A Bibliometric Analysis of Current Advancements in Iris Feature Extraction and Recognition

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ABSTRACT

Iris recognition has rapidly advanced due to deep learning and hybrid models that have transformed feature extraction and identification processes. However, research remains scattered across various subfields, necessitating a systematic synthesis. This bibliometric and systematic review explores recent developments in iris feature extraction and recognition by analyzing literature published over the past seven years. Using bibliometric mapping, the study identifies leading authors, journals, and collaborative networks shaping the discourse. Technological advancements, including non-segmentation deep learning models, attention-based mechanisms, cross-spectral recognition, and hybrid approaches integrating periocular features, are critically examined. Additionally, the review highlights emerging challenges such as recognition in unconstrained environments, post-mortem scenarios, mobile device adaptation, and presentation attack resilience. Results reveal significant progress alongside persistent research gaps, particularly in the areas of cross-domain generalization. This comprehensive analysis provides critical insights and outlines future research directions, guiding scholars and practitioners in advancing iris biometric systems toward greater robustness, scalability, and adaptability across constrained and unconstrained operational environments.

Keywords: Deep Learning, Iris Recognition, Feature Extraction, Bibliometric Analysis

INTRODUCTION

A biometric is a measurable physical or behavioral characteristic used to identify or verify the identity of an individual (Vensila & Boyed Wesley, 2024; Yang & Wang, 2023). The most often used physiological biometric traits include face, hand geometry, fingerprints, iris, and retinal pictures (Gomez-Barrero et al., 2022). However, the traditional means of identification involve using cards or passwords where passwords can be forgotten, cards can be lost or stolen, and these mechanisms can also be damaged (Makrushin et al., 2023). Hence, there is a need for biometric identification systems that can recognize individuals in cognizance with physical or behavioral characteristics (Farouk et al., 2022). The identification of individuals using biometric methods can be achieved effectively and reliably through iris recognition (Szymkowski et al., 2021). Furthermore, iris recognition systems have shown resilience against common biometric vulnerabilities such as fingerprint wear or facial changes due to aging and expression variations (Nsaif et al., 2022a).

Iris is a well-protected internal organ with distinct characteristics that will remain stable for a long time. Compared to other biometric traits, iris characteristics are more distinct due to their non-uniform texture (Daugman, 2004). The unique patterns of the human iris remain stable over a person's lifetime, making it an ideal candidate for identity verification in high-security environments such as border control, banking, and access management systems (Assari & Dehghan, 2019). However, despite its robustness, iris recognition systems are not impervious to security challenges. Presentation attacks, where adversaries attempt to deceive the system using artifacts like high-resolution images or contact lenses, pose significant threats. To counteract these vulnerabilities, liveness detection techniques have been developed to ascertain the authenticity of the presented iris (Nguyen et al., 2024). These methods aim to distinguish between live and fake irises by analyzing physiological responses or employing machine learning algorithms trained on various spoofing attempts (Tapia et al., 2022). Moreover, the iris recognition system can generally be achieved through four stages, namely data collection, data pre-processing, feature extraction and matching/recognition (Panwar & Pooja, 2022).

Feature extraction is a critical component in the efficacy of iris recognition systems, as it involves distilling the unique patterns of iris into a mathematical representation for comparison and identification (Chen, Wu, & Wang, 2020; Divya & Rajendra, 2022). This stage ensures the uniqueness and discrimination texture and complex patterns of iris image that are highly unique to each individual even between identical twins (Zambrano et al., 2022). Feature extraction reduces the size of the data while preserving discriminative information, which speeds up the matching process and robustness to noise even under challenging conditions (e.g., partial occlusion, poor lighting, or pupil dilation). It also improves matching accuracy as accurate features mean better match scores and reduced FAR or FRR rates. Poor feature extraction can ruin system performance even if the other stages are perfect. However, notable issues of feature extraction include occlusions caused by eyelids, eyelashes, and specular reflections, along with variations in illumination, viewing angles, and pupil dilation, all of which contribute to significant intra-class variability. Moreover, the presence of low-resolution or blurred images, partial iris visibility, and sensor-induced noise can compromise the quality and stability of the extracted features. Therefore, this study systematically investigates the scholarly landscape of iris feature extraction and recognition (IFER) by evaluating the performance of contributing authors and publication outlets through descriptive statistical analysis. It identifies and analyzes the most influential and prolific entities, including countries, authors, studies, and journals, that have shaped IFER research. Furthermore, the study explores emerging research themes and topics, delineates research hotspots, frontiers, and developmental trajectories within the field through thematic mapping, and critically examines recent leading publications to articulate future research directions and highlight potential avenues for continued scholarly advancement.

PROCEDURE FOR RETRIEVING DATA AND SCREENING

The Scientific publications used for this research were sourced from the Scopus and Web of Science databases, which are recognized for providing standardized information suitable for bibliometric analysis (Singh et al., 2021). These databases offer access to journal articles, conference proceedings, and technical reports. The procedure for screening, data extraction, and analysis is illustrated in Figure 1. The search strategy employed the terms from web of science and Scopus include ”((“iris recognition” OR “iris identification”) AND (“feature extraction” OR “feature selection” OR “feature representation”) AND PUBYEAR > 2019 AND PUBYEAR < 2026 AND (LIMIT-TO (SUBJAREA , “COMP”) OR LIMIT-TO (SUBJAREA , “ENGI”) AND (LIMIT-TO (DOCTYPE , “ar”) AND (LIMIT-TO (LANGUAGE, “English”) AND (LIMIT-TO (EXACTKEYWORD, “Feature Extraction”) OR LIMIT-TO (EXACTKEYWORD , “Iris Recognition”))”. Using this strategy, a total of 1086 records including articles, review articles, book chapters, and conference papers were retrieved. Publications considered were limited to those written in English and categorized under the subject areas of computer sciences and engineering. The first screening is done by reading the title of retrieved articles where a total of 259 Scopus articles and 188 WOS articles were selected. After the removal of duplicates and the application of exclusion criteria, 247 publications were retained for further analysis. For each publication, bibliometric data including title, authorship details, corresponding authors’ countries, publication count, citation metrics, journal sources, keywords, institutional affiliations, and countries of origin were systematically extracted for comprehensive analysis.

Bibliometric analysis has become an established and systematic approach for assessing and visualizing scientific literature, citation dynamics, and patterns of scholarly collaboration within defined research domains (Chopra et al., 2024). This study conducted a bibliometric analysis to examine scientific trends within the domain of iris feature extraction and recognition as grounded in the principles of Scientometrics (Pranckutė, 2021). It addresses some aspects and presents the results through histograms, collaboration networks, mapping, and tables.

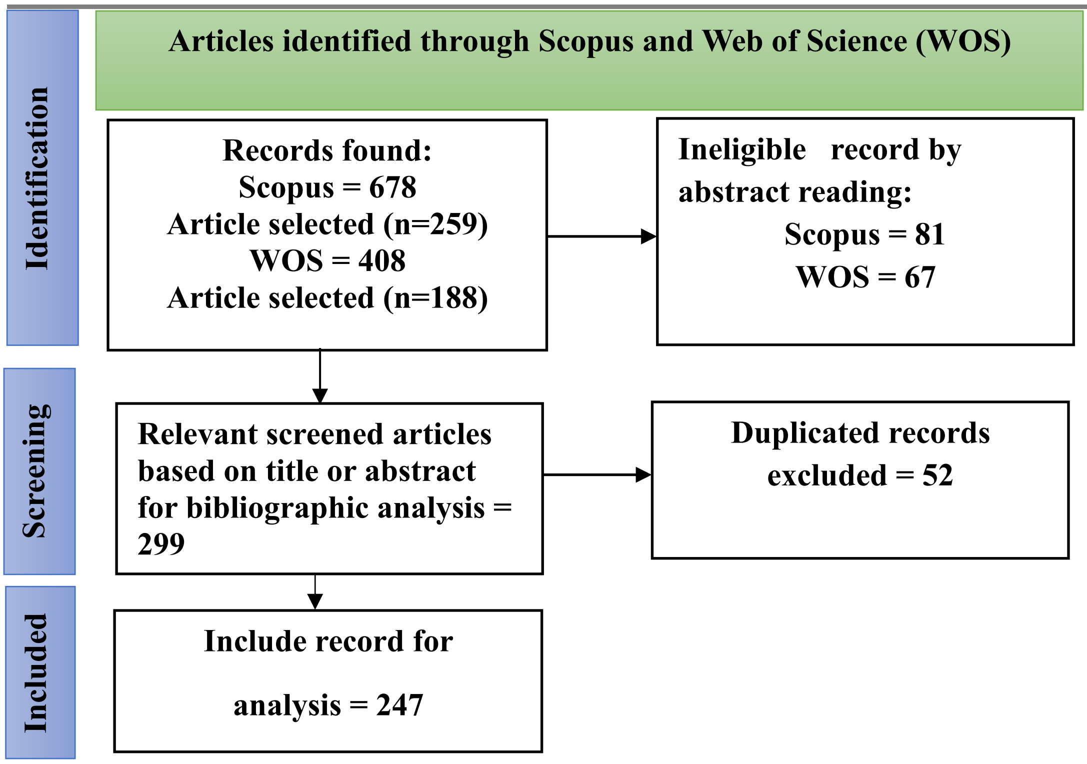

Fig. 1. Comprehensive data search flowchart for Bibliometric analysis

The chronological evolution of iris feature extraction and recognition research were assessed by analyzing the annual publication output over the study period. The analysis of leading authors presents a ranking based on publication volume, citation metrics, research impact, and the structure of collaboration networks among the most prolific contributors. The ranking of the most productive authors is based on their number of publications, while the most cited authors are determined by the frequency of citations received from other researchers (Donthu et al., 2021). In this research, two powerful software tools, VOSviewer and Bibliometrix were used to extract and analyze data. VOSviewer is particularly advantageous for handling large datasets and visualizing research hotspots and thematic developments within a research field (Cheng et al., 2021; Arruda et al., 2022), while Bibliometrix is well-suited for conducting comprehensive science mapping analyses (Aria & Cuccurullo, 2017; Huang, 2025).

RESULTS AND DISCUSSION

The analysis of the IFER-selected articles spans the period from 2019 to 2025, encompassing 247 documents retrieved from 116 distinct journals, books, and other publication types, as indexed in the Scopus and Web of Science (WoS) databases. Despite the relatively broad period, the annual growth rate of publications shows a decline of -33.15%, with the average age of documents being 3.55 years and 14.18 average citations in each document. The description of each parameter with result is shown in Table 1 where the total number of references cited across all documents is 10,520, 1,487 Keywords Plus entries and 713 author's keywords. The author analysis indicates contributions from 691 authors, among whom only 6 produced single-authored documents. In terms of scholarly collaboration, the dataset reveals an average of 3.64 co-authors per document, with 23.48% of the publications emerging from international collaborative efforts.

The number of articles published annually from 2019 to 2025 regarding iris feature extraction exhibits fluctuations, with a significant peak in 2019, where 56 articles were published, as shown in Fig. 2. However, this momentum sharply declined in 2020, with publications falling to 30, perhaps reflecting external disruptions like the global COVID-19 pandemic, which affected research outputs across various fields. Post-2020, a declining trend continued until 2024, with a minor recovery in 2025 that attributed to the year being incomplete at the time of data collection, rather than a true collapse in research activity. Therefore, the field exhibits resilience and a capacity for recovery after downturns, the irregular pattern suggests that research on IFER topic is sensitive to broader academic and socio-economic factors.

Table 1. Descriptive Summary of the Dataset

Category	Metric	Value
Data Information	Timespan	2019–2025
	Number of Sources (Journals, Books, etc.)	116
	Number of Documents	247
	Annual Growth Rate (%)	–33.15%
	Average Document Age (Years)	3.55
	Average Citations per Document	14.18
	Total References Cited	10,520
Document Contents	Keywords Plus (ID)	1,487
	Author's Keywords (DE)	713
Authorship	Total Number of Authors	691
	Authors of Single-Authored Documents	6
Collaboration Indicators	Single-Authored Documents	6
	Average Co-authors per Document	3.64
	International Co-authorships (%)	23.48%
Document Types	Articles	247

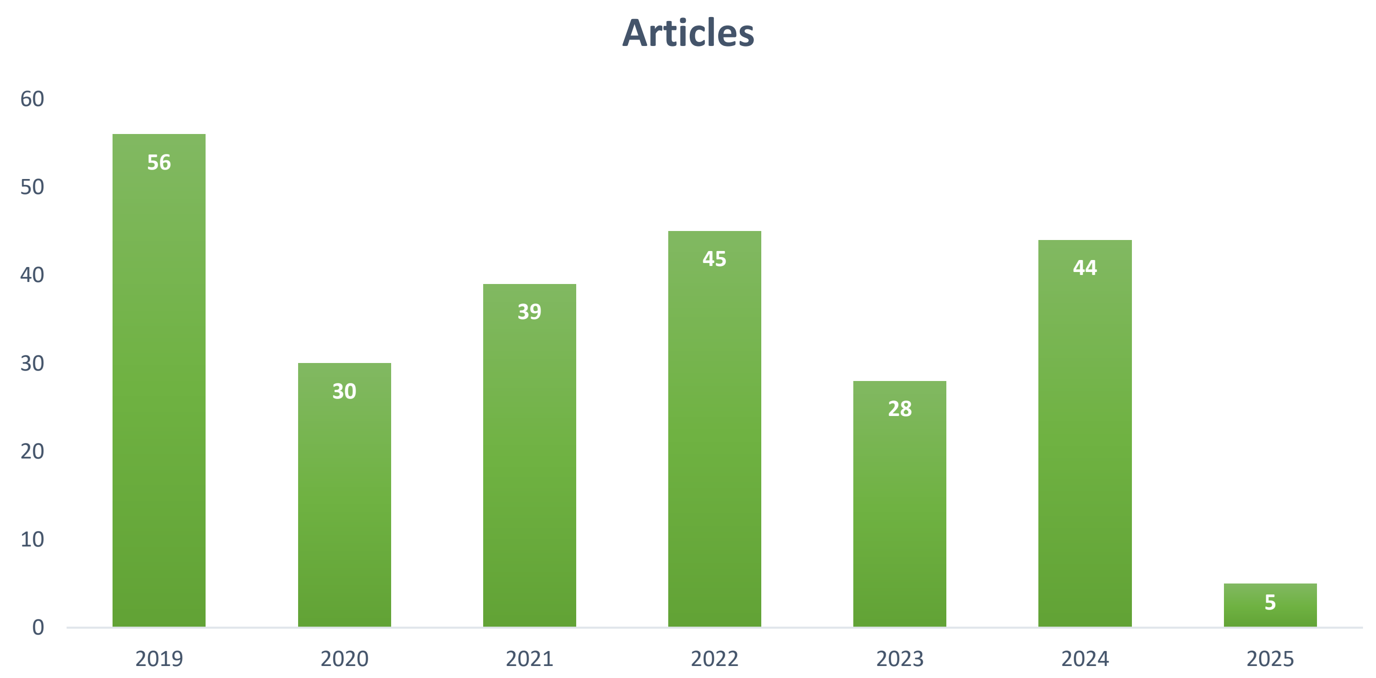

Fig. 2. Scholarly contribution trend

International Collaboration: Countries engaged in co-authoring publications on IFEG with researchers from other nations

Figure 3 illustrates the global distribution and intensity of international research collaborations in the field of IFER, with the number of publications serving as a quantitative indicator of each nation's research output. Notably, China and India emerge as the most dominant contributors, indicated by their darker shades, suggesting both high publication output and extensive collaborative activities. India appears to be the central hub, forming multiple strong cross-national linkages, particularly with countries across Asia, North America, and Europe. China also demonstrates a high level of international collaboration, reinforcing its growing prominence in global research networks. Secondary collaboration nodes are evident in the United States, Australia, Brazil, and several European countries, which are shaded in lighter but still significant tones as it links with major Asian countries. Strengthening these partnerships, especially with underrepresented regions, could enhance innovation and dissemination in the field.

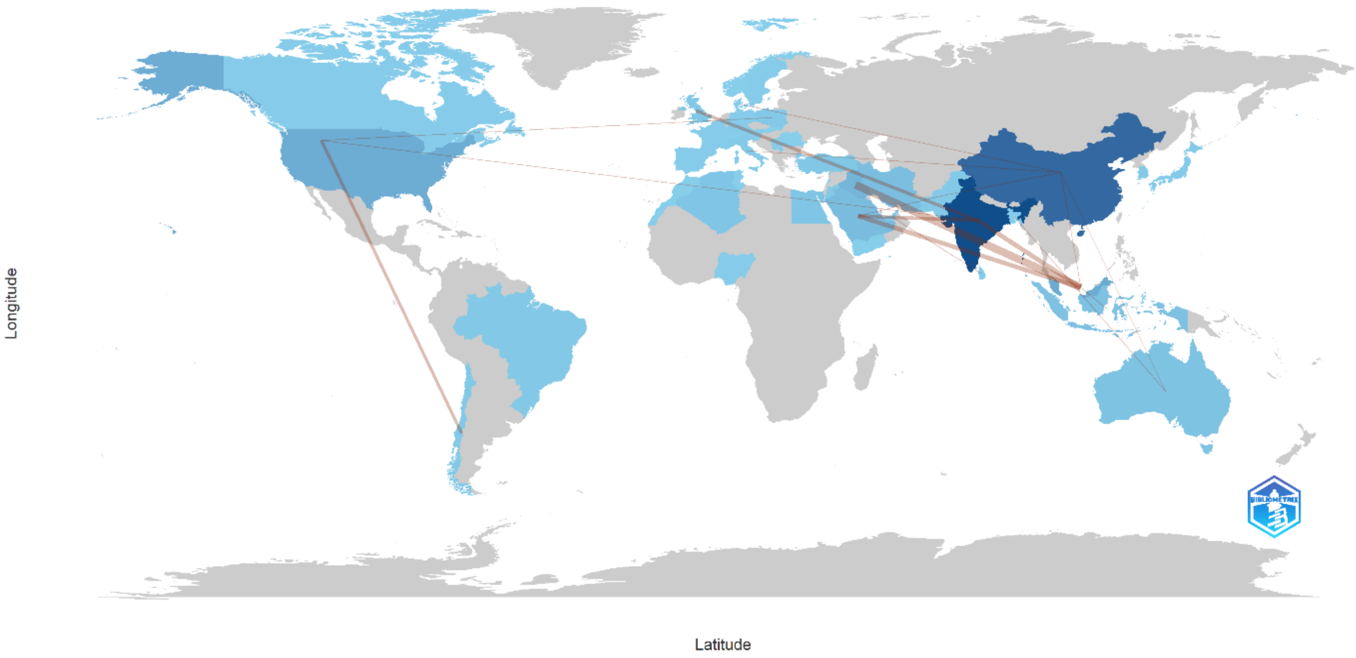

Fig. 3. Countries collaboration map

Table 2 presents the ten most prolific countries in the field of IFER, with China ranking as the leading contributor. The country recorded 59 publications and amassed 1,217 citations, underscoring its significant research output and notable scholarly impact within the domain. India ranks second in terms of productivity, contributing 78 publications and receiving 717 citations, reflecting its strong presence in the global IFEG research landscape. Subsequently, the United States exhibit 20 publications, with 433 and Malaysia is fourth in the ranking with 21 publications with 214 citations. This is followed by Australia, with 11 publications and 188 citations while the least among the remaining countries contributed 3 publications.

Table 2. Top 10 nations with highest citation

Country	Citation	Number of Document	Total link strength
China	1138	59	18
India	717	78	20
United States	433	20	12
Malaysia	214	21	31
Australia	188	11	24
Iran	160	10	3
Iraq	146	15	17
Saudi Arabia	141	13	22
United Kingdom	118	5	4
South Korea	101	3	6

The international collaboration network within the field of iris feature extraction and recognition is presented in Figure 4. Each node in the network indicates a contributing country, with the node size proportional to the country's research output in this domain. The links between nodes represent co-authorships across national boundaries, and the colors highlight distinct collaborative clusters. The link strength in Table 2 shows collaboration with other nations; the stronger the link, the more collaboration there is. According to the findings, India is most central and active participant in global iris recognition research as its collaborative ties with countries such as Australia, Iraq, Jordan, the United Arab Emirates, and Portugal. China also plays a crucial role, forming a densely connected with countries including Indonesia, Italy, and Saudi Arabia. While Malaysia comparatively moderate in output, acts as a key regional hub, facilitating collaborations between Southeast Asia and the broader global research community. Saudi Arabia and Egypt exhibit similar bridging functions within the Middle East, reflecting their increasing academic investments in cybersecurity and biometric research.

However, the overall network illustrates a globally distributed yet hierarchically structured pattern of collaboration in iris feature extraction and recognition research.

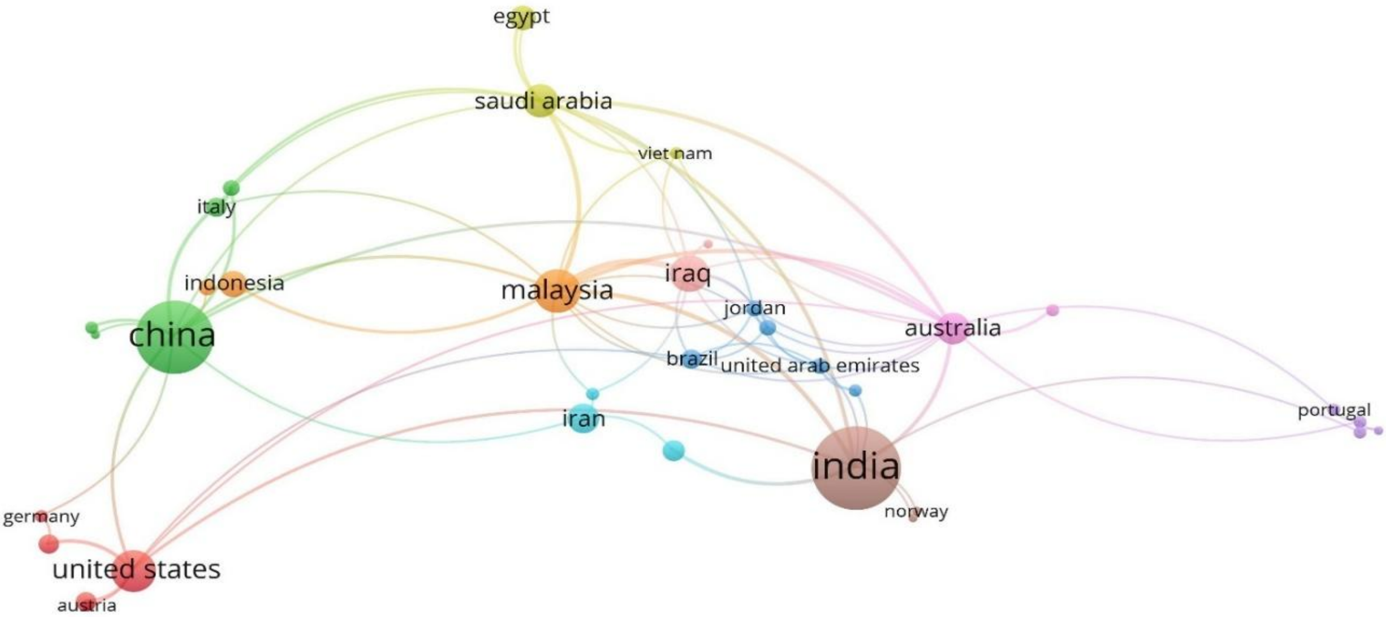

Fig. 4. Countries' collaboration network

Leading Contributors in the Field of IFEG

A bibliometric evaluation of the top contributing authors in the field of iris feature extraction and recognition where 691 authors with 3.64 Co-Authors per Document are shown in Table 3 based on H-index (a measure of impact and productivity), total citations (TC), and number of publications (NP). This analysis highlights both the quantity and the influence of research outputs among the most active author in the iris feature extraction and recognition domain. Wang Y from "University of Chinese Academy of Sciences China" is the most productive author with 11 publications, an H-index of 6, and a total citation count of 130. His work reflects a sustained and influential presence in the field of IFEG. Similarly prolific is Liu Y from "Baotou Medical College", who has also authored 11 publications but exceeds Wang in TC of 164, although with a slightly lower H-index of 5. The third author Sun Z. has 7 publications with TC=82 and 3 H-index affiliated with the "University of Chinese Academy of Sciences". Among the Indian contributors, Shirke S. D from "NBN Sinhgad School of Engineering" has published seven papers, although with a relatively modest citation impact (TC = 12, H-index = 2), indicating early-career contributions or niche thematic focus. This finding implies a persistent and long-lasting interest in the topic. It helps researchers who want to discover more about IFEG and may find this compilation useful for exploring possible collaborations and developing a thorough understanding of the field of study.

Table 3. Top 10 leading authors

Authors	**Affiliation**	**H-Index**	**TC**	**NP**
Wang Y.	"University of Chinese Academy of Sciences, China"	6	130	11
Liu Y.	"Baotou Medical College, Inner Mongolia University of Science and Technology, China."	5	164	11
Sun Z.	"University of Chinese Academy of Sciences, China"	3	82	7
Shirke S. D.	"NBN Sinhgad School of Engineering, Ambegaon, Pune, India"	2	12	7
Bowyer K. W.	"University of Notre Dame, United States"	5	169	6
Chen Y.	"National Sun Yat-sen University, Taiwan"	5	145	6
Wang X.	"Qingdao University of Technology, China"	5	45	5
Kanumuri T.	"National Institute of Technology Delhi, New Delhi, India"	4	61	5
Sheoran G.	"National Institute of Technology Delhi, New Delhi, India"	4	61	5
Vyas R.	"Lancaster University, Lancaster, United Kingdom"	4	61	5

The articles with high citations have been presented in Table 4 for top-cited articles. The analysis results show that Jia et al. (2022) ranked the highest with 397 citations with 99.25 number of citations per year (NCY) as it becomes a pivotal reference in biometric feature optimization, which underpins many iris recognition systems that rely on high-dimensional data representations. followed by (Wang & Kumar, 2022) with 91 citations that making it one of the most impactful contributions specifically targeting spectral variability. Then Hofbauer et al. (2019) has 86 citations while, (Chen et al., 2023; Long et al., 2019), have the same NC of 76 and (Ammour et al., 2020; Liu et al., 2020) also share the same citation of 75. Therefore, these highly cited works collectively illustrate the field's evolution from traditional pipeline-based approaches to integrated, end-to-end deep learning architectures. The citation trends affirm the field's maturation and its orientation toward addressing practical challenges such as spectral variability, liveness detection, and real-time recognition.

Table 4. Top cited articles

Article	Title	NC	NCY
(W. Jia et al., 2022)	"Feature dimensionality reduction: a review"	397	99.25
(Wang & Kumar, 2019)	"Cross-spectral iris recognition using CNN and supervised discrete hashing"	91	13.00
(Hofbauer et al., 2019)	"Exploiting superior CNN-based iris segmentation for better recognition accuracy"	86	12.29
(Chen et al., 2023)	"Accurate iris segmentation and recognition using an end-to-end unified framework based on MADNet and DSANet"	76	25.33
(Long et al., 2019)	"Detecting Iris Liveness with Batch Normalized Convolutional Neural Network"	76	10.86
(Ammour et al., 2020)	"Face–Iris Multimodal Biometric Identification System"	75	12.50
(M. Liu et al., 2020)	"Fuzzified Image Enhancement for Deep Learning in Iris Recognition"	75	12.50
(Toğaçar et al., 2020)	"Classification of flower species by using features extracted from the intersection of feature selection methods in convolutional neural network models"	66	11.00
(Zhao & Kumar, 2019a)	"A deep learning based unified framework to detect, segment and recognize irises using spatially corresponding features"	66	11.00
(Luo et al., 2021)	"A deep feature fusion network based on multiple attention mechanisms for joint iris-periocular biometric recognition"	58	11.60

This study also examined a total of 247 publications distributed across 116 distinct sources. Table 6 presents the performance of journals in terms of their contributions to the field of iris feature extraction and recognition (IFEG). The analysis highlights both the number of publications associated with each source and the total citations accrued by those publications, thereby offering insight into the scholarly impact and dissemination of IFEG-related research across different outlets. The table shows the top 19 sources, including journals and books. It reveals that Multimedia Tools and Applications and IEEE Access emerge as the most prolific venues, with 27 and 21 publications respectively, both beginning their contributions in 2019. They also lead in citation metrics, with h-indices of 11 and 10 and nearly identical TC counts (288 and 287, respectively), reflecting their pivotal role in disseminating high-quality research. The IEEE Transactions on Information Forensics and Security stands out with an h-index of 6 and 178 citations from only 6 publications, while other IEEE journals like IEEE Transactions on Biometrics, Behavior, and Identity Science (h-index = 4, TC = 67) and IEEE Signal Processing Letters (h-index = 2, TC = 60) also feature prominently, suggesting IEEE's strong influence in shaping foundational research in biometrics and signal processing related to iris recognition. Among peer-reviewed academic journals outside the IEEE ecosystem, Soft Computing (Springer) and Visual Computer also demonstrate significant engagement with 121 and 83 citations respectively, highlighting their selective but impactful contributions to the integration of machine learning and vision-based iris recognition. Furthermore, emerging contributions from journals like IAES International Journal of Artificial Intelligence and Telkomnika highlight a growing interest in iris recognition across diverse regional and open-access platforms, especially within the artificial intelligence research community.

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Table 6. Top journals and publication year

Source	H_index	TC	NP	PY_Start
“Multimedia Tools and Applications”	11	288	27	2019
“IEEE Access”	10	287	21	2019
“Journal of Electronic Imaging”	4	34	11	2019
“IEEE Transactions on Biometrics, Behavior, and Identity Science”	4	67	8	2021
“IEEE Transactions on Information Forensics and Security	6	178	6	2019
“Sensors”	4	47	6	2021
“International Journal of Advanced Computer Science and Applications”	3	18	6	2019
“Visual Computer”	5	83	5	2019
“Soft Computing”	3	121	5	2019
“International Journal of Recent Technology and Engineering”	1	1	5	2019
“Neural Computing and Applications”	3	51	3	2020
“Pattern Analysis and Applications”	3	17	3	2019
“Pattern Recognition and Image Analysis”	3	17	3	2019
“IAES International Journal of Artificial Intelligence	2	7	3	2022
“IEEE Signal Processing Letters”	2	60	3	2021
“Image And Vision Computing”	2	61	3	2021
“International Journal of Innovative Technology and Exploring Engineering”	2	4	3	2019
“Telkomnika (Telecommunication Computing Electronics and Control)”	2	30	3	2022

Exploring the Knowledge Structure of IFEG Research via Science Mapping

Thematic Mapping

This is a bibliometric technique that visualizes research themes based on centrality (relevance), which reflects the importance of the theme and connectivity to other themes, density, and indicates the degree of internal development. The map is divided into four quadrants: motor themes (Q1) are both well-developed and highly central, serving as the driving forces of the research field; niche themes (Q2) are internally well-developed but weakly connected to other themes, often representing specialized areas; emerging or declining themes (Q3) are characterized by low development and low connectivity, suggesting nascent or fading interest; and basic themes (Q4) are foundational and widely connected, yet still underdeveloped. This analytical approach provides valuable insights for scholars by identifying areas of strength, potential growth, and gaps for future research development within iris recognition domain. Figure 5 presents the thematic map of the IFEG research trends based on the four quadrants of thematic mapping.

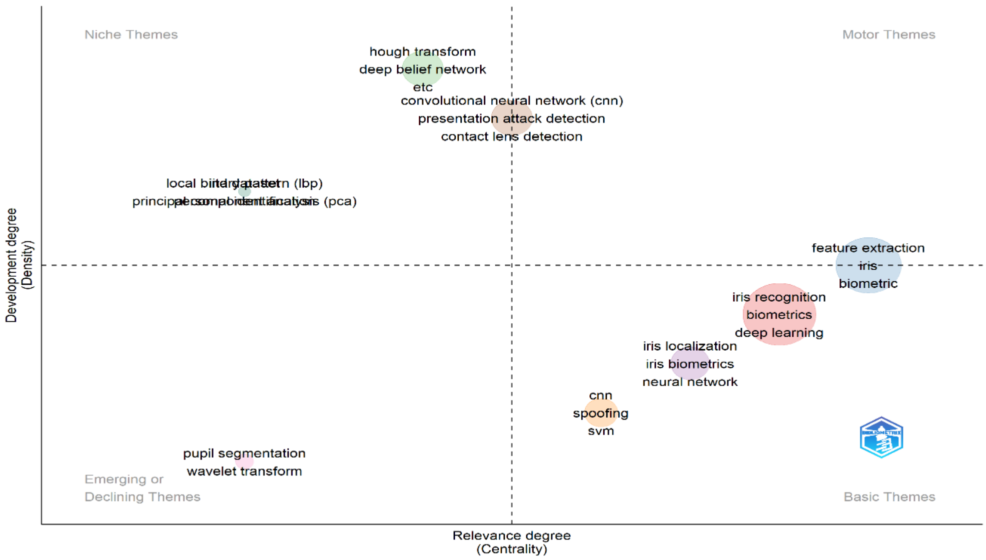

Fig. 5. Thematic mapping of IFEG research topics

The Motor themes (Q1) are both well-developed and central to the field, indicating maturity and relevance where "feature extraction, iris, and biometric" appear, confirming their foundational and driving role in iris recognition research. The proximity of "iris recognition, biometrics, and deep learning" further supports the observation that advanced machine learning techniques have become integral to the core of the field. The niche themes (Q2) involve "deep belief networks, Hough transform, presentation attack detection, and contact lens detection" that are highly developed but have limited centrality. However, these advance topics, may serve specific sub-domains (e.g., anti-spoofing and robustness enhancement) without exerting wide influence across the broader iris recognition area. In Emerging or Declining Themes (Q3) include "pupil segmentation and wavelet transform," indicating either nascent or declining interest, low density and centrality suggest minimal current impact and limited ongoing development. There is need for researchers to explore more wavelet transform due to its discriminating feature in extracting both special and frequency information from iris image. The Basic Themes (Q4) comprises "iris localization, iris biometrics, neural network, CNN, and spoofing". This quadrant includes essential but underdeveloped themes but appears to be in varying stages of methodological consolidation. Therefore, more research is required to develop and test more frameworks in these themes.

Knowledge Domain Clustering

This bibliometric analysis employs bibliographic coupling cluster analysis to enhance the reader's understanding by visualizing the underlying concepts and thematic structures as interconnected networks (Huang, 2025). This approach facilitates the identification of research patterns, relationships among key topics, and emerging areas within the field. VOSviewer, which facilitates visual and multidimensional representation was employed for cluster analysis (Arruda et al., 2022). The publications that met the requirement also contained at least 96 total link strengths. The best 80 documents out of 247 were extracted from the database based on their link strength and reviewed. Four clusters were generated, each cluster contain a significant number of authors where cluster1 contains 34 articles, cluster2 has 31 articles, cluster3 has 10 articles where 9 of them were able retrieved, and cluster4 covers 5 articles. Each cluster was named according to common issues, tools or methods discussed in the articles as shown in Table 7. A graphical representation of the four thematic clusters is presented in Figure 6, with Cluster 1 shown in red, Cluster 2 in green, Cluster3 in yellow and Cluster 4 in blue. The visualization comprises a total of 80 nodes and exhibits a cumulative link strength of 310, illustrating the interconnections and co-occurrence relationships among key concepts within the field.

Table 7. Themes and Author co-occurrence

Clusters	Authors
Cluster 1 red color: Advancements in Robust and Secure IFER Systems Under Challenging Acquisition Conditions	(Jan et al., 2024), (Mukherjee et al., 2024), (Lin et al., 2023), (Chakraborty et al., 2023), (Li & Feng, 2023), (Hafeez et al., 2022.), (Nsaif et al., 2022a), (Lu et al., 2022.), (Nachar & Inaty, 2022), (Saraf et al., 2022), (Gowroju et al., 2022), (Garg et al., 2021), (Yang et al., 2021), (Jan et al., 2020), (Papic et al., 2020), (Madhe et al., 2020), (Vyas et al., 2020), (Soliman et al., 2020), (Soliman et al., 2019), (Dua et al., 2019), (Ahmadi et al., 2019), (Fathi & Mohamadi, 2019), (Shirke & Rajabhushnam, 2019), (Aruna Kumari & Jaya Suma, 2019), (Winston & Hemanth, 2019), (Tobji et al., 2019), (Barpanda et al., 2019), (Vyas, Kanumuri, Sheoran, & Dubey, 2019a), (Zhang et al., 2019), (Hofbauer et al., 2019), (Vyas, Kanumuri, & Sheoran, 2019), (Nithya et al., 2019), (Vyas, Kanumuri, Sheoran, Optik, et al., 2019), (Karn et al., 2020).
Cluster 2 green color:	(X. Sun et al., 2024), (Zambrano et al., 2024), (Bonyani et al., 2022), (Lin et al., 2024), (Babu &

Deep Learning Paradigms and Domain Adaptation in Modern Iris Recognition Systems	Pinjari, 2024), (Nguyen et al., 2023), (HATTAB et al., 2023), (L. Jia et al., 2023), (Malgheet et al., 2023), (Zambrano et al., 2022), (Winston et al., 2022), (Wei et al., 2022), (Lat et al., 2022), (L. Sun et al., 2022), (Babu & Khayum, 2022), (Wei et al., 2022), (G. Liu et al., 2021), (Chen et al., 2021), (Guang Huo et al., 2021), (M. B. Lee et al., 2021), (Chen et al., 2021), (Melek et al., 2021), (Chen, Wu, Access, et al., 2020), (Abbasi, 2019), (Proenca & Neves, 2019), (Zhao & Kumar, 2019a), (M. Lee et al., 2019), (Abdulhasan et al., 2024), (Mostofa et al., 2021).
Cluster 3 yellow color: Security Challenges and Presentation Attack Detection in Iris Recognition Systems	(Kaur & Saini, 2024), (Nguyen et al., 2024), (Al-Rajeh & Al-Shargabi, 2024), (Verma et al., 2023), (Agarwal et al., 2022), (Choudhary et al., 2020), (Boyd et al., 2020), (Czajka et al., 2019), (Omelina et al., 2021).
Cluster 4 blue color: Fusion and Enhancement Techniques for Robust and Cross-Spectral Iris Recognition.	(Algashaam et al., 2021), (Umer et al., 2020), (Umer et al., 2019), (Alonso-Fernandez et al., 2019), (Wangkeeree & Boonkrong, 2019).

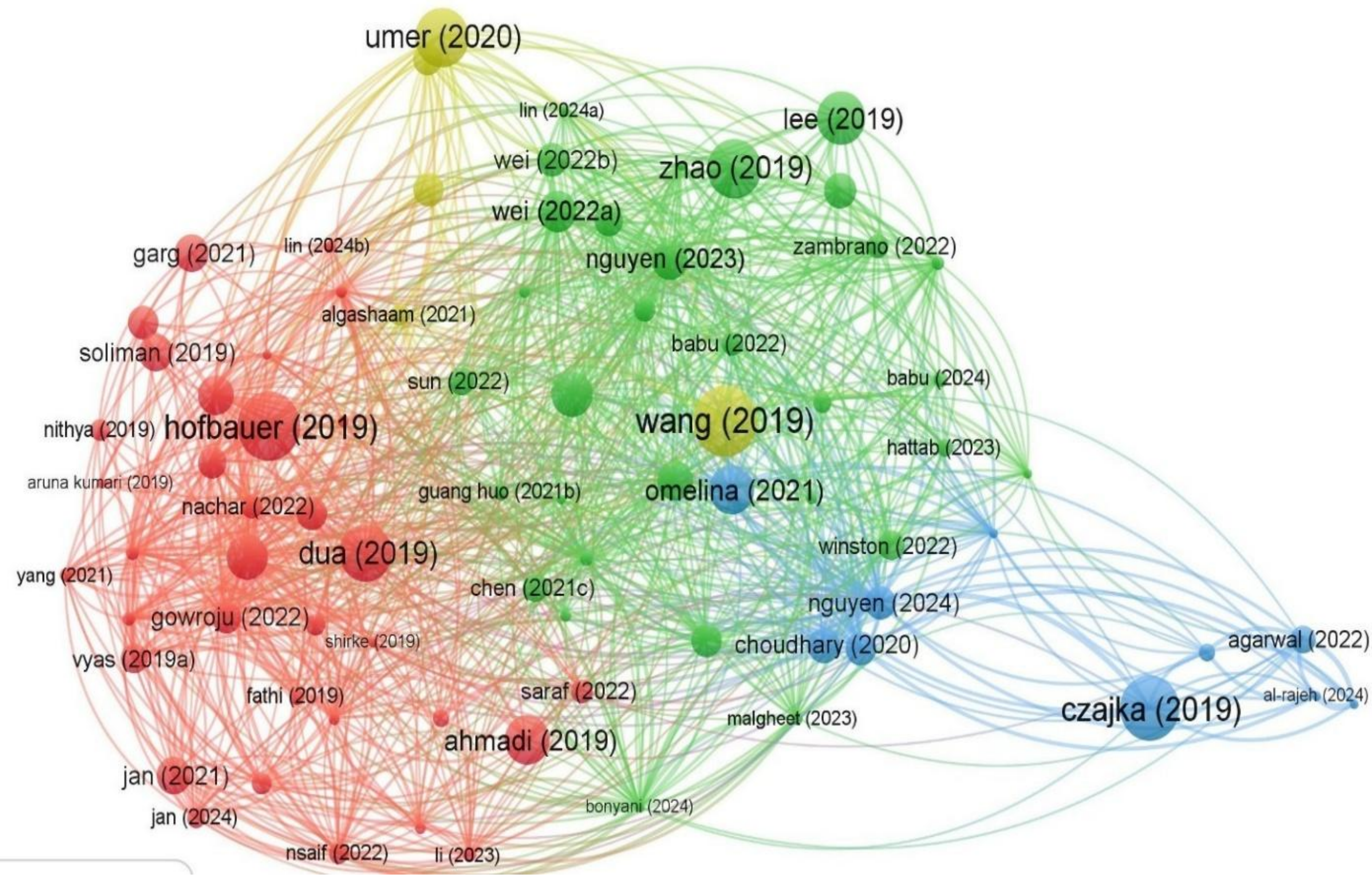

Fig. 6. Network of Authors co-occurrence

- **Cluster 1: Advancements in Robust and Secure IFER Systems Under Challenging Acquisition Conditions**

This cluster comprising 34 articles that encapsulate a diverse yet interrelated body of research that collectively addresses the limitations and innovations in modern iris feature extraction and recognition. A dominant theme across the studies is the drive to enhance iris recognition systems' performance in non-ideal, real-world acquisition scenarios ranging from poor lighting, motion blur, and occlusions to mobile and long-distance imaging environments. Several papers (Jan et al., 2024Li & Feng, 2023; Nsaif et al., 2022a) tackle the fundamental challenge of accurate iris segmentation under such conditions, proposing improved methods such as circular and double-center-based iris localization networks, multi-scale co-occurrence and Hough transform fusion, and iterative enhancements for boundary detection. These segmentation techniques are foundational to the reliability of subsequent recognition stages, especially in datasets captured under uncontrolled environments such as the CASIA-IrisV4-Distance and MICHE. Furthermore, feature extraction and representation are the central focus of this theme, where studies introduce a variety of innovative descriptors tailored for iris texture, which is rich in information but susceptible to degradation under environmental noise. For instance, local binary pattern blocks (LBPb) (Mukherjee et al., 2024), 2D Gabor filter banks with Difference of Variance (Vyas et al., 2019), and curvelet transform-based descriptors (Vyas et a., 2019a) have been leveraged to enhance the discriminatory capacity of iris features. These techniques are complemented by dimensionality reduction strategies, such as PCA, 2DPCA, and novel backward feature selection algorithms (Hafeez et al., 2022; Garg et al., 2021; Nithya et al., 2019), which aim to preserve critical identity information while reducing computational complexity. A notable development in this context is the introduction of hybrid feature representations (Vyas et al., 2019) and optimization algorithms like VLBHO (Saraf et al., 2022), which further streamline the feature space for faster and more efficient recognition. Additionally, the issue of security and privacy in iris biometric systems also receives considerable attention in this cluster. Traditional iris recognition pipelines are increasingly integrated with cryptographic and cancelable biometrics frameworks. For instance, the error-correction-based iris recognition scheme (Chakraborty et al., 2023) employs LDPC coding and dominating feature point extraction to improve both accuracy and security, while cancelable approaches such as comb filtering (Soliman et al., 2020) and random projection (Soliman et al., 2019) mask original feature vectors to prevent reverse engineering and identity theft. These privacy-preserving strategies are vital for applications in border control, digital forensics, and national ID systems, where biometric data must be protected against breaches. Moreover, deep learning plays a transformative role in the recent wave of iris recognition innovations. Studies such as (Chakraborty et al., 2023; Lu et al., 2022; Hofbauer et al., 2019) propose end-to-end convolutional neural network (CNN) frameworks capable of performing segmentation, feature learning, and matching in unified architecture. These models outperform traditional baselines and exhibit robustness to noise, off-angle images, and low-resolution input conditions prevalent in mobile or surveillance-based deployments. Furthermore, mobile-specific adaptations (Vyas et al., 2020; Shirke & Rajabhushnam, 2019) and cross-spectral recognition efforts (Vyas, Kanumuri, & Sheoran, 2019) highlight the growing demand for iris recognition on handheld devices, where computational resources and image quality are often constrained. The articles within this cluster collectively investigate the trajectory of iris recognition research from constrained laboratory settings to real-world deployments that require adaptability, robustness, and security. By addressing fundamental challenges such as segmentation in noisy environments, designing compact and discriminative feature descriptors, and integrating privacy-enhancing technologies, these works set the foundation for scalable, secure, and intelligent biometric systems suited for both civil and security-critical applications.

- **Cluster 2: Deep Learning Paradigms and Domain Adaptation in Modern Iris Recognition Systems**

This cluster focuses on the modern advancement of iris recognition systems with a central emphasis on deep learning techniques, domain adaptation, and robust representation learning. The surge in deep CNNs, attention-based architectures, and generative models has enabled breakthroughs in constrained and unconstrained iris recognition tasks. For example, specialized Transformer architectures such as IrisFormer (Sun et al., 2024) and lightweight deep learning backbones (Wei et al., 2022; Guang Huo et al., 2021) have dramatically improved the learning of discriminative, fine-grained features under various noise and occlusion conditions. Additionally, works like (Babu & Pinjari, 2024; Hattab et al., 2023; Jia et al., 2023) demonstrate enhancements in segmentation, recognition speed, and anatomical attention through approaches like Faster-RCNN, YOLOv4-tiny, and unified radial-angular attention modules. Furthermore, segmentation remains a cornerstone of high-performance iris recognition. Advanced networks such as DGNet (Bonyani et al., 2022) and MS-Net (Malgheet et al., 2023) introduce collaborative gaze modeling and multi-scale context extraction to handle distortions in non-cooperative scenarios effectively. Alongside segmentation, several works (Nguyen et al., 2023; Lat et al., 2022; Chen et al., 2021) move beyond conventional pipelines by proposing complex-valued neural networks, uncertainty-guided curriculum learning, and non-segmentation-based frameworks, offering a shift toward more adaptive and end-to-end learning models.

A prominent trend across the cluster is the challenge of domain generalization and cross-spectrum matching. Studies such as (Wei et al., 2022; Chen et al., 2021; Mostofa et al., 2021) address cross-spectral and cross-sensor variations using domain-adaptive architectures like Gabor Trident Networks, DenseSENets, cGAN-based pipelines, and CDBN-DBN models. These methods tackle the performance gap introduced by variations in imaging conditions (e.g., NIR vs. VIS) and device heterogeneity, ensuring the scalability and deployment of iris recognition systems across real-world platforms. Furthermore, the integration of error-correction coding (Lin et al., 2024), loss function engineering (Lat et al., 2022; Chen et al., 2020), and hybrid optimization techniques (Babu & Khayum, 2022; Abbasi, 2019) reflect the community's increasing awareness of the need for secure and efficient identity verification. For instance, the use of Tight Center Loss (Chen et al., 2020) or the combined ArcFace and Triplet loss functions (Lat et al., 2022) increase intra-class compactness and inter-class separability, crucial for large-scale applications and open-set recognition (Sun et al., 2022). Moreover, the cluster embraces generative augmentation and lightweight models to combat the challenges of data scarcity and computational constraints (Zambrano et al., 2024; Lee et al., 2019). These include conditional GAN-based augmentation (M. Lee et al., 2019) and pre-trained CNNs with minimal fine-tuning (Zambrano et al., 2022; Guang Huo et al., 2021), which improve performance in low-data or real-time settings. This cluster represents a comprehensive body of research that advances iris recognition from a traditional, handcrafted feature domain to a data-driven, adaptive, and secure deep learning-based discipline, where challenges of cross-domain generalization, low-quality imaging, and real-time constraints are addressed.

- **Cluster 3: Security Challenges and Presentation Attack Detection in Iris Recognition Systems**

A central theme in this cluster critically explores the intersection of security vulnerabilities, presentation attack detection (PAD), and performance challenges in modern iris recognition systems, particularly in adversarial or real-world conditions. As iris recognition becomes more integrated into high-security applications such as border control, mobile authentication, and digital identity systems (Kaur & Saini, 2024; Agarwal et al., 2022), the integrity of biometric matching processes is increasingly threatened by presentation attacks attempts to spoof or deceive recognition systems using artifacts like textured contact lenses or high-quality images (Al-Rajeh & Al-Shargabi, 2024; Verma et al., 2023; Czajka et al., 2019). Several works in this cluster investigate the impact of contact lenses on iris biometric reliability, demonstrating how even partial occlusion of the iris texture can significantly affect recognition accuracy or lead to false matches or mismatches (Kaur & Saini, 2024; Agarwal et al., 2022). This issue is further intensified by cross-sensor acquisition and heterogeneous environments, as addressed in (Choudhary et al., 2020), which proposes ensemble CNN-residual networks and score-level fusion for more resilient recognition across different image acquisition platforms. Furthermore, deep learning and data-driven approaches for PAD are central themes across the documents. For instance, (Verma et al., 2023; Al-Rajeh & Al-Shargabi, 2024) provide in-depth taxonomies and performance evaluations of machine learning (ML) and deep learning (DL) models designed to distinguish between genuine and spoofed iris images, while (Nguyen et al., 2024) reviews over 200 publications and tools relevant to DL for iris segmentation, recognition, and PAD including post-mortem applications (Boyd et al., 2020). The evolution of biometric spoof detection algorithms has led to the development of sophisticated PAD techniques using CNNs and generative adversarial networks (GANs), although generalization to unseen attack domains remains an ongoing challenge (Agarwal et al., 2022). Moreover, this cluster also contributes to the standardization of datasets and evaluation protocols, with (Omelina et al., 2021) presenting a bibliometric review of 158 iris datasets to support reproducibility and benchmarking. Finally, Boyd et al. (2020) introduces a unique domain of post-mortem iris recognition, addressing forensic and humanitarian use-cases where ante-mortem and post-mortem biometric comparisons are required. It highlights that iris recognition is not just a security measure but also a viable tool for forensic identity verification. However, it introduces new challenges in terms of physiological variability and data reliability. In summary, this cluster serves as a comprehensive overview of the threats, defenses, datasets, and future directions in the secure deployment of iris biometrics. It emphasizes that while iris recognition systems are highly accurate, they are not immune to sophisticated attacks, and ensuring robustness requires a combination of attack-specific detection algorithms, cross-domain generalization, dataset standardization, and biometric ethics in emerging applications.

- **Cluster 4: Fusion and Enhancement Techniques for Robust and Cross-Spectral Iris Recognition**

The collection of papers in this cluster reflects contemporary advances in fusion strategies, image enhancement, and cross-spectral matching for robust iris recognition across varying conditions and modalities. A central theme in the cluster is multimodal fusion, particularly the combination of iris and periocular features to boost recognition performance. Both Algashaam et al. (2021) and Umer et al. (2020) propose innovative architectures that integrate the complementary strengths of these ocular regions. In Algashaam et al. (2021) a hierarchical fusion network built on transformation-based and classification-based score-level fusion approaches significantly improves performance using a sparse autoencoder-enforced parent neural network. Similarly, Umer et al., (2020) employs well-established deep architectures such as VGG16, ResNet50, and Inception-v3, fusing features from iris and periocular modalities for robust recognition under both constrained and unconstrained lighting conditions, with extensive validation across benchmark datasets like MMU1, UPOL, and CASIA-Iris-Distance.

In addition, Umer et al. (2019) introduces a robust iris recognition system capable of operating effectively under both near-infrared (NIR) and visible wavelength (VIS) environments. The system uses a patch-based statistical texture feature, demonstrating strong performance across ten public databases. This cross-illumination flexibility is crucial as it directly supports applications in mobile authentication and outdoor scenarios where image capture conditions are less controlled. The image enhancement subtheme is explored in (Alonso-Fernandez et al., 2019), which surveys iris super-resolution methods and introduces an eigen-patch-based reconstruction framework. By restoring low-resolution iris images using PCA-trained dictionaries, the method significantly outperforms bilinear and bicubic interpolation even with input resolutions as low as 15×15 pixels. This is especially important in low-cost hardware systems or legacy datasets where high-resolution capture is unavailable. Furthermore, (Wangkeeree & Boonkrong, 2019) addresses the critical challenge of cross-spectral iris matching, which remains a bottleneck in integrating NIR-acquired databases with VIS-acquired images from smartphones and webcams. The study proposes the use of CNN-based feature extraction followed by supervised discrete hashing, reducing not only the feature dimensionality but also the template size, making the system scalable and memory-efficient for large-scale deployments. This dual benefit of performance and compression strengthens the applicability of iris biometrics in constrained environments. Together, these works mark a significant shift from conventional single-modality, single-spectrum iris systems toward adaptive, fusion-driven, and resource-efficient recognition frameworks. The synergy between deep learning, feature-level integration, and resolution-aware preprocessing forms the backbone of this evolution, addressing both accuracy and usability in next-generation biometric systems.

FUTURE DIRECTION AND LIMITATIONS

This review employed keyword co-occurrence analysis and network visualization to help comprehend the information architecture for IFEG worldwide. Based on the analysis, several studies emphasize the challenge of handling non-ideal and unconstrained image conditions, where factors like specular reflections, blurring, occlusions, gaze deviations, and low-quality acquisition complicate iris recognition accuracy (Karn et al., 2020; Vyaset al., 2019a; Vyas et al., 2019b; Jia et al., 2023; Babu & Khayum, 2022; Kaur & Saini, 2024). To address these, innovative deep learning models such as DGNet and MS-Net and non-segmentation-based CNN frameworks like NSNet have emerged, delivering robust segmentation and direct feature extraction without relying on heavy pre-processing. Likewise, hybrid methods integrating traditional approaches (MSGLCM plus Hough Transform) and metaheuristics with deep models optimize both accuracy and processing efficiency. Cross-spectral and cross-sensor recognition remains another pivotal focus. Works deploying Gabor Trident Networks, GAN-based domain alignment, and coupled generative adversarial networks (cpGAN) tackle the device- and spectrum-induced discrepancies between NIR and VIS iris imagery, significantly improving inter-spectral matching performance. Furthermore, mobile-based recognition challenges are tackled through lightweight CNNs, optimal bit-transition codes, and MobileNet fused with customized losses as discussed in Cluster 1&3. Scalability, particularly in large-scale biometric deployments, is addressed through efficient feature learning mechanisms. Studies explore optimized center loss functions (Tight Center Loss), binary iris codes with adaptive thresholding, and complex-valued CNNs to reduce intra-class variance and boost recognition accuracy (Bonyani et al., 2022; Li & Feng, 2023). Furthermore, attention-enhanced and hybrid CNN architectures including UGRAA-Net and multi-branch learning deliver improved generalization in diverse and challenging datasets.

The Traditional handcrafted feature extraction techniques, including Curvelet transform, Gabor filters, and Optimized Bit Transition Codes (OBTC), have provided a strong foundation by capturing multi-scale and local texture information critical for iris representation. However, these approaches face inherent limitations in adapting to variations in acquisition conditions such as cross-spectral (NIR vs VIS) environments and noisy imaging scenarios (Zhao & Kumar, 2019b; Lee et al., 2021). In response to these challenges, deep learning has emerged as a transformative paradigm, offering automatic and hierarchical features of learning capabilities. Convolutional Neural Networks (CNNs), particularly lightweight architectures like MobileNet and hybrid attention-enhanced models such as UGRAA-Net, have demonstrated superior performance in capturing discriminative iris patterns under unconstrained settings (Jia et al., 2023; Babu & Khayum, 2022).

Recognition performance significantly declines in the presence of lighting fluctuations, off-angle gaze, motion blur, occlusions, and sensor heterogeneity. These challenges are particularly acute in cross-sensor or cross-spectral scenarios where images captured under near-infrared (NIR) and visible light (VIS) must be matched (Al-Rajeh & Al-Shargabi, 2024; Alonso-Fernandez et al., 2019). Additionally, deep learning systems often fail to generalize when exposed to unseen domains due to their dependence on large, labeled training datasets (Wei et al., 2022). Furthermore, Presentation attacks (PAs) where attackers present fake biometric pose a significant threat to system integrity. Though several PAD methods have been proposed, they often lack generalizability to new attack types or imaging conditions (Agarwal et al., 2022). Both hardware and software-based solutions have limitations: the former incur additional costs, while the latter often struggles with high false acceptance or rejection rates (Al-Rajeh & Al-Shargabi, 2024), (Verma et al., 2023). Moreover, realistic spoofing datasets remain limited, making robust evaluation difficult (Czajka et al., 2019). Therefore, PAD systems need to become more resilient to evolving threats, possibly through multi-modal fusion, which incorporate not only iris patterns but also periocular cues and contextual facial information (Umer et al., 2020; Umer et al., 2019).

A growing concern with the adoption of deep neural networks in iris biometrics is their lack of interpretability. These models, while highly accurate, are often “black boxes,” offering little insight into how decisions are made. This poses challenges in forensic applications, legal settings, or high-security environments where explainability is critical (Nguyen et al., 2023; Verma et al., 2023). Currently, very few studies systematically explore explainable AI (XAI) techniques in the iris recognition domain. Although a wide array of public datasets exists such as CASIA, UBIRIS, MMU, and IITD, there is a lack of standardization in preprocessing, segmentation methods, and evaluation protocols. This makes it difficult to compare models fairly across studies (Omelina et al., 2021; Zhao & Kumar, 2019a). The lack of unified benchmarks also hinders progress toward real-world deployment, especially for applications that must operate across different imaging conditions and devices. Hence, there is a need to incorporate explainability frameworks into iris recognition pipelines. By leveraging XAI techniques, developers can provide transparent justifications for classification outcomes, improving user trust and legal acceptability in sensitive applications such as forensics or post-mortem identification (Nguyen et al., 2023; Boyd et al., 2020). Table 8 shows the summary of future direction and limitations in the IFEG field based on the reviewed articles.

Table 8. feature direction and limitation

Source	**Current Status**	**Limitation**	**Future Direction**
(Vyas, Kanumuri, Sheoran, & Dubey, 2019a), (Vyas et al., 2020)	Handcrafted features (Curvelet, Gabor, OBTC).	Limited generalization across spectra and sensors; sensitive to acquisition variations.	Develop unified handcrafted + learned domain-agnostic feature representations.
(Nsaif et al., 2022b), (Vyas, Kanumuri, Sheoran, & Dubey, 2019a)	Deep learning features (CNNs, MobileNet, UGRAA-Net).	Heavy computational cost: real-time application on edge devices is challenging.	Design lightweight and adaptive deep models for real-time and mobile usage.

(Nguyen et al., 2024), (Malgheet et al., 2023)	Non-segmentation feature extraction (NSNet, Anchor-Free Models.	Trade-off between segmentation precision and recognition accuracy.	Enhance segmentation-free models with dynamic robustness and hybrid integration.
(Li & Feng, 2023)	Complex-Valued Neural Networks (CVNN).	Underexplored potential; limited validation across large-scale datasets.	Advance CVNN and validate on diverse, unconstrained iris datasets.
(Kaur & Saini, 2024)	Meta-heuristic optimized feature selection (EH-WOA, DNN-LDA).	Computationally expensive; lacks scalability for large-scale deployment.	Improve cross-spectral domain adaptation through adversarial and self-supervised learning.
(Karn et al., 2020)	Cross-Spectral learning and domain adaptation (GTN, cGAN, cpGAN).	Cross-spectral models still face domain shift issues in real-world scenarios.	Improve cross-spectral domain adaptation through adversarial and self-supervised learning.
(Zambrano et al., 2024)	Attention-based deep feature enhancement (UGRAA-Net, Multi-Scale Attention models).	Requires large and high-quality datasets; may not generalize to unconstrained settings.	Combine attention mechanisms with transfer learning to enable better generalization.

CONCLUSION

This bibliometric and systematic review has provided an in-depth exploration of the global research landscape on iris feature extraction and recognition (IFER) from 2019 to 2025. The findings demonstrate that the field has advanced considerably, driven by innovations in deep learning, hybrid models, and segmentation-free architectures. These have collectively addressed traditional challenges linked to unconstrained environments, cross-spectral variability, and robustness in noisy conditions. However, despite these strides, several limitations persist. Traditional handcrafted methods, while foundational, struggle with generalization, whereas deep learning approaches face issues related to computational cost and real-time deployment. Similarly, hybrid methods and complex feature fusion strategies raise concerns about redundancy and scalability. The thematic mapping and cluster analysis underscore that current research has increasingly pivoted towards resolving these issues, with a strong emphasis on scalable deep learning solutions, cross-spectral adaptation, and robust segmentation techniques. Nonetheless, basic and emerging themes, such as efficient iris localization and spoofing detection, remain underdeveloped, offering fertile ground for future inquiry. The future trajectory of IFER research is likely to focus on dynamic feature extraction methods, lightweight and adaptive deep models suitable for mobile and embedded systems, enhanced multi-modal fusion, and the integration of meta-learning strategies to automate feature optimization. Furthermore, improving cross-domain and cross-spectral generalization capabilities, while addressing presentation attack vulnerabilities, will be critical to realizing truly ubiquitous and secure iris recognition systems. This study, by synthesizing key trends and highlighting research gaps, contributes to shaping future research agendas and facilitating more robust, scalable, and adaptive applications of iris biometrics in both academic and industrial domains.

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Conflict of Interest

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

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