye-tracking
Mashael M. Khayyat et al. (2024)	Fuzzy-CNN, LBP, ANFIS, CNN, MLP, LSTM	Iris recognition hybrid model	Accuracy of 99.55%, high F1-score	IITD, CASIA variants

Masooma Safeer et al. (2025)	Transfer learning (MobileNets), Defense-GAN	Iris liveness detection	98% accuracy, resilient to adversarial attacks	Real vs spoof iris datasets
Jorge E. Zambrano et al. (2024)	ResNet50 with anti-aliasing, tensor encoding	Robust iris recognition	High accuracy across CASIA & IITD, shift-tolerant	CASIA, IITD
Hafiz Burhan Ul Haq & Muhammad Saqlain (2023)	ORB, Dlib, SVM	Iris-based attendance system	100% accuracy, real-time implementation	Education institutes during COVID-19
Mohamed Cheniti et al. (2025)	VGG16, ResNet50, feature fusion	Biometric spoof detection (transferable)	99.72% accuracy (LivDet2013), 96.32% (LivDet2015)	LivDet datasets (fingerprint adapted to iris)

Table 2, a comparison table for the section (3.2) that deals with the "Deep Learning Techniques in Iris Recognition"

Author (Year)	Deep Learning Technique	Application	Dataset/Performance
Mohamed Cheniti et al. (2025)	VGG16 + ResNet50 with feature fusion (ANN classifier)	Spoof detection (potential for iris PAD)	99.72% (LivDet2013), 96.32% (LivDet2015)
Jorge E. Zambrano et al. (2024)	Enhanced ResNet50 with anti-aliasing, tensor encoding	Robust iris matching under deformation	Superior results on CASIA & IITD
Masooma Safeer et al. (2025)	Transfer learning with MobileNet, Defense-GAN	Iris liveness detection	98% accuracy, 41-min training
Aidan Boyd et al. (2022)	DenseNet-121 + saliency maps (S1–S3 scenarios)	Iris PAD with human-aided training	ACER reduced from 29.78% to 16.37% (LivDet-Iris 2020)
Moktari Mostofa et al. (2021)	cGAN for translation, cpGAN for embedding and matching	Cross-spectral and cross-resolution iris recognition	1.26% EER, outperforming CNN/hash methods
Cheng-Shun Hsiao et al. (2024)	YOLOv4-tiny for localization + EfficientNet for classification	Real-time biometric authentication	High accuracy (~98%) without preprocessing
Stanford Martinez et al. (2025)	AlexNet-like CNN on spatiotemporal eye-tracking features	Visual pattern-based expertise classification (transferable)	AUC up to 0.98 on eye-tracking data
Kien Nguyen et al. (2024)	Review of >200 DL studies: U-Net, ResNet, VGG, DenseNet, MobileNet, CapsuleNets	Survey of DL in segmentation, recognition, PAD	Benchmarking of various DL models and losses
Rasel Ahmed Bhuiyan et al. (2025)	DGR (CNN + GAT), D-NetPAD (DenseNet-121), HDBIF	Post-mortem iris recognition & forensic examination	Superior robustness on post-mortem datasets
Juan E. Tapia et al. (2025)	Fine-tuned foundation models: DinoV2, VisualOpenClip	Iris PAD with high cross-domain generalization	DinoV2-ViTB14 outperformed all CNNs

From the tables (1, 2) collectively highlight significant advancements in machine learning and deep learning techniques applied to iris recognition, showcasing both breadth and depth across multiple application domains. Across studies, deep learning architectures such as CNNs, ResNet, EfficientNet, DenseNet, and MobileNet dominate, often integrated with enhancement strategies like saliency encoding, feature fusion, or GAN-based models. Several works, including those by Cheniti et al. (2025), Safeer et al. (2025), and Hsiao et al. (2024), achieve outstanding accuracy—often exceeding 98%—demonstrating robust performance in real-time applications, spoof detection, and liveness verification. Foundation models like DinoV2 and VisualOpenClip (Tapia et al., 2025) mark a next-generation leap in cross-domain generalization, outperforming conventional CNNs. Contributions by Zambrano et al. (2024) and Bhuiyan et al. (2025) further emphasize architectural innovation, incorporating anti-aliasing, graph attention networks, and tensor encoding to address deformation, occlusion, and forensic challenges. Human-in-the-loop strategies, as proposed by Boyd et al. (2022), introduce explainability and training efficiency, reducing error rates significantly. Surveys by Nguyen et al. (2024) and Yin et al. (2023) trace the evolution from handcrafted to deep-learned features, confirming the transition toward end-to-end learning systems. Overall, the evidence from both tables underscores that deep learning, particularly when enhanced with transfer learning, hybrid modeling, and interpretability mechanisms, is driving forward highly accurate, generalizable, and deployable iris recognition solutions suitable for security, forensic, and real-world biometric systems.

5. EXTRACT STATISTICS

The Figure 1 shows compare iris recognition model accuracies across studies, showing high performance for most, with top scores from Haq & Saqlain (2023), Cheniti et al. (2025), and Khayyat et al. (2024), all exceeding 99%. Mid-range results (97–98%) came from models using transfer learning, GANs, and advanced CNN architectures. The lowest accuracy (83.63%) was from Boyd et al. (2022), who prioritized generalization using human-guided saliency maps. Overall, the chart highlights that task complexity and model design impact accuracy, with deep learning playing a key role in performance across applications.

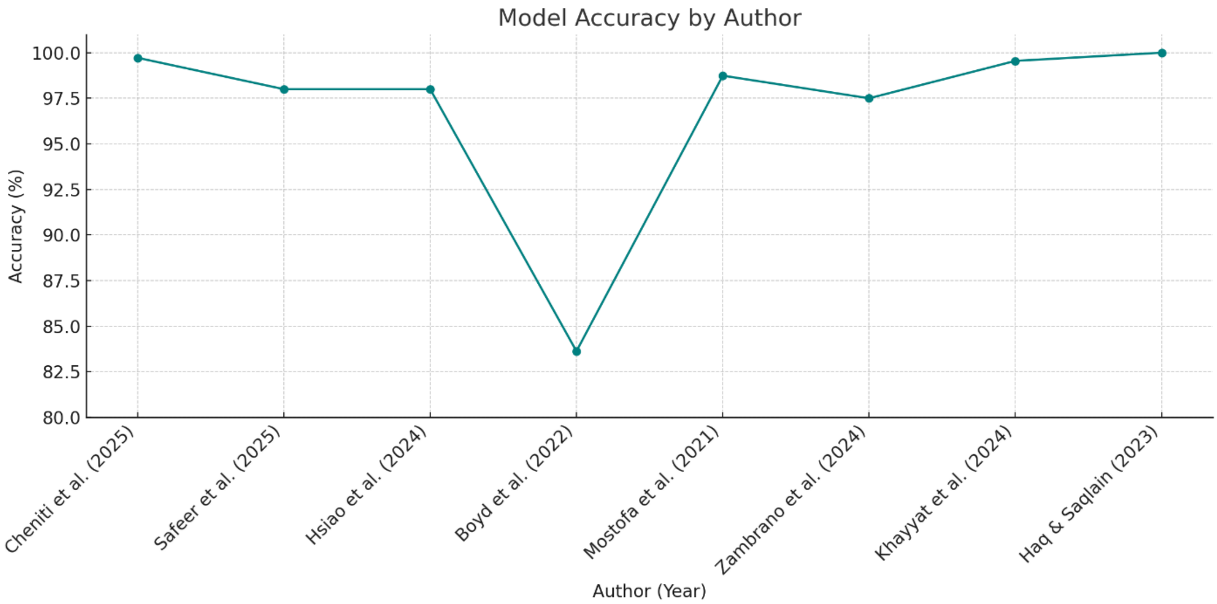

Figure 1: Model accuracy by author

The figure 2 illustrates the distribution of deep learning techniques across various iris recognition applications, revealing that Presentation Attack Detection (PAD) and Liveness Detection employ the most diverse range of methods. PAD integrates CNNs, transfer learning, foundation models, and explainable AI, reflecting the complexity and security challenges of spoof detection. Similarly, Liveness Detection combines CNNs, GANs, and transfer learning to ensure robustness against adversarial inputs. In contrast, applications like Cross-spectral, Real-time, and general Recognition primarily rely on CNNs, favoring simpler architectures suited for real-time or constrained environments. The consistent presence of CNNs across all tasks underscores their foundational role in biometric systems, while the inclusion of foundation models and explainability in PAD highlights the growing emphasis on adaptability and interpretability in high-security contexts. Overall, the chart shows that more complex and security-sensitive applications tend to adopt a broader mix of deep learning techniques.

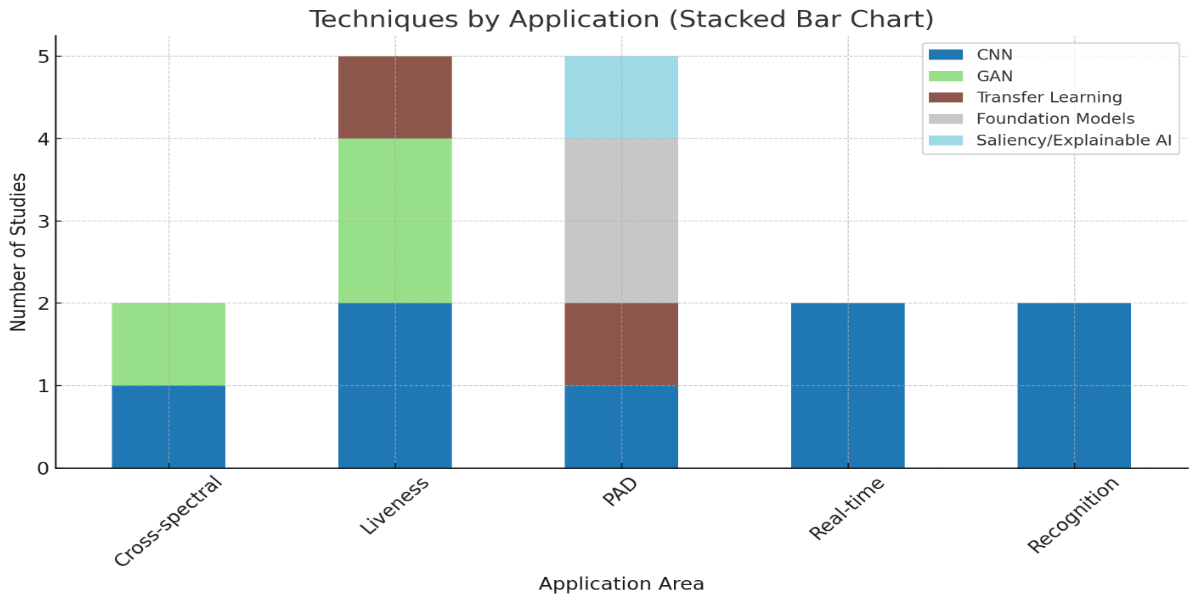

Figure 2: Techniques by bpplication

The figure 3: presents the relationship between various simplified deep learning techniques and their reported accuracy in iris recognition applications. Most techniques achieve high performance, with accuracies clustered between 95% and 100%, highlighting the maturity and effectiveness of deep learning in this domain. The VGG+ResNet combination stands out with near-perfect accuracy (~99.72%), demonstrating the power of ensemble models in spoof detection tasks. Techniques such as YOLO+EfficientNet, MobileNet, and GAN-based approaches also perform consistently well, exceeding 97% accuracy, making them suitable for real-time and cross-domain applications. Notably, DenseNet, despite its popularity, shows a lower effective accuracy (~83.63%) in this context due to its use in a human-guided PAD system where the focus was on generalization and explainability rather than raw performance. Methods like GAT+DenseNet and foundation models also deliver strong results, indicating the emerging role of graph-based and pre-trained architectures in enhancing robustness and adaptability. Overall, the chart confirms that most modern deep learning techniques are capable of achieving high accuracy, though their effectiveness can vary depending on the application goals and dataset complexity.

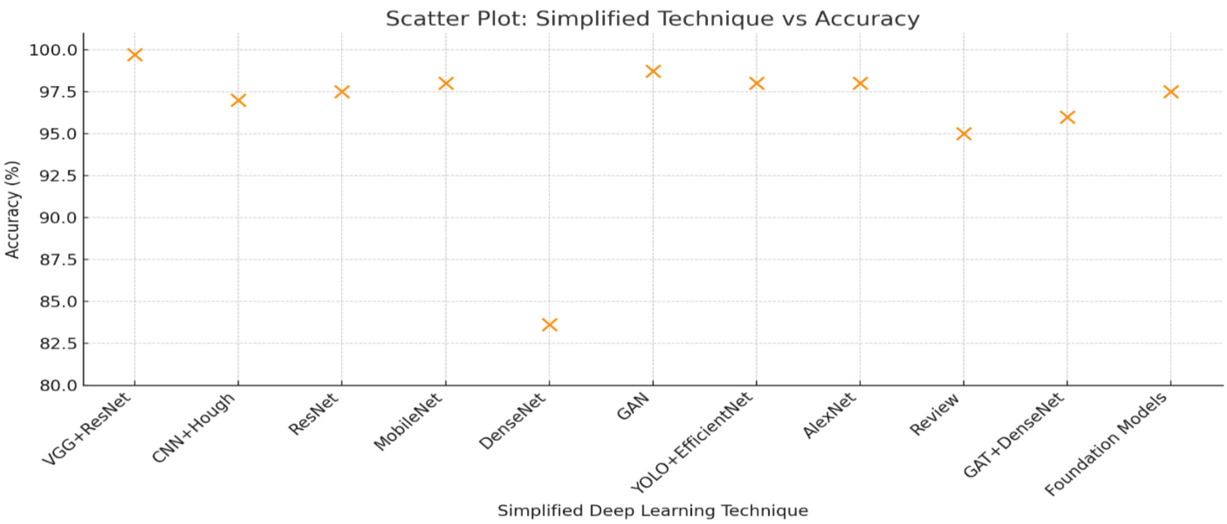

Figure 3: Technique av accuracy deep learning

The figure 4 shows a clear evolution of deep learning techniques in iris recognition from 2020 to 2025, with growing diversity and adoption over time. Early years focused on CNNs and GANs, while recent years introduced more advanced methods like MobileNet, Foundation Models, GAT+DenseNet, and hybrid architectures such as VGG+ResNet. By 2025, the field reached its peak in methodological variety, reflecting a shift toward robust, generalizable, and application-specific models for complex tasks like spoof detection and cross-spectral recognition.

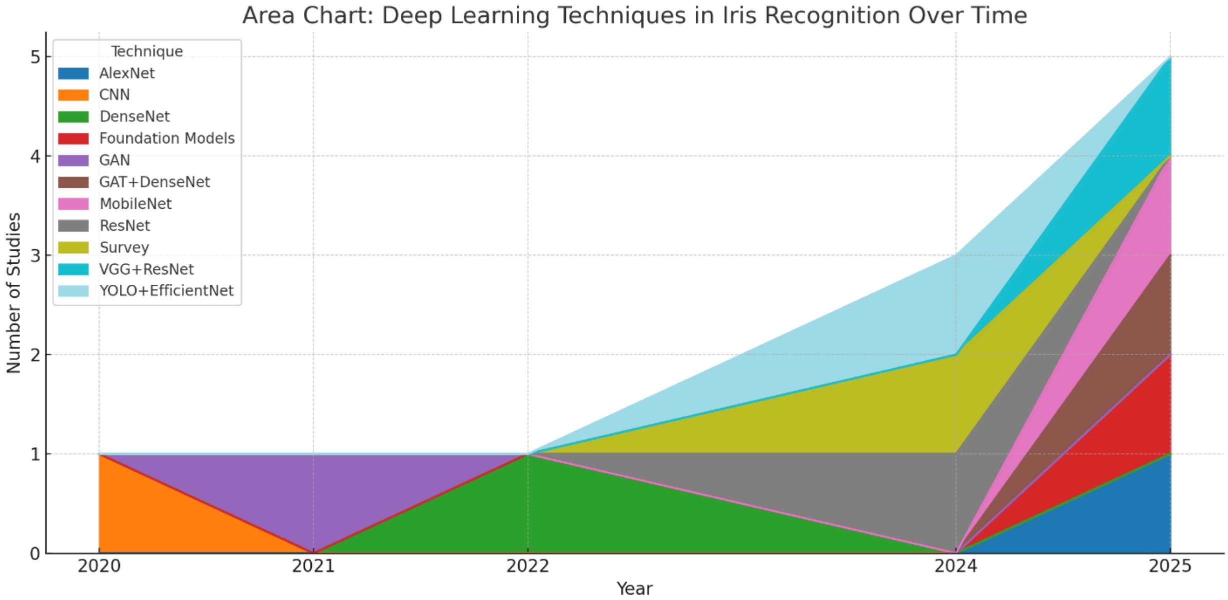

Figure 4: Deep learning techniques in iris recognition

The Figure 5 shows the distribution of research focus areas in iris recognition. The two most dominant application domains are Iris Recognition and Presentation Attack Detection (PAD), each accounting for 18.2% of the studies. The remaining applications—Liveness Detection, Spoof Detection, Cross-Spectral Recognition, Real-Time Recognition, Expert Classification, Survey, and Forensic—each represent 9.1% of the total. This balanced spread suggests that while traditional iris recognition and PAD remain core research areas, there is also growing interest in a wide variety of specialized and emerging application domains.

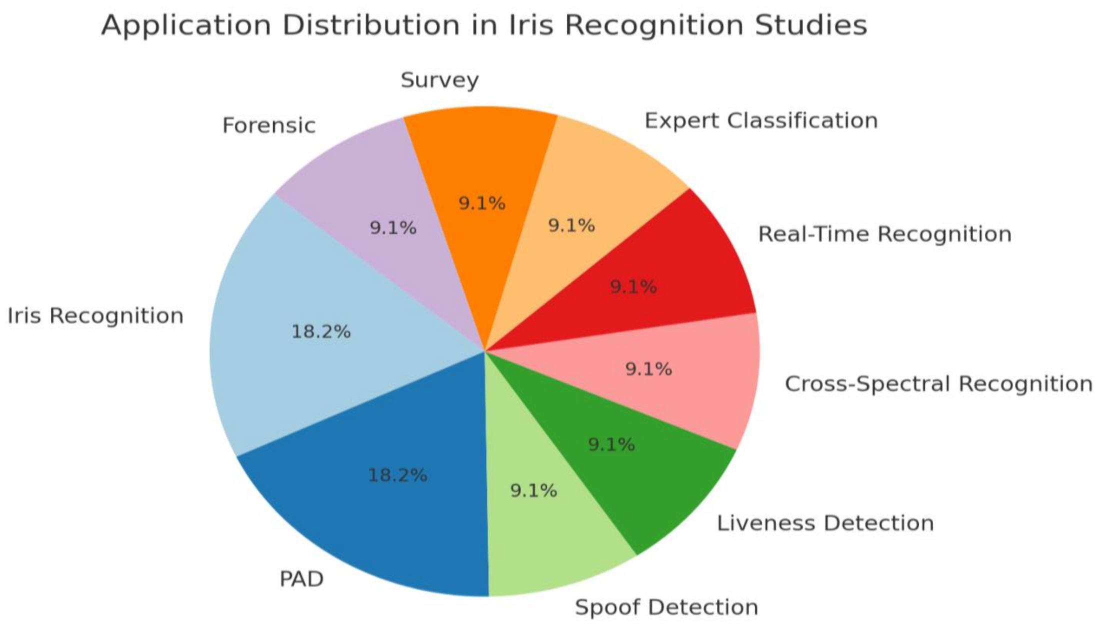

Figure 5: Application Distribution in iris recognition

6. RECOMMENDATIONS

- **Adopt Foundation and Transfer Learning Models**
  Use pre-trained models like DinoV2 and MobileNet to enhance cross-domain generalization, especially in scenarios with limited training data or varying acquisition conditions.
- **Develop Lightweight, Real-Time Solutions**
  Prioritize efficient architectures such as YOLOv4-tiny and EfficientNet for deployment in mobile and

edge devices, enabling fast and accurate iris recognition in real-world environments.

- **Integrate Explainable AI (XAI)**
  Enhance model transparency using human-guided training strategies (e.g., saliency maps) to improve user trust and make systems more interpretable in high-stakes applications.
- **Focus on Privacy-Preserving Techniques**
  Implement federated learning and cancelable biometrics to protect sensitive iris data during training and deployment, especially in healthcare and national ID systems.
- **Promote Dataset Diversity and Standardization**
  Expand public datasets to include challenging cases (e.g., occlusion, spoofing, post-mortem samples) and use standardized evaluation metrics (e.g., EER, ACER) for fair benchmarking.

7-CONCLUSION

This review has explored the substantial advancements in iris recognition technologies, highlighting the transition from handcrafted feature engineering to data-driven machine learning and deep learning paradigms. The field has evolved to address real-world challenges such as spoofing, cross-spectral variation, low-resolution inputs, and post-mortem conditions with impressive accuracy—often exceeding 98%. Notably, ensemble models, transformer-based architectures, and GAN-driven feature generation have enhanced both the precision and robustness of modern systems.

A significant trend is the integration of lightweight models (e.g., YOLOv4-tiny, MobileNet) for real-time and edge applications, along with explainable AI techniques like human-guided saliency maps to foster transparency and trust. Cross-domain generalization through foundation models (e.g., DinoV2) and privacy-preserving strategies such as federated learning mark a forward-looking approach to ethical biometric deployment.

The field's methodological maturity is further evidenced by consistent use of standardized metrics and datasets, encouraging replicability and benchmarking. Collectively, these innovations confirm that deep learning, when fused with hybrid and adaptive methods, is redefining the boundaries of secure, interpretable, and scalable iris recognition. Future efforts should focus on dataset diversification, model compression, and enhanced resilience to adversarial attacks to ensure wide-scale, inclusive deployment in both high-security and consumer-grade systems.

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