The Application of Artificial Intelligence-Based Facial Recognition Technology in the Medical Field: Bibliometric analysis

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ABSTRACT

Background: Specific facial features play a crucial role in the clinical screening and diagnosis of diseases. However, the subtle changes in these features during the early stages of disease can be challenging for clinicians to detect with the naked eye, leading to delays in diagnosis and treatment and, consequently, adversely affecting patient outcomes.With the continuous development of artificial intelligence(AI) and computer vision,facial recognition technology has significant advantages in extracting facial feature analysis and processing.This technology has gradually been applied to various medical fields, including early disease screening and prevention, diagnosis and treatment, and psychological assessment, demonstrating superior performance. As a result, facial recognition technology has become a focal point in cross-disciplinary research between medicine and AI.

Purpose: In this study, we utilized a bibliometric approach to analyze and visualize the developmental trajectory, current research status, and leading edge areas of AI-based facial recognition technology within the medical field. The aim was to present emerging trends and identify potential research focal points within this domain.

Methods: We retrieved all articles published in the Web of Science database from 2004 to April 2024 related to the research of AI-based facial recognition technology in the field of medicine. A comprehensive bibliometric analysis and visualization were conducted using CiteSpace, VOSviewer, and the R software package Bibliometrix.

Results: A total of 379 articles published between 2004 and 2024 were included in this study, involving 2,126 authors from 876 institutions across 60 countries/regions, and published in 202 journals. The top three countries by publications were China (n=126), the United States (n=80), and India (n=46), accounting for 66.5% of the total number of articles and representing the most active countries/regions in this field of research. Shanghai Jiao Tong University (n=16), the University of California System (n=12), Peking University (n=13), Peking Union Medical College (n=11), and the Chinese Academy of Sciences (n=11) were identified as the leading research institutions. Currently, most studies are based on geographical collaboration, with limited international cooperation, indicating the need for stronger inter-country collaboration.The most prolific author was Nicole Fleischer (n=5) of FDNA Inc., USA. Paul Ekman(n=107 citations) from the University of California, San Francisco, was the most co-cited author.The journal publishing the most research in this area was IEEE ACCESS (n=25 publications;IF,3.9; Q2). IEEE Transactions on Pattern Analysis and Machine Intelligence was the most co-cited journal (n=282 citations; IF, 23.6; Q1). "Deep learning," "face recognition," and "machine learning" were the most common keywords in this field of research, with deep learning and machine

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learning being a frequently used method for facial recognition in the medical field. The most cited article was "Emotional Expressions Reconsidered: Challenges to Inferring Emotion from Human Facial Movements" by Barrett, L. F. (2019).

Conclusion: The utilization of AI-based facial recognition presents vast potential in the medical domain, facilitating a transition toward precise and personalized medical interventions. This domain has recently garneredc attention as a focal point for interdisciplinary exploration at the nexus of medicine and AI. This study employs bibliometric methods to identify research hotspots and future research directions.It is anticipated that AI-driven facial recognition technology will remain at the forefront of medical research, especially in enhancing swift disease screening, detecting rare genetic disorders, and providing an objective assessment of emotional states.

Keywords: Facial recognition; Artificial intelligence; Bibliometric analysis; Medicine;Visualization

1. Introduction

Diseases not only impact physiological functions and structures，but also often accompany changes in facial phenotype. Facial images serve as a valuable source of clinical data. The morphology of the face is influenced by genetic factors, psychological well-being, and environmental factors. Specific facial features play a crucial role in the diagnosis of patients with genetic syndromes, neurodegenerative conditions, and other disorder [1, 2]. Additionally, facial expressions can reflect an individual's emotional state, and the analysis of facial emotions is important for psychiatric diagnosis and treatment interventions [3, 4]. However, due to the complexity of the disease and the secretive nature of the initial symptoms, these subtle changes can be easily overlooked, which may result in a delay in the treatment of the patient and an adverse effect on the prognosis [5]. Therefore, extracting diagnostic and therapeutic insights from subtle changes in facial images and developing precise treatment strategies in the early stages of a disease are vital for enhancing patient outcomes and prognosis.

The rise of artificial intelligence(AI) and computer vision has enabled the accurate and swift prediction of diseases through facial depth phenotyping. This integration of medicine and AI has been expedited by the onset of the big data era,leading to notableadvancements in image acquisition, processing,deep learning,and algorithms [6-8]. These advancements have revolutionized conventional medicine into intelligent medicine, facilitating the transition towards precision and personalized healthcare. AI is now extensively employed in medical domains for disease diagnosis, therapeutic decision support, prognostic regression prediction, and histological analysis [9]. Telemedicine is emerging following a period when the global reduction in resources for traditional diagnosis and treatment was driven by the COVID-19 pandemic. With the maturation of computer vision-based AI technology, facial recognition has become a prominent area of research at the intersection of medical and engineering disciplines. This approach effectively tackles diagnostic and treatment delays arising from lack of experience and subjective factors, addresses disparities in medical resource distribution, and enables cost-effective and rapid disease screening and diagnosis [10]. Although the academic results of facial recognition in the medical field are increasing, there is a lack of synthesis and updating of the research results, as well as prediction of the development trend.

Bibliometrics is a quantitative analysis method grounded in mathematical statistics. It focuses on studying the external characteristics of scientific literature, visualizing and quantifying this literature, and delving into the evolutionary path of the field's development, the latest research trends, key areas of interest, research trajectories, emerging domains, and collaborations [11, 12]. Even though scholars across various research fields have utilized bibliometrics, there has been no prior bibliometric analysis on the usage of

AI-based facial recognition in the medical domain. This study aims to gather relevant literature spanning the past two decades to conduct a quantitative, qualitative, and visual analysis of research on AI-based facial recognition within the medical sector. Through this analysis, a structured understanding of the field's knowledge framework can be attained, research focal points and future research directions can be identified, and it can aid in the strategic planning of scientific research institutions along with the rational allocation of resources.

2. Methods

2.1. Data sources and search strategy

The primary data source selected for this study was the Web of Science Core Collection (WOSCC) database, which offers a comprehensive coverage of over 13,000 scholarly journals and more than 2.2 billion cited references from high-quality, impactful journals published globally since 1900. The WOSCC database is recognized as one of the most influential databases for bibliometric analyses [13].

To ensure the reliability and precision of the research data, two independent authors independently conducted searches for pertinent publications. In cases of dispute, we consulted a third investigator. The search encompassed publications indexed in the Science Citation Index Expanded (SCI-EXPANDED) and Social Science Citation Index (SSCI) for the duration spanning 1900 to 2024. The final inclusion criteria for articles ranged from January 1, 2004, to April 30, 2024.

"Facial recognition","Artificial intelligence" and "Medical field" were used as search terms, with their relevant synonyms or abbreviations.Then compared their respective findings to ensure the integrity and accuracy of search results.

To identify articles about facial recognition, perform #1 search using the following formula: TS = ("facial recognition" OR "face recognition" OR "facial expression recognition" OR "visual scanning strategy" OR "facial expression*" OR "face detection*" OR "image recognition technology" OR "face feature recognition" OR "image data processing" OR "facial imaging" OR "facial video*" OR "facial feature*" OR "three-dimensional facial-image*" OR "facial complexion*" OR "facial landmark*" OR "facial emotion recognition").

To identify articles about artificial intelligence, perform #2 search using the following formula: TS = ("artificial intelligence" OR "AI" OR "deep learning" OR "artificial neural network*" OR "computer vision*" OR "machine learning" OR "neural network*" OR "data mining" OR "supervised learning" OR "unsupervised learning" OR "transfer learning" OR "reinforcement learning" OR "computer-aided diagnosis" OR "feature* fusion" OR "feature* learning").

To identify articles about the research in the medical field, perform #3 search using the following formula:TS = ("medical field*" OR "medical science realm*" OR "medicine domain*" OR "medical image processing" OR "medical image analysis" OR "medical data" OR "medicine" OR "disease*" OR "sickness*" OR "ailment*" OR "disorder*" OR "preventive medicine" OR "phylaxiology" OR "medical examination*").

The time span for searches #1, #2, and #3 is from 1900 to 2024, limited to English articles. The integration of search strategies #1, #2, and #3 was accomplished using the "Combine #1 and #2 and #3" method. Detailed search strategies can be found in Fig. 1. This study utilizes data from the WOS database and does not require ethical approval. It is important to highlight that the literature identified through the above search strategy includes studies beyond the direct search topic. This encompasses research on utilizing deep learning models to detect changes in patients' physiological responses after recognizing images depicting various emotions [14, 15], as well as functional neuroanatomical models related to facial recognition deficits in patients with various neurological disorders [16]. Additionally, it involves research in the field of otorhinolaryngology focusing on the anatomical structure of CT scans of the skull [17]. These articles were specifically excluded after a meticulous manual review.

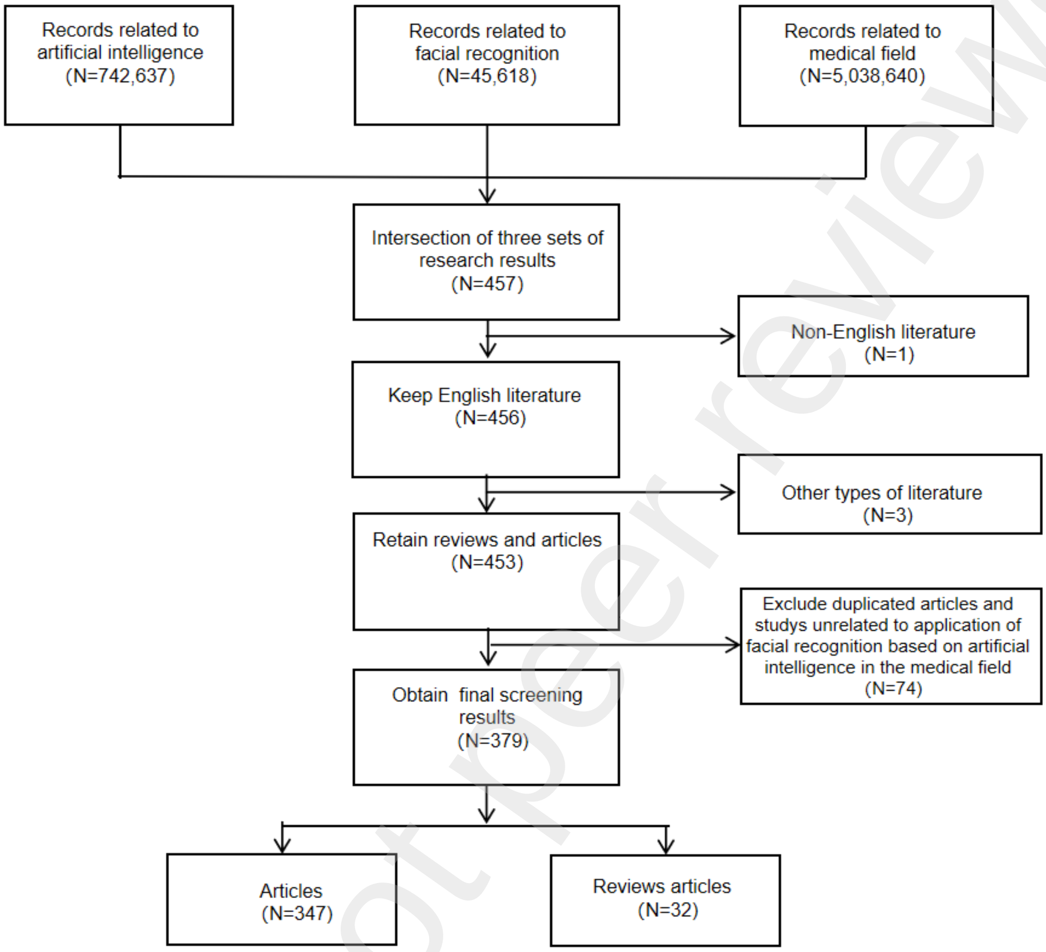


Fig. 1. Flowchart of the publications selection in the study.

2.2. Analysis tools and field analyses

In this study, a bibliometric analysis was conducted utilizing VOSviewer, CiteSpace, and R version 4.3.3 on various elements including title, keywords, authors, author institutions, author countries/regions, journal names, total number of citations, and average number of citations per year. The frequency of collaboration between countries was calculated, and the geographic distribution of total publications for different countries/regions was plotted using the Bibliometrix R package version 4.3.3 in R. Additionally, the Bibliometrics Platform (https://bibliometric.com/) was used to visualize international collaboration between countries.

VOSviewer was utilized to calculate the number of publications, as well as to analyze countries, institutions, authors, citation counts, co-authorship between countries, institutions, and authors, and co-citation analysis of the literature. The number of citations can serve as an indicator of a study's impact. We conducted a statistical analysis of authors, countries/regions, institutions, and journals based on citation counts to assess their significance within the field. To more comprehensively evaluate the quantity and quality of scholarly output in the field, the h-index was utilized. CiteSpace was employed to analyze various metrics including the annual number of publications, keywords, high-frequency keyword clustering, keyword and citation bursts, as well as to create timeline visualizations of keywords and highly cited literature.

3. Results

3.1. Global trends of publication outputs and citations

This study ultimately included 379 papers, consisting of 347 articles and 32 reviews. The advent of AI technology has spurred a surge in medical AI research, with automatic medical image processing emerging as the most rapidly evolving field in medical AI research [18, 19]. Facial recognition, a pivotal component of image analysis, has demonstrated significant potential in the medical domain. As illustrated in Fig. 2, the publication volume in this field was relatively low before 2017, with an average annual growth rate of 31.78%. However, the number of publications has increased rapidly since then, stabilizing at over 60 articles per year after 2022, including as many as 92 articles in 2022, reflecting an average annual growth rate of 61.16%. Notably, 94.2% (357/379) of the literature was published in the last six years (2018–2024). The advent of big data-driven computational models of AI and the concurrent boom in computer vision have significantly accelerated the assessment of patients' facial features [20, 21], contributing to the exponential growth in research output during this period. The total number of citations has also shown rapid growth since 2018, indicating that AI-based facial recognition technology has garnered increasing attention from scholars and has become a new focal point and direction of research in the medical field.

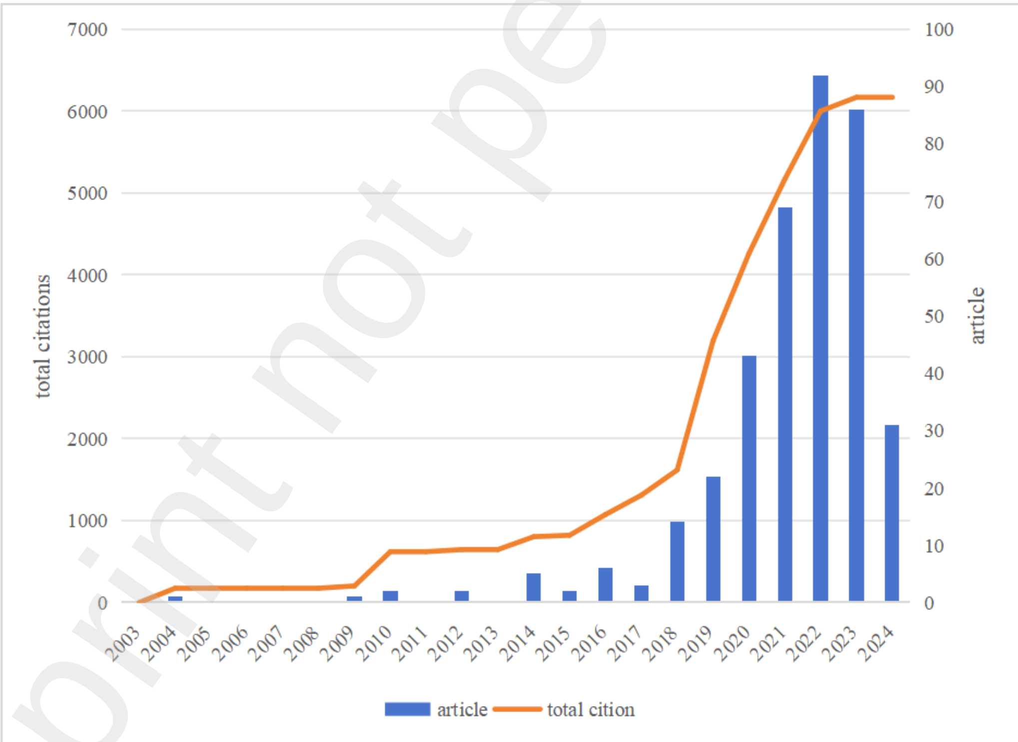


Fig. 2. Global trend of publications and total citations on AI-based facial recognition research in the medical field over the past 20 years.

3.2. Contributions of countries and regionals

A total of 60 countries/regions have engaged in AI-based facial recognition technology research within the medical field. As demonstrated in Table 1, among the top 10 countries by publication volume, China, the United States, India, the United Kingdom, and Saudi Arabia are recognized as high-productivity nations. It is noteworthy that most of the top 10 contributors are developed countries, indicating a strong correlation between research output and economic strength.

Quantitative analysis indicates that Chinese scholars have produced the highest number of papers (n=126), accounting for 33.33% of the total. However, the average number of citations per paper is relatively low. The United States follows with 80 papers and the highest total number of citations, totaling 2974. Together, China and the United States represent 54.35% of total publications. The top three countries by average number of citations per paper are the United Kingdom, the United States, and Italy. The United Kingdom leads with an average of 50.09 citations per paper, totaling 1,152 citations from 23 papers. Statistical analysis reveals a significant disparity in the number of national publications, with a notable Matthew effect, where the majority of papers are produced by a select few countries. A comprehensive analysis of research outputs and citation counts shows that although China leads in terms of quantity, the United States remains at the forefront of cutting-edge development and academic influence in the field. The distributional trends observed in this analysis align with the country scores in the Tortoise Global AI Index, as published by Tortoise Media in 2023 in the UK.

Fig. 3A illustrates the publication volume changes for the top ten countries from 2004 to 2024. The United Kingdom and Canada were pioneers in collaborative research in this domain as early as 2004. From 2009 to 2019, the United States led in publication volume until 2020, when China assumed the leading position, relegating the United States to second place. Fig. 3B presents the global distribution of the publication volume, and the research output in this field exhibits a clear geographic distribution, with the majority of output concentrated in North America, Northwestern Europe, and East Asian countries.

A statistical analysis of single-country publications (SCP) and multicountry publications (MCP) revealed (Fig. 3C) that among the top 10 countries, most studies were conducted by a single country. The exceptions were Saudi Arabia and Canada, where international collaborations were equally balanced with national studies. A collaborative network analysis was conducted on countries with more than 3 publications（31 countries in total） using the standardized Louvain clustering algorithm. The analysis was based on associations, with isolated nodes removed while considering a minimum edge weight of 1. In Fig. 3D, larger round nodes indicate a higher number of articles. The strength of association is depicted by the thickness of the connecting line, with thicker lines indicating a greater number of collaborations between the two countries. Additionally, node color represents different clusters.In total, these collaborative clusters can be categorized into five main groups: The first cluster primarily consists of China, which contributes the highest number of articles, along with Saudi Arabia, Pakistan, and several other countries. The second cluster stands out for having the highest total citations of articles and includes countries such as the USA, Germany, and Spain, among others. The third cluster encompasses countries like India, France, and the United Arab Emirates. The fourth cluster is represented by the United Kingdom and Turkey. Lastly, the fifth cluster involves nations such as Italy, Canada, and the Netherlands (Fig. 3D).

Table 1

Top 10 productive countries/regions related to AI-based facial recognition in the medical field.

Rank	Country	Publications	Percentage	Citations	Average Citation
1	China	126	33.25	1366	10.87
2	USA	80	21.11	2974	37.18
3	India	46	12.14	274	5.96
4	United kingdom	23	6.07	1152	50.09
5	Saudi Arabia	22	5.80	242	11
6	Germany	20	5.28	532	26.6
7	Italy	17	4.49	560	32.94
8	Canada	16	4.22	443	27.69
9	Pakistan	15	3.96	131	8.73
10	France	14	3.69	222	15.86

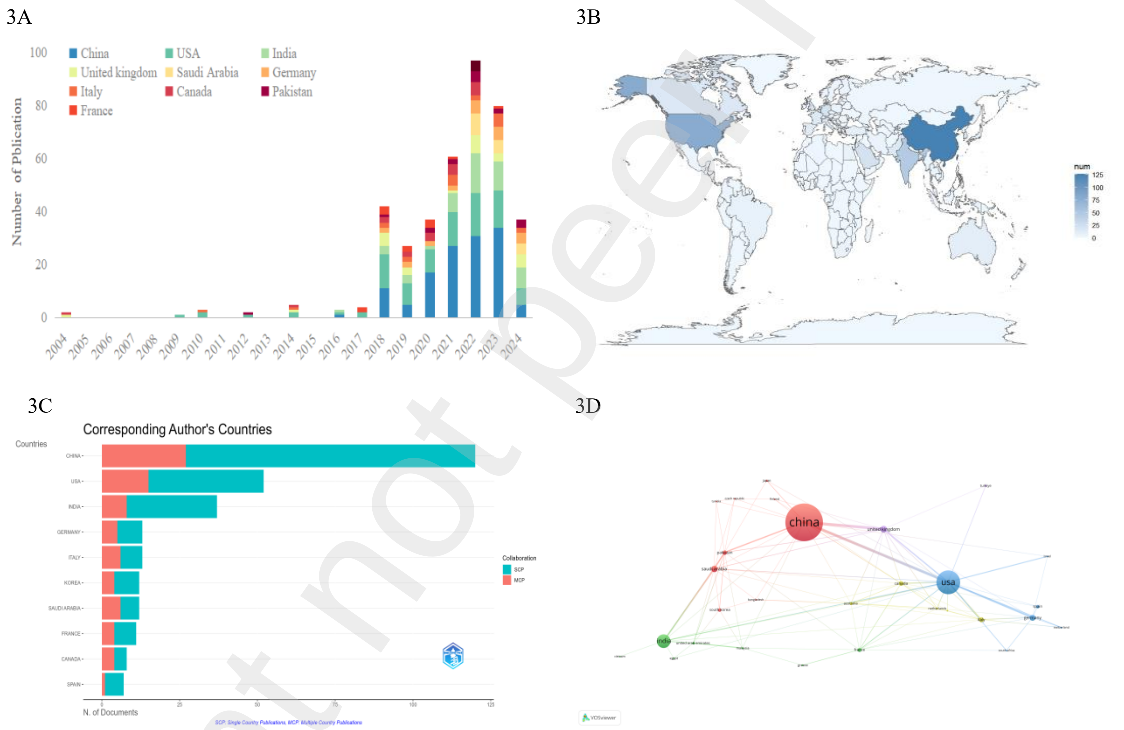


Fig. 3. (A) The changing trend of the annual publication quantity in the top 10 countries/regions over the past 20 years. (B) Geographic distribution map based on the total publications of different countries/regions. (C) Top 10 most productive countries chart, divided by single country publications (SCP) and multiple country publications (MCP). (D) The countries/regions citation overlay visualization map generated by using VOS viewer.

3.3. Analysis of top institutions

A total of 876 institutions were included in this study. The top three institutions in terms of publications were Shanghai Jiao Tong University (n=16), the University of California System (n=12), Peking Union Medical College (n=11), and the Chinese Academy of Sciences (n=11). As illustrated in Table 2 and Fig. 4A and Fig. 4B, Chinese institutions accounted for 60% of the top 10 institutions with the highest publication output, indicating a notableinterest in facial recognition research in the medical field and a prominent role in this research area. Among them, Peking Union Medical College and the Chinese Academy of Sciences exhibited a particularly high degree of centrality, with mediator centrality of 0.1. Betweenness centrality is a crucial metric for assessing the structural characteristics of a node within a network. A node with high betweenness centrality serves as a connector between multiple nodes, occupying a key position within the network [22, 23]. The centrality of the institutional collaboration network highlights the extent of international cooperation and exchange that an institution engages in. Nodes with centrality values of at least 0.1 indicate that the institution has a greater number of international collaborations and exchanges, and that it has strong connectivity within the institutional collaboration network. Harvard University has the highest total and average citations, which indicates that the research related to facial recognition applications in the medical field has an important research status.

Institutions with at least two publications were imported into VOSviewer to generate a clustering diagram (Fig. 4C). This revealed four main clusters. The blue cluster is composed of institutions in China, led by Shanghai Jiao Tong University. The purple cluster is primarily comprised of the United States institutions, with the University of California System and FDNA serving as its main components. Within these institutions, FDNA plays a key role by connecting the purple cluster to the red cluster. This indicates that FDNA has a strong foundation for international exchange and collaboration, positioning it as a significant node with substantial research potential within the collaborative network of institutions. The green cluster is led by Harvard University, University of Cambridge, King's College London, and the Chinese Academy of Sciences. These institutions are located in China, the United Kingdom, and the United States, which are all important research hubs in their respective countries. The red cluster, led by the University of Bonn and Charité Universitatsmedizin Berlin, is concentrated in Germany.

Table 2

Top 10 productive organization related to AI-based facial recognition in the medical field.

Rank	Organization	Count	Total Citation	Average Citation	Centrality	Country
1	Shanghai Jiao TongUniversity	16	158	9.88	0.04	China
2	University of California System	12	470	39.17	0.09	USA
3	Peking Union Medical College	11	179	16.27	0.1	China
4	Chinese Academy of Sciences	11	166	15.09	0.1	China
5	Harvard University	8	1056	132	0.07	USA
6	Tsinghua University	7	179	25.57	0.06	China
7	Peking University	7	164	23.43	0	China
8	Centre National de la Recherche Scientifique (CNRS)	6	89	14.83	0.01	France
9	Egyptian Knowledge Bank (EKB)	6	46	7.67	0.07	Egypt
10	Sichuan University	6	35	5.83	0.01	China
11	National Institutes of Health (NIH)	6	33	5.5	0.07	USA

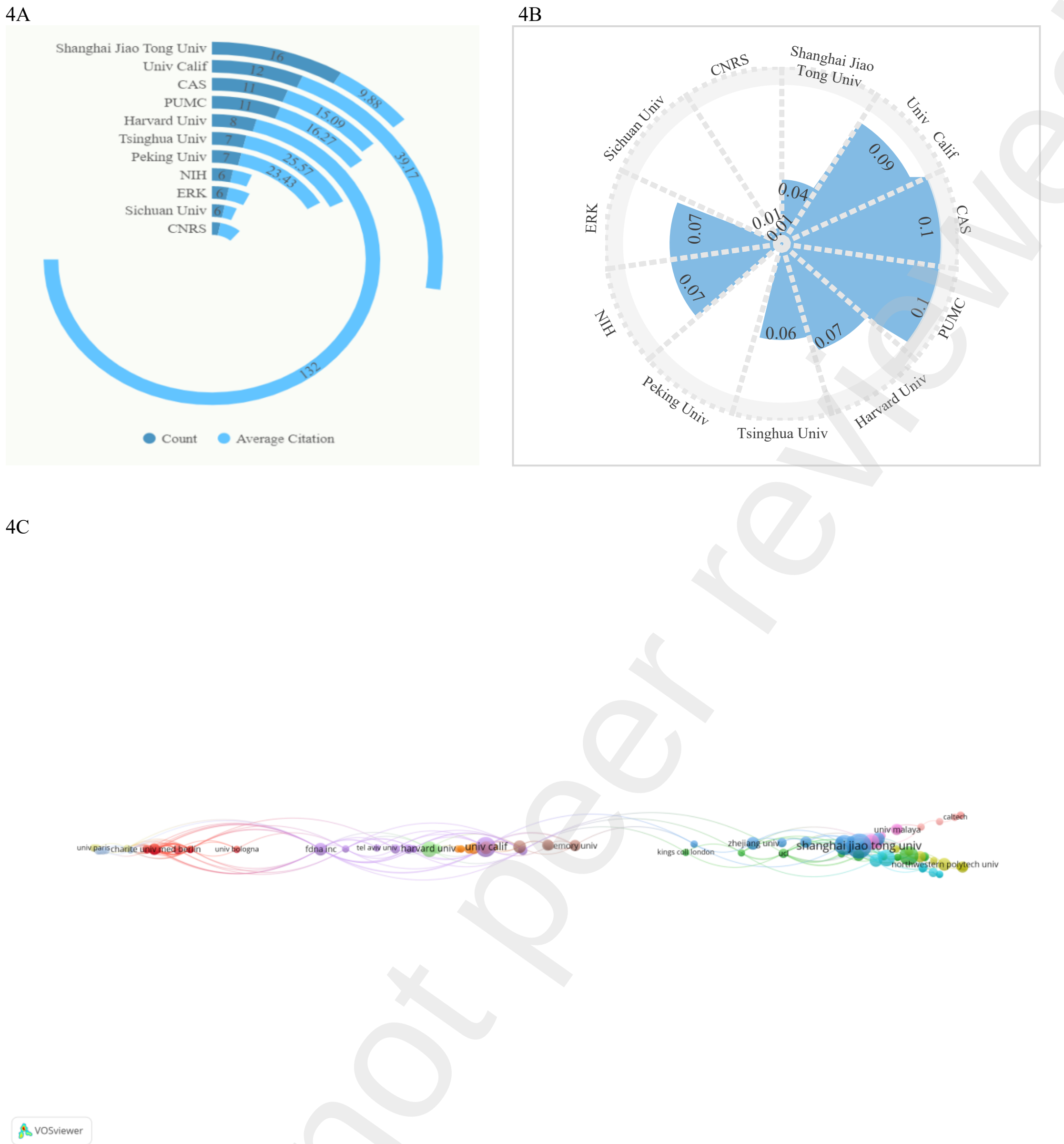


Fig. 4. (A) The centrality of the top 10 most productive organizations. (B) The total publications and total citations of the top 10 institutions. (C) The visualization map of institutions co-authorship analysis generated by VOSviewer.

3.4 Analysis of the active authors and co-cited authors

A total of 2,126 authors and 12,244 co-cited authors were included in the analyzed literature, with an average of 5.61 authors per paper. The number of citations can be used to measure the influence of authors to some extent [24]. In addition, analyzing co-cited authors enables the exploration of related research domains. Statistical analysis was conducted on the top 10 authors based on publication frequency and co-citation counts, detailed in Table 3， Table 4, and Fig. 5A， Fig. 5B. Among the most prolific authors, Nicole Fleischer from FDNA, Inc. stands out with the highest number of publications. FDNA possesses the world's most comprehensive database of genetically related phenotypic information, which forms the foundation for FDNA™'s next-generation phenotyping (NGP) artificial intelligence technology. This technology is employed to capture and analyze human phenotypic data, aiming to determine the relationships between phenotypes, genomes, and genetic diseases. Fleischer's primary research focuses on investigating the relationship between the molecular genomics of genetic diseases and facial phenotypic features using AI facial analysis systems [25-27].

Ekman, P.(H-index=34), a professor in the Department of Psychology at the University of California, San Francisco, is the most co-cited author. He is renowned for his pioneering work in the study of facial expressions and emotion recognition, and was named one of the 100 most important psychologists of the 20th century by the American Psychological Association. Among his significant research achievements are the confirmation of commonalities in facial expressions across different cultures, the recognition of basic emotions universally, and the development of the Facial Action Coding System (FACS). This system provides a fundamental basis for subsequent AI applications aimed at recognizing facial expressions across diverse populations [28-31].

Additionally, Zhai Guangtao (H-index=50) from Shanghai Jiao Tong University holds the distinction of having the highest H-index among authors. His notablecontributions include the construction of predictive models and optimization evaluations using AI in computer vision technology [32, 33]. Zhai's applied research in the medical field primarily focuses on developing a multimodal medical image acquisition and fusion system utilizing deep point neural networks, monitoring the breathing patterns of critically ill patients using video pairs, and devising a learning approach for segmenting lung CT images. Such applications have significantly enhanced the efficiency of disease monitoring and diagnosis [34-36].

A visual representation of the co-author analysis was generated using VOSviewer (Fig. 5C). While there are instances of international collaboration among some scholars, such as Nicole Fleischer and Peter M. Krawitz, the majority of the author clusters are primarily concentrated within the same national institutions, with fewer studies involving international collaboration.

Table 3

The top 10 most productive authors.

Rank	Author	Documents	Citations	Average Citation	H-index	Country
1	Fleischer, Nicole	5	433	86.60	11	USA
2	Krawitz, Peter M	4	440	110.00	36	Germany
3	Zhai, Guangtao	4	57	14.25	50	China
4	Pan, Hui	4	38	9.50	40	China
5	Chen, Shi	4	38	9.50	5	China
6	Linguraru, Marius George	3	91	30.33	28	USA
7	Hsieh, Tzung-Chien	3	86	28.67	8	Germany
8	Danyel, Magdalena	3	76	25.33	6	Germany
9	Horn, Denise	3	76	25.33	48	Germany
10	Mensah, Martin Atta	3	76	25.33	12	Germany
11	Pantel, Jean Tori	3	76	25.33	7	Germany

Table 4

The top 10 co-cited authors.

Rank	Co-cited Author	Citations	H-index	Country
1	Ekman, Paul	107	34	USA
2	He, Kaiming	66	62	USA
3	Lucey, Patrick	57	18	USA
4	Simonyan, Karen	52	24	USA
5	Szegedy, Christian	52	11	USA
6	Viola, P	43	23	England
7	Gurovich, Yaron	38	5	Israel
8	Baltrusaitis, Tadas	36	23	USA
9	King, Davis E	33	1	USA
10	Dalal, Neal	31	13	USA
11	Hossain, Mohammad Alamgir	31	4	Saudi Arabia

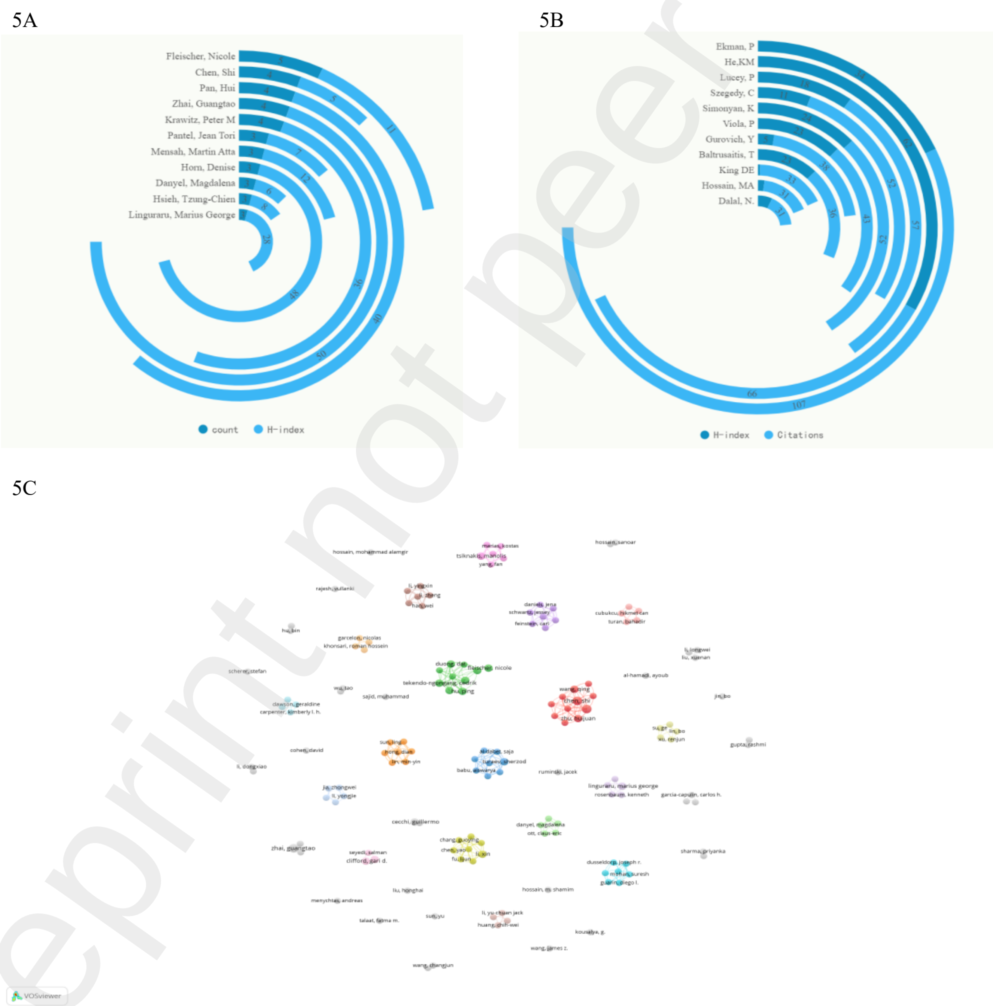


Fig. 5. (A) The total publications and H-index of the top 10 most productive authors. (B) The total citations and H-index of the top 10 10 co-cited authors. (C) The visualization map of author co-authorship analysis generated by VOSviewer.

3.5. Analysis of top journals and co−cited journals

Academic journals serve as critical platforms for scientific and technological communication, fostering advancements in knowledge. A statistical analysis of the literature indicates that research on the application of AI-based facial recognition technology in medicine has been published in 202 academic journals and 6,243 co-citation sources. Table 5 and Table 6 summarize the top 10 journals and co-cited journals, detailing the number of publications, total citations, average citations, Impact Factor (IF), Journal Citation Report (JCR) category , and Essential Science Indicators Subject Classification (ESI) to comprehensively assess their impact.

Among the top 10 journals by number of publications (Table 5), three are classified as Q1 and seven as Q2 by the JCR. The leading fields to which the journals belong, according to the ESI classifications, include engineering, computer science, clinical medicine, and multidisciplinary disciplines. These fields emphasize the promotion of interdisciplinary research between medicine and computer engineering.

The number of papers published in these journals reflects the level of attention given to this area of research and identifies emerging areas of interest. The journal with the highest number of publications is IEEE Access (n=25 publications), followed by Multimedia Tools and Applications (n=17 publications) and Applied Sciences-Basel (n=15 publications). In terms of average citations per article, the top three journals are IEEE Transactions on Affective Computing (19 citations/article), Sensors (16.13 citations/article), and Journal of Medical Internet Research (16 citations/article). Notably, the Journal of Medical Internet Research is a leading journal in the medical field, focusing on digital health, data science, health informatics, and emerging technologies in health, medicine, and biomedical research. This journal significantly contributes to the multidisciplinary convergence of medicine and engineering.

The pattern of research paper distribution across journals in this field was analyzed using Bradford's Law, and the results are presented in Table 6. The analysis reveals that the number of papers in the three zones is roughly equal, with the ratio of the number of journals approximating 1:3:9 （$1:3:3^2$）. This suggests that the distribution of research papers in journals related to AI-based facial recognition in medicine from 2004 to 2024 generally aligns with the empirical formula described by Bradford's Law.

The top 10 co-cited journals (Table 7), primarily belonged to the Q1 or Q2 categories, with the only exception being the American Journal of Medical Genetics Part A, where half of the classifications were under Q1. These leading journals' subject classifications spanned across engineering sciences, computer sciences, multidisciplinary studies, psychiatry/psychology, and molecular biology and genetics. Co-citation relationships serve as pivotal indicators of a journal's influence within the academic landscape. Noteworthy among these relationships are the top three co-cited journals: IEEE Transactions on Pattern Analysis and Machine Intelligence (cited 282 times), IEEE Transactions on Affective Computing (cited 234 times), and IEEE Access (cited 230 times).

IEEE Transactions on Pattern Analysis and Machine Intelligence ranked first in frequency and impact factor among the co-cited journals, which indicates that the journal has a high academic level and receives much attention in the application of AI-based facial recognition in the medical field. The journal, positioned among the leading publications in computer science, strives to share research findings concerning the development of systems capable of recognizing, interpreting, and simulating human emotions and related affective phenomena. It emphasizes advancing the creation of multi-modal methods for recognizing affective states through facial expressions, body language, and speech, along with data collection techniques and annotation tools that generate emotional datasets. These efforts aim to facilitate machine learning applications by exploring verbal and nonverbal modes of emotional expression across a spectrum of emotions.

Furthermore, two significant non-journal sources with high co-citation rates, namely the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (cited 711 times, a leading conference in computer vision) and arXiv (cited 380 times, the most authoritative international preprint platform), were not included in the ranking of co-cited journals.

Table 5

The top 10 journals.

Rank	Journal	Output	Citations	Average Citation	JCR	IF	ESI
1	Ieee Access	25	255	10.2	Q2	3.9	Engineering
2	Multimedia Tools And Applications	17	132	7.76	Q2	3.6	Computer Science
3	Applied Sciences-Basel	15	127	7.47	Q2	2.7	Engineering
4	Sensors	10	242	16.13	Q2	3.9	Chemistry
5	Journal of Medical Internet Research	9	144	16	Q1	7.4	Clinical Medicine
6	Ieee Transactions on Affective Computing	8	152	19	Q1	11.2	Computer Science
7	Ieee Journal of Biomedical and Health Informatics	6	35	5.83	Q1	7.7	Computer Science
8	Plos One	5	67	13.4	Q2	3.7	Multidisciplinary
9	Scientific Reports	5	60	12	Q2	4.6	Multidisciplinary
10	Neural Computing & Applications	5	41	8.2	Q2	6	Engineering

Table 6

Journal partion.

Zone	Publications/Journal	Number of journal	Number of Publications
First Zone	≥5	13	120
Second Zone	2-4	50	120
Third Zone	1	139	139

Table 7

The top 10 co-cited journals

Rank	Co-cited journal	Citations	JCR	IF	ESI
1	IEEE Transactions on Pattern Analysis and Machine Intelligence	282	Q1	23.6	Engineering
2	IEEE Transactions On Affective Computing	234	Q1	11.2	Computer Science
3	IEEE Access	230	Q2	3.9	Engineering
4	Plos One	181	Q2	3.7	Multidisciplinary
5	Sensors - Basel	181	Q2	3.9	Chemistry
6	Journal of Autism and Developmental Disabilities	166	Q1	3.9	Psychiatry/Psychology
7	IEEE Transactions on Image Processing	125	Q1	10.6	Engineering
8	American Journal of Medical Genetics Part A	122	Q3	2	Molecular Biology& Genetics
9	Image and Vision Computing	115	Q1	4.7	Engineering
10	Multimedia tools and applications	115	Q2	3.6	Computer Science

3.6. Keyword analysis

The keywords or subject terms in an article are distilled from its core content or main themes. By analyzing word frequency and visualizing co-occurring keywords in a network map, researchers can identify and understand the research trends and focal points within this specific field [37]. In this study, a total of 1823 keywords were extracted from 379 documents, with 19 keywords appearing more than 20 times. These keywords were visualized using CiteSpace (Fig. 6). In the visualization, each node represents a keyword, with the node size indicating its frequency. The nodes are encircled by chronological rings, where the color corresponds to the keyword's appearance over time. The innermost rings represent earlier appearances, progressing outward to depict newer occurrences. Lines connecting nodes indicate co-citation relationships, with the thickness indicating the strength of these relationships.In Fig. 6, the largest node is "deep learning", followed by "face recognition", "machine learning", "convolutional neural network", and "facial expression".

The keywords underwent clustering using CiteSpace software. Each cluster is denoted by a number sign "#". The significance of the community structure was assessed based on the Q and S values. A clustering is considered significant when $Q > 0.3$ and $S > 0.7$. Higher values reflect a more pronounced clustering effect [38, 39]. As depicted in Fig. 7A, a total of 14 clusters were identified. The Q value of 0.7951 and S value of 0.9403 confirm the significant clustering effect. The largest clusters are "classification" #5 and "face detection" #1, with subsequent notableclusters including "autism spectrum disorder"#9, "artificial intelligence" #3, and "stress" #4.

In order to better discover the evolution of the keyword network for the application of AI-based facial recognition in medicine, Timeline View analysis was utilized. To conduct temporal clustering, choose "Find Clusters," select "LLR," and opt for "Timeline View." The horizontal positioning of each cluster indicates the start and end time, while the node size reflects the frequency of occurrence. The connections between nodes represent the co-occurrence relationship.The analysis revealed that terms like "diagnose," "facial expression recognition," and "machine learning" appeared early and remained popular research topics. Recent years have seen a shift towards exploring new research directions in fields such as "algorithm," "computer vision," "facial expression recognition," "autism spectrum disorder," and "Parkinson's disease."

The advancement of AI and computer vision technology has broadened the application of facial recognition across various medical domains. Current research areas experiencing significant attention include machine learning, facial recognition, disease diagnosis, monitoring, and emotion recognition.

In Cluster 0, the emergence of the term "diagnose" as a high frequency terminology in machine learning research dates back to 2004, with researchers exploring the potential of machine learning in constructing surface models for three-dimensional facial morphology analysis [40]. The close connection of "diagnosis" to AI signifies the gradual integration of AI technology into disease diagnosis processes, especially in aiding clinics in diagnosing complex genetic conditions effectively. Due to advancements in image acquisition and analysis systems alongside AI, the focal point in face detection technology research has transitioned from "data mining,""3D face recognition," "image analysis," towards "computer vision," and "feature extraction" within the timeline of Cluster 1. Significantly, following its initial appearance in 2016, "computer vision" became a high-frequency term in 2019, closely associated with "facial expression" and "recognition" in Cluster 2, as well as "early detection" in Cluster 4. This illustrates the progressive application of computer vision technology for facial recognition and the early screening of diseases. In Cluster 2, the term "facial expression recognition" has notably risen in frequency since 2020, suggesting a growing interest among researchers in utilizing AI technology to objectively evaluate a patient's psychological state and degree of pain. This approach aims to provide more objective assessments compared to traditional subjective evaluations [41, 42]. In the timeline within Cluster 4 focusing on "artificial intelligence," AI was initially employed to detect patients' facial expressions and behaviors for objective psychological analysis [43]. This application later extended to encompass predictive diagnosis of psychiatric disorders and mood monitoring [44]. Previously, psychiatry and psychology relied on subjective assessments for clinical evaluations. The introduction of AI-based facial testing addresses the lack of objective assessment tools within psychiatry, enabling the extraction of valuable objective data for tailored interventions. In Cluster 5, the term "recognition" emerged as early as 2010, primarily emphasizing the application of image-based machine learning in medical image analysis [45]. This theme later extended to the quantitative assessment of facial phenotype and emotional states in patients with genetic conditions [46-48], aiding in the diagnostic process of genetic syndromes. In Cluster 6 "affective computing," deep learning-based methodologies have been utilized to detect various conditions such as pain, stress, and Alzheimer's disease. "Depression detection" has emerged as a key area of research within affective computing. This focus is closely linked with the recent research advancement in Cluster 2 on "facial recognition" under the "feature fusion" umbrella. Through the analysis of facial cues related to depressive behaviors in videos and subsequent feature integration, the aim is to automate the identification of depression [49]. In cluster 9, "autism spectrum disorder" is a significant application of facial recognition in medicine, closely connected to "machine learning" within the cluster. Computational assessment of facial expressions plays a pivotal role in the early detection of autism symptoms, offering crucial insights for timely interventions that can significantly impact the prognosis of children with autism. This area holds substantial research value, positioning it as a key focus that is likely to remain prominent in future research endeavors [47].

The burst detection algorithm in CiteSpace software was utilized to identify keywords that experienced a sudden and notablesurge in frequency or appeared abruptly in a short timeframe. This technique aimed to aid in uncovering emerging research frontiers and trends within the field [23]. Fig. 7C highlights the top 10 keywords displaying the most pronounced bursts. The blue line in the figure illustrates the time interval, while the red line indicates the duration of the burst. The keyword "face" exhibited the highest intensity of burst, with its initial appearance recorded in 2018 and a duration spanning from 2018 to 2020. This period coincides with the emergence of the COVID-19 outbreak. Similarly, the keyword "phenotype" experienced a prolonged burst during this time frame. Significantly, "phenotype" stands out as the earliest and most enduring keyword, underscoring scholars' recognition of a connection between the disease and the patient's facial characteristics. Since 2022, the study of facial features has emerged as a prominent research area, hinting at a promising pathway for future investigations in this field.

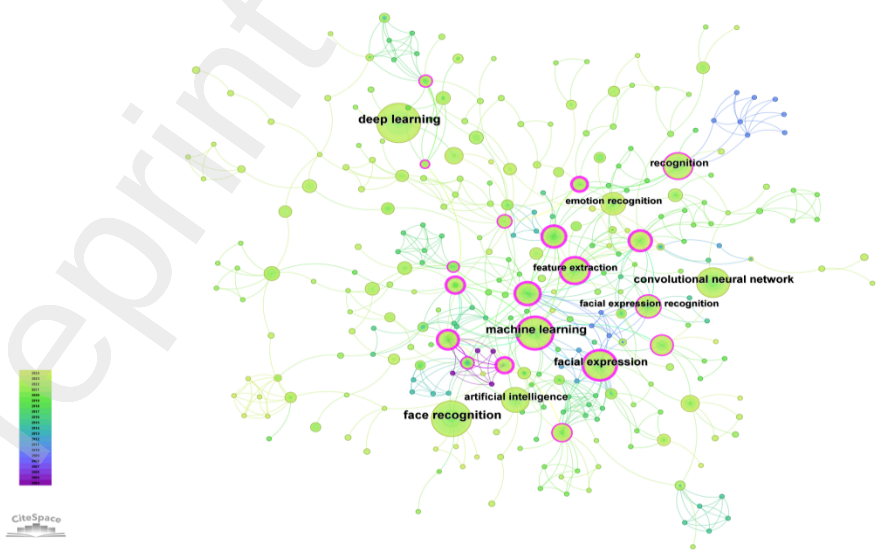
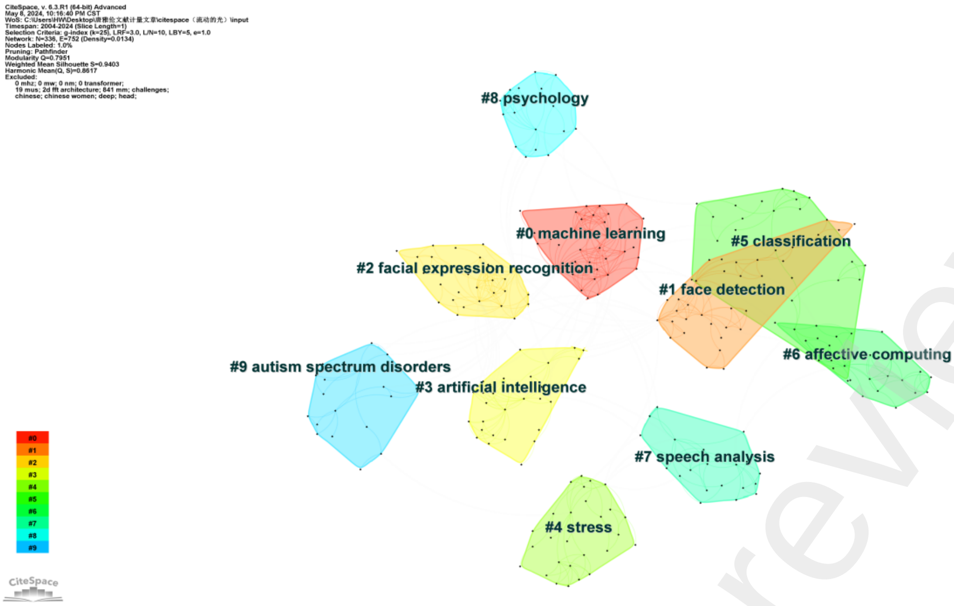
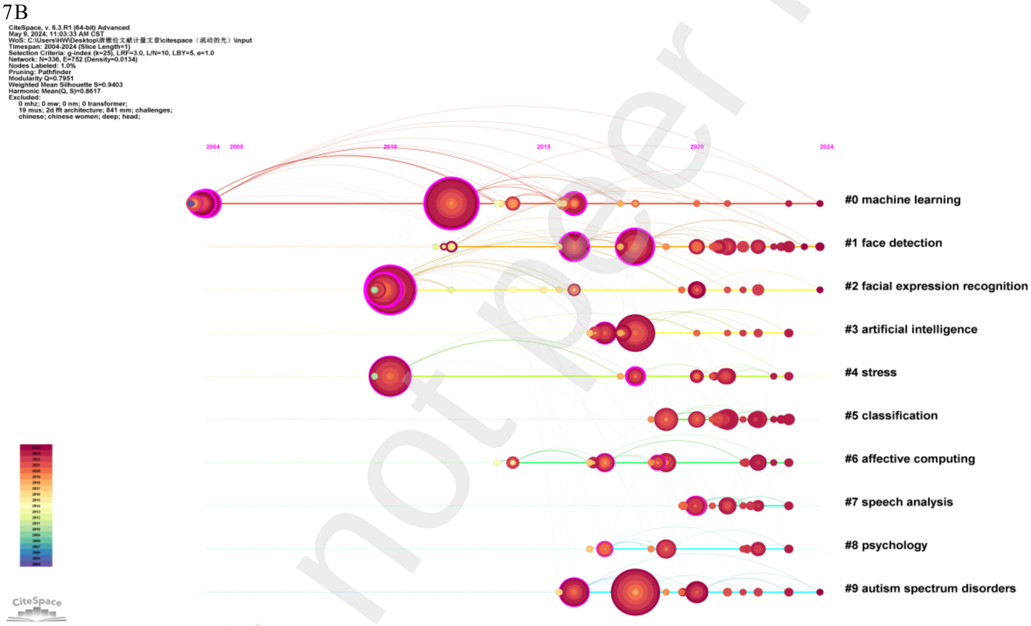


Fig. 6. The overlay visualization map of author keywords co-occurrence analysis.

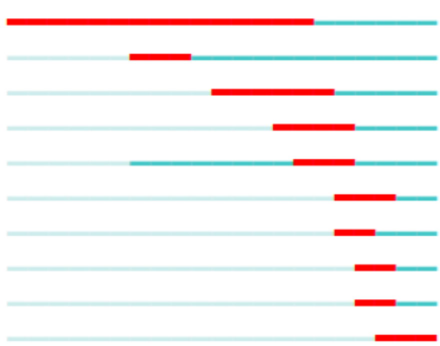
7A



7B



7C



Top 10 Keywords with the Strongest Citation Bursts

Keywords	Year	Strength	Begin	End	2004 - 2024
phenotype	2004	1.78	**2004**	2018	
support vector machine	2010	1.89	**2010**	2012	
mutations	2014	1.82	**2014**	2019	
age	2017	1.84	**2017**	2020	
face	2010	2.14	**2018**	2020	
expression	2020	1.75	**2020**	2022	
disease	2020	1.53	**2020**	2021	
brain	2021	1.48	**2021**	2022	
fusion	2021	1.48	**2021**	2022	
facial features	2022	1.54	**2022**	2024	

Fig. 7. (A) The cluster view map of keyword. (B) The cluster timeline view map of keywords analysis. (C) Visualization map of top 10 keywords with the strongest citation bursts in AI-based facial recognition in the medical field.

3.7. Most cited papers and references

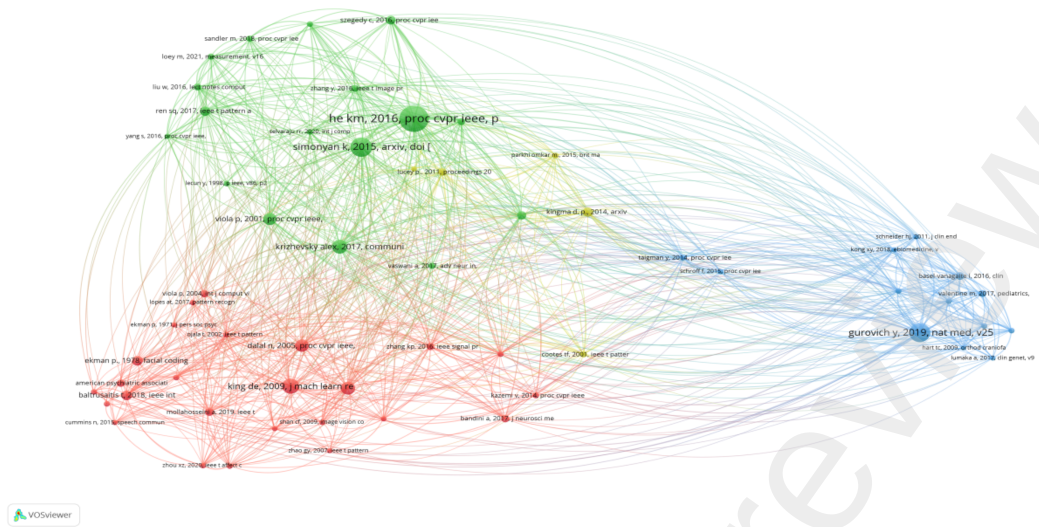
A total of 379 papers were included in this study, and 22 papers were cited on more than 50 occasions. Table 8 presents a list of the ten most frequently cited papers. The most frequently cited paper is Barrett, Lisa Feldman et al.'s study on the correlation between facial movements and emotional states, published in 2019 (791 citations). The subsequent most cited papers were from Nanni, Loris et al. and Gurovich, Yaron et al.The top 10 papers primarily delved into topics such as facial recognition for disease diagnosis, emotion recognition, and optimization of AI algorithms.

In total, 16,060 references were cited across all articles, with 60 receiving more than 10 citations. Using VOSviewer for reference co-citation mapping and setting a minimum cited reference threshold of 10, 60 documents were retained for co-citation analysis, categorized into three primary clusters. In Fig. 8A, the green cluster focuses on the development of AI models and neural networks in image recognition. The red cluster pertains to computer vision techniques and deep learning algorithms applied in facial recognition. The blue cluster is dedicated to specific applications of facial recognition technology in the medical domain, particularly in early screening and detection of genetic diseases. The top ten most cited documents are detailed in Table 9. Gurovich, Yaron et al (36 citations). received the highest number of citations for their research on utilizing computer vision techniques and deep learning algorithms for recognition of facial phenotypes in genetic diseases. This was followed by King, Davis E et al. (29 citations) and Krizhevsky, Alex et al. (26 citations). These top ten literature works cover a range of topics including face detection, facial image recognition, and specialized applications of facial recognition in the medical field.

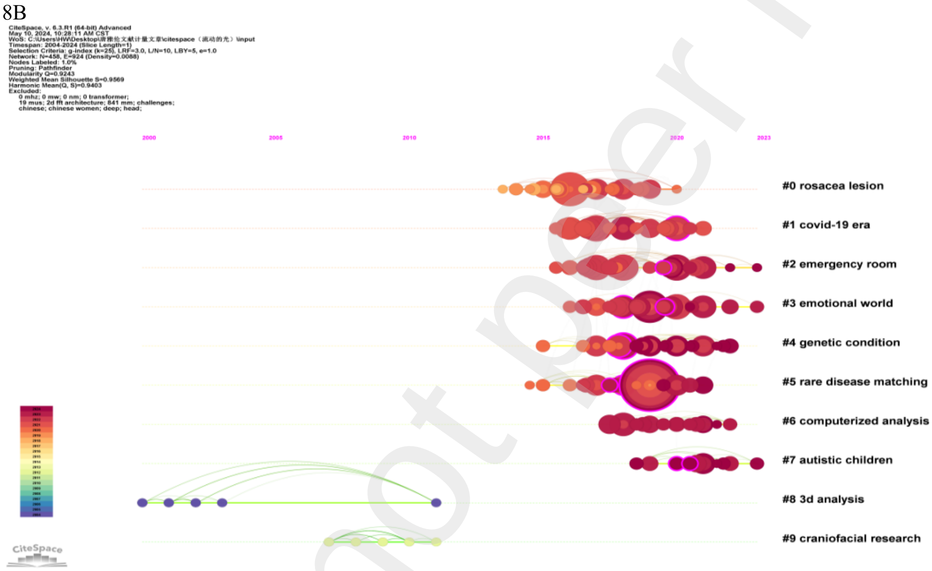
The timeline graph (Fig. 8B) illustrated the categorization and temporal distribution of references, which revealed a significant increase in publications post-2015. The clustering analysis categorized the cited literature into 16 distinct categories, primarily revolving around computer vision methods and their specific applications. notableapplications in the medical field include COVID-19 (#1), stroke (#2), non-contact respiratory monitoring (#4), Parkinson's disease (#6), autism (#7), and emotional state analysis (#13). Various computer vision technology approaches encompass diverse methods, ranging from face processing (#15), extraction of facial features (#5), artificial intelligence (#16), dense surface modeling (#8), image analysis (#9), mask analysis (#10), to texture description (#11).

The top 20 citation outbreaks are shown in Fig. 8C. The references of citation outbreaks have peaked since 2019, indicating the rapid development of AI-based facial recognition in the medical field after 2019. Among them, the strongest citation explosion value was published by Kaiming He et al. on optimizing residual learning framework (RLF) in visual recognition tasks to enhance the accuracy of depth representation acquisition [50].

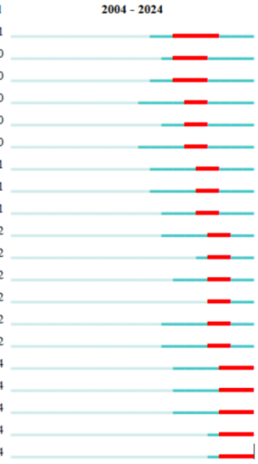
8A



8B



8C



Top 20 References with the Strongest Citation Bursts

References	Year	Strength	Begin	End	2004 - 2024
Basel-Vanagaite L, 2016, CLIN GENET, V89, P557, DOI 10.1111/cge.12716, DOI	2016	2.7	**2018**	2021	
Krizhevsky A, 2017, COMMUN ACM, V60, P84, DOI 10.1145/3065386, DOI	2017	2.06	**2018**	2020	
Goodfellow I, 2016, ADAPT COMPUT MACH LE, V0, P1	2016	2.06	**2018**	2020	
Simonyan K, 2015, ARXIV, V0, P0	2015	4.38	**2019**	2020	
Krizhevsky Alex, 2017, COMMUNICATIONS OF THE ACM, V60, P84, DOI 10.1145/3065386, DOI	2017	3.75	**2019**	2020	
Schroff F, 2015, PROC CVPR IEEE, V0, PP815, DOI 10.1109/CVPR.2015.7298682, DOI	2015	2.18	**2019**	2020	
He KM, 2016, PROC CVPR IEEE, V0, PP770, DOI 10.1109/CVPR.2016.90, DOI	2016	5.99	**2020**	2021	
Zhang Y, 2016, IEEE T IMAGE PROCESS, V25, P0, DOI 10.1109/TIP.2016.2549360, DOI	2016	2.59	**2020**	2021	
Kruszka P, 2017, AM J MED GENET A, V173, P879, DOI 10.1002/ajmg.a.38199, DOI	2017	2.22	**2020**	2021	
Ren SQ, 2017, IEEE T PATTERN ANAL, V39, P1137, DOI 10.1109/TPAMI.2016.2577031, DOI	2017	2.51	**2021**	2022	
Selvaraju RR, 2020, INT J COMPUT VISION, V128, P336, DOI 10.1007/s11263-019-01228-7, 10.1109/ICCV.2017.74, DOI	2020	2.25	**2021**	2022	
Thevenot J, 2018, IEEE J BIOMED HEALTH, V22, P1497, DOI 10.1109/JBHI.2017.2754861, DOI	2018	2.25	**2021**	2022	
Loey M, 2021, MEASUREMENT, V167, P0, DOI 10.1016/j.measurement.2020.108288, DOI	2021	2.25	**2021**	2022	
Bandini A, 2017, J NEUROSCI METH, V281, P7, DOI 10.1016/j.jneumeth.2017.02.006, DOI	2017	2.25	**2021**	2022	
Howard AG, 2017, ABS170404861 CORR, V1704, P4861	2017	2	**2021**	2022	
Zhu Y, 2018, IEEE T AFFECT COMPUT, V9, P578, DOI 10.1109/TAFFC.2017.2650899, DOI	2018	2.38	**2022**	2024	
Cao Q, 2018, IEEE INT CONF AUTOMA, V0, PP67, DOI 10.1109/FG.2018.00020, DOI	2018	2.38	**2022**	2024	
Sandler M, 2018, PROC CVPR IEEE, V0, PP4510, DOI 10.1109/CVPR.2018.00474, DOI	2018	2.38	**2022**	2024	
Ali MR, 2021, NPJ DIGIT MED, V4, P0, DOI 10.1038/s41746-021-00502-8, DOI	2021	2.08	**2022**	2024	
Minaee S, 2021, SENSORS-BASEL, V21, P0, DOI 10.3390/s21093046, DOI	2021	2.08	**2022**	2024	

Fig. 8. Analysis of reference citations (The circle represents the number of citations. The line represents two articles cited by the same article.). (A) Co-citation analysis of references (The colors represent the clustering of references.). (B) Timeline diagram of references (The color represents the average time the reference was cited.). (C) Top 20 references cited in burst.

Table 8

The top ten articles with the most total citations.

Rank	Paper	Journal	First Author	Year	Total Citations	JCR	IF	ESI
1	Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements	Psychological Science in the Public Interest	Barrett, Lisa Feldman	2019	791	Q1	7.3	Clinical Medicine
2	Local binary patterns variants as texture descriptors for medical image analysis	Artificial Intelligence in Medicine	Nanni, Loris	2010	397	Q1	7.5	Clinical Medicine
3	Identifying facial phenotypes of genetic disorders using deep learning	Journal Information	Gurovich, Yaron	2019	376	Q1	82.9	Clinical Medicine
4	Instagram photos reveal predictive markers of depression	EPJ Data Science	Reece, Andrew	2017	244	Q1	3.6	Social sciences, General
5	3D analysis of facial morphology	American Journal of Medical Genetics Part A	Hammond, Peter	2004	204	Q3	2	Molecular biology &genetics
6	Deep Pain: Exploiting Long Short-Term Memory Networks for Facial Expression Classification	IEEE Transactions on Cybernetics	Rodriguez, Pau	2022	158	Q1	11.8	Computer Science
7	Identifying children with autism spectrum disorder based on their face processing abnormality: A machine learning framework	Autism Research	Liu, Wenbo	2016	151	Q1	4.7	Psychiatry /Psychology
8	Deep Facial Diagnosis: Deep Transfer Learning From Face Recognition to Facial Diagnosis	IEEE Access	Jin, Bo	2020	131	Q2	3.6	Engineering
9	Adversarial Examples—Security Threats to COVID-19 Deep Learning Systems in Medical IoT Devices	IEEE Internet of Things Journal	Rahman, Md Anisur	2021	111	Q1	10.6	Computer Science
10	Visually InterpreTable Representation Learning for Depression Recognition from Facial Images	IEEE Transactions on Affective Computing	Zhou, Xiuzhuang	2020	114	Q1	11.2	Computer Science

Table 9

The top 10 references with the most citations.

Rank	Paper	Journal	Journal Impact Factor	First Author	Year	Total Citations	ESI
1	Identifying facial phenotypes of genetic disorders using deep learning	Natural Medicine	82.9	Gurovich, Yaron	2019	36	Molecular biology &genetics
2	Dlib-ml:A Machine Learning Toolkit	Journal of Machine Learning Research	6	King, Davis E	2009	29	Computer Science
3	ImageNet Classification with Deep Convolutional Neural Networks	Communications of the ACM	22.27	Krizhevsky, Alex	2017	26	Computer Science
4	Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks	IEEE Transactions on Pattern Analysis and Machine Intelligence	23.6	Ren, Shaoqing	2017	18	Engineering
5	AffectNet: A Database for Facial Expression, Valence, and Arousal Computing in the Wild	IEEE Transactions on Affective Computing	11.2	Mollahosseini, Ali	2019	15	Computer Science
6	Recognition of the Cornelia de Lange syndrome phenotype with facial dysmorphology novel analysis	Clinical Genetics	3.5	Basel-Vanagaite, Lina	2016	15	Clinical Medicine
7	Robust real-time face detection	International Journal of Computer Vision	19.5	Viola, P	2004	14	Engineering
8	Analysis of facial expressions in parkinson's disease through video-based automatic methods	Journal of Neuroscience Methods	3	Bandini, Andrea	2017	14	Neuroscience & Behavior
9	Compact Representation of High-Dimensional Feature Vectors for Large-Scale Image Recognition and Retrieval	IEEE Transactions on Image Processing	10.6	Wang, Lanjun	2016	13	Engineering
10	Computer-Aided Recognition of Facial Attributes for Fetal Alcohol Spectrum Disorders	Pediatrics	8	Valentine, Matthew	2017	13	Clinical Medicine

4. Discussion

The rapid progress of information technology, including big data, computational power, and algorithms, coupled with computing platforms like pervasive perceptual data and graphic processors, has propelled the swift evolution of AI technology. This advancement has notably enhanced the capabilities of AI models to analyze and extract features from a diverse set of medical data and images. This has greatly reduced the technological disparity between scientific theories and practical applications, thus fostering the gradual shift from traditional healthcare practices toward precision medicine [51, 52]. In the realm of medical applications of AI, medical image analysis emerges as a focal point, with facial recognition demonstrating substantial potential in facilitating swift, precise, and low-cost diagnosis and treatment of diseases [25, 53].

Since 2020, there has been an exponential increase in the volume of literature exploring the application of AI-based facial recognition technology in medicine. Nevertheless, the numerous research findings in this field are widely distributed, and there is a noticeable absence of all-encompassing summary studies that effectively capture the breadth, depth, and predicting research trends. To address this gap, bibliometric methods were employed to analyze literature spanning the past two decades. Utilizing tools such as Citespace and VOSviewer, data was visualized, historical developments were summarized, and current state-of-the-art applications were highlighted in the field over the last 20 years. Furthermore, these analyses were used to anticipate future research directions.

Research on facial recognition originated in the 1960s. Nevertheless, hindered by constraints in image acquisition, storage, computational capabilities, algorithms, feature extraction, and related technologies,it was only gradually applied to the medical field research after 2000 [54]. Initially, progress in applying AI-based facial recognition technology within the medical domain was gradual, with a pivotal shift observed in 2018. This shift has resulted in a significant rise in relevant studies, attributed to advancements in deep learning techniques enhancing computer vision capabilities [55, 56]. Early facial biometric systems heavily relied on manual labeling during image segmentation, preprocessing, feature extraction, and classification. However, given the intricate nature of facial information, manual extraction was prone to omitting crucial details, besides being labor-intensive [57]. Deep learning models have revolutionized this process by autonomously extracting features from images, mitigating bias stemming from subjective interventions and resource-intensive tasks. Moreover, AI-driven systems exhibit robustness and precision, offering notableadvantages across various computer vision applications [58]. Consequently, an increasing number of researchers are developing facial biometric systems grounded in AI, making this area one of the most dynamically evolving research domains in recent years, with an average annual growth rate of 61.16%, particularly prominent in 2020 (Fig. 2). While the study scope includes literature up to May 2024, considering the prevailing research trajectory and AI trends, the application of facial recognition in the medical sector is anticipated to sustain its prominence within computer vision and biometric recognition technology research endeavors.

Currently, the top two countries in terms of the number of papers published in this field are China and the United States, collectively representing 54.35% of all publications, underscoring their prominent roles in research. The 2024 Artificial Intelligence Index Report from Stanford highlights the United States and China as global leaders in AI technology investment, research, and development. Basic models are pivotal in cutting-edge AI, with the United States leading with 109 models, followed by China with 20, and the United Kingdom in third with 8 models, potentially explaining the elevated publication volume of China and the U.S. [59]. While Chinese scholars have produced 126 papers, the average citation count stands at 10.87 per paper, suggesting a need for enhanced paper quality and innovation. In comparison, American scholars rank second in both publication count and average citations, with 80 papers and an average of 37.18 citations per paper. The United States maintains the highest number of top global AI models at 63, surpassing the EU's 21 and China's 15 models, indicating advanced and credible research contributing to higher average citation rates [59]. The United Kingdom boasts the highest average citation rate per article at 50.09, having pioneered research in this field and consistently producing research at a steady pace. Further analysis of the data reveals that China only began venturing into this area of research in 2016. Subsequently, its research efforts surged, surpassing the U.S. in 2020. The annual article output from China doubled that of the U.S. from 2020 to 2023, reflecting China's rapid research growth fueled by governmental policies and funding. This rapid progress may partly explain the lower average citation frequency in China. However, while publication count and citation rates provide initial insights into national research impact, a comprehensive analysis should incorporate research duration, institution caliber, academic policies, and journal prestige to gauge research influence effectively.

Fig. 3C and Fig. 3D illustrate the collaboration between different countries. Among the top 10 countries, most studies are conducted predominantly by a single nation, with the exceptions of Saudi Arabia and Canada, which participate in half of the collaborative studies. The quality and volume of the dataset are crucial factors in determining the effectiveness of a model. Promoting international cooperation can help build high-quality databases and mitigate biometric biases caused by racial differences. The close cooperation among European countries, such as Germany, the UK, Switzerland, France, the Netherlands, and Italy, indicates primarily regional collaborations. The United States, on the other hand, collaborates with various countries across different regions, including China, the UK, India, Saudi Arabia, and Canada. This extensive network of collaborations reflects the U.S.'s leadership in this research field. An example of such collaboration is the Human Malformation Syndrome Atlas (https://research.nhgri.nih.gov/atlas/), created by clinical geneticists, teratologists, and other medical experts worldwide, with funding from the U.S. National Human Genome Research Institute (NHGRI). This website focuses on collecting facial photographs and other relevant data, as well as molecular diagnostics, aiming to provide comprehensive coverage of syndromic phenotypes across different human populations. This extensive dataset likely contributes to the U.S.'s capability in predictive macromodeling.

Among the top 10 organizations (including 11 institutions), there are 6 in China, 3 in the United States, and 1 each in France and Egypt. China leads in the number of research institutions and publications, with policy and financial support significantly driving the development of AI organizations. China's vast data resources also contribute to the strong foundation for AI-based facial recognition technology in medical applications. The University of California System, renowned as one of the most influential public university systems globally, boasts the highest average number of citations and serves as a pivotal institution in this research domain. A key contributor in this field is Prof. Lynne Bird's team at the University of California, San Diego (H-index=36). Their notablework, "Identifying facial phenotypes of genetic disorders using deep learning," published in NATURE MEDICINE in 2019, emphasizes their focus on Genetics & Heredity and Neurosciences & Neurology. The team developed DeepGestalt, a facial image analysis framework utilizing computer vision and deep learning algorithms. They trained the framework on a dataset of over 17,000 images representing more than 200 syndromes to quantitatively distinguish similarities between syndromic genetic disorders. This framework demonstrates significant potential for phenotype assessment in clinical genetics, genetic testing, research, and precision medicine [5].

Notably,FDNA Inc., collaborating with Prof. Lynne Bird's team, focuses on using AI to detect physiological patterns indicating disease-causing genetic variations. It currently maintains the largest global network of clinicians, laboratories, and researchers, creating one of the fastest-growing and most comprehensive genome databases [25, 60]. As illustrated in Fig. 4C, FDNA Inc. collaborates with prestigious institutions such as Harvard University, the National Human Genome Research Institute (NHGRI), the University of Bonn, the University of California System, and the University of Ottawa. This indicates FDNA Inc.'s significant role in the field of facial recognition for genetic diseases, making it a high-quality candidate for research collaboration.

The analysis of authors in this field, illustrated in Table 4, identifies Nicole Fleischer as the author with the highest number of publications, totaling 5 papers, with an average number of 86.60 citations per paper as of the present day. Their research primarily focuses on utilizing deep learning models for recognizing facial phenotypes associated with rare genetic disorders [5, 25, 27, 60, 61]. Peter M Krawitz holds the highest average number of citations per article at 110 and ranks second in terms of the number of publications, with four articles. The H-index is a metric that evaluates the academic achievement and impact of researchers comprehensively. It overcomes the limitations of evaluating researchers solely based on total citations or the number of papers, making it a more realistic assessment of scholars' academic achievements and the impact of their papers [62]. Zhai, Guangtao holds the highest H-index among researchers and plays a significant role in this research field. Zhai's work predominantly revolves around constructing prediction models of computer vision technology utilizing AI [63, 64].

In the co-cited authors, Paul Ekman from the Department of Psychology at the University of California, San Francisco, emerges as the most frequently referenced author. Ekman, a renowned American psychologist and expert in stress micro-responses, is a trailblazer in the study of emotions and facial expressions. He is acclaimed as one of the 100 most distinguished psychologists of the twentieth century. Paul Ekman's emotion theory falls within the Basic Emotion Models category, making a notablecontribution by validating the consistency of facial expressions across diverse cultures. This foundation paved the way for subsequent advancements in AI to recognize facial emotions among individuals from varied ethnic and cultural backgrounds [30, 65, 66]. Another notableachievement by Ekman is the development of the Facial Action Coding System (FACS), which maps facial muscle movements to expressions through observation and biofeedback. FACS not only serves as the authoritative standard for facial expression muscle movements, but also provides an essential resource for emotion theory research spanning nearly four decades. This system offers a robust base for AI applications in facial biosystem recognition, furnishing a solid theoretical underpinning for the field [65, 66].

The academic standing and impact factor of a publication can serve as an indicator of the research level to a certain extent [67]. Analyzing publications in this field aids researchers in swiftly accessing the latest academic insights and selecting appropriate journals to disseminate their research findings. An analysis of the journals (Table 7) indicates that the top 10 journals in this field hold JCR rankings of Q1 and Q2. Their ESI subject classifications encompass Engineering Science, Computer Science, Clinical Medicine, Multidisciplinary, and Chemistry, highlighting the interdisciplinary nature of the intersection between AI-based facial recognition and the medical field. This convergence represents an emerging field that continues to be actively explored.Among the top three journals are IEEE Access, Multimedia Tools And Applications, and Applied Sciences-Basel, with publications numbering 25, 17, and 15. This indicates that the above-mentioned journals prioritize the publication of research results in this field. Given its emergent nature, the surge in article publications has been gradual since 2018, resulting in a comparatively lower volume of articles historically, which may account for the lesser publication output in these journals compared to other fields.

The top 3 co-cited journals are IEEE Transactions on Pattern Analysis and Machine Intelligence, IEEE Transactions on Affective Computing, and IEEE Access. Among these, IEEE Transactions on Pattern Analysis and Machine Intelligence stands as a leading journal in the field of computer science, focusing on various traditional areas of computer vision, image understanding, pattern analysis, recognition, and key aspects of machine learning. This journal places particular emphasis on machine learning for pattern analysis, with a focus on important research areas such as medical image analysis and facial recognition within its publications. In addition, it is important to note that due to the interdisciplinary nature of the field, there are instances where facial recognition research in the medical field has been published in journals of different disciplines. Therefore, comparing impact factors alone doesn't definitively establish the superiority of one journal over another. A more scientific comparison necessitates a side-by-side evaluation within the same discipline and research scope.

Keyword analysis aids in identifying current trends and emerging areas of focus within a research field. Utilizing visualization tools like VOSviewer and CiteSpace, a keyword co-occurrence map was generated (Fig.6). The keywords representing the research hotspots include "deep learning", "face recognition", "machine learning", "convolutional neural network", and "facial expression", among others. These keywords signify the prevalent areas of focus within the medical research domain. The utilization of deep learning, machine learning, and convolutional neural networks reinforces the development of facial recognition AI predictive models.

CiteSpace is utilized to analyze keyword clusters in which nouns and terms from the keywords serve as clustering labels, with the log-likelihood ratio (LLR) algorithm selected for keyword extraction. As shown in Fig. 7A, the largest clusters identified are "classification" #5 and "face detection" #1. Stanford's "AI Index Report 2024" specifically highlights computer vision technology as one of the core applications of AI in its technology trends. In 2024, substantial breakthroughs have been achieved in face recognition and image classification, enhancing model accuracy through deeper neural networks and improved training datasets [59]. These developments underscore the potential application of AI-based facial recognition technology in the medical realm, propelled by technological progress.

Within the Timeline View, nodes are organized in chronological rings, where the color and thickness of the rings correspond to the cited time and number of citations, respectively, within a specific time frame [68]. As shown in Fig. 7B, although machine learning-based facial recognition has been used for genetic syndrome diagnosis since as early as 2004, most of the keyword research is focused on 2020 and beyond. The continuous enhancements in image acquisition and processing capabilities, algorithms, computational power, and databases have significantly boosted AI's capacity to analyze detailed facial phenotypic information. This progress has broadened research applications from genetic syndromes to diverse clinical fields, such as autism spectrum disorders, emotional state recognition, psychological analysis, pain level assessment, diagnosis of skin disorders, health monitoring, and personalized treatment. Notably, 2020 and 2021 emerge as prolific keyword years, potentially influenced by decreased medical resources due to the COVID-19 pandemic and heightened demand for telemedicine.

In the year 2020, computer vision technology witnessed remarkable advancements across three main areas: the triumph of self-supervised learning over supervised pre-training for the first time [69]; successful application of Transformer attention modeling for computer vision tasks [70]; and the introduction of Neural Radiance Field (NERF) technology for view synthesis [71]. In the same year, Google and Facebook introduced two unsupervised learning algorithms, SimCLR and MoCo, known for their ability to develop representations of image data from unlabeled datasets. As shown in Fig. 7C, "facial feature" is the keyword with the strongest outbreak so far in 2022, underscoring the ongoing research focus on facial features in medical facial recognition applications, representing the forefront of research and development in this domain.

The utilization of AI-based facial recognition technology in the medical domain can be broadly divided into four main categories. The first category involves applications in disease surveillance and prevention. Proper mask-wearing has been identified as one of the most effective non-pharmacological measures to mitigate the spread and transmission of COVID-19 [72]. Kong, XJ et al. [73] developed a facial image mask recognition framework known as ECMask, utilizing an Edge-Computing-Based Deep Learning Framework. This model utilizes real-time video data to accurately recognize individuals wearing masks, thereby aiding in the prevention of epidemic spread. Moreover, strategies such as maintaining physical distancing and tracking primary contacts of infected individuals play a crucial role in controlling the spread of COVID-19. Haripriya, R et al. [74] employed YOLO V3 (You Only Look Once) to detect study subjects and utilized facial detection and recognition algorithms based on dlib and OpenCV models to identify primary contacts of patients who tested positive for COVID-19. This approach facilitates the swift isolation of close contacts, effectively containing further transmission of the disease.

Furthermore, facial recognition technology has demonstrated promise in real-time disease monitoring. Zlatintsi, A, et al. [75] proposed that facial expressions could serve as a valuable indicator for assessing cognitive impairment. They developed a method to predict PANSS values by analyzing facial expression features extracted from interview videos of patients with mental disorders. By combining this analysis with physiological data captured by wearable devices and tracking patients' spontaneous speech from videos, they created an e-medical prevention system for individuals with mental disorders. This system continuously and passively monitors patients' behavioral changes, predicts disease relapse tendencies, and ultimately enhances the quality of life for patients with mental health conditions.

The second category of applications focuses on early screening, diagnosis, and disease identification. At present, AI facial recognition technology is primarily employed for early screening and diagnosis of conditions such as genetic syndromes, autism, Parkinson's disease, facial palsy, stroke, and visual impairment in young children. Children, particularly, are the primary targets for early screening and diagnosis utilizing facial recognition due to challenges in effectively communicating discomfort symptoms and the less pronounced facial phenotypic characteristics during early childhood. Porras, AR et al. [76] analyzed 2800 facial images of children of different races who had been diagnosed with genetic syndromes through clinical or genetic assessments. They developed an automated screening model for children with genetic syndromes using facial deep phenotyping techniques, employing deep neural networks and facial statistical shape models. The model demonstrated an average accuracy of 88% in diagnosing children with genetic syndromes, effectively reducing the number of missed high-risk patients, and offering remote genetic risk stratification in regions with limited clinical genetic resources. This approach facilitates early intervention and treatment initiatives. Chen, WB, et al. [77] leveraged smartphone technology to capture gaze behavior and facial characteristics of visually impaired children in response to visual stimuli. Utilizing deep learning algorithms, they created the Apollo Infant Sight (AIS) system to assess children's phenotypic features for detecting visual impairment. The system effectively identified 16 types of visual impairments in a real-world multi-center validation, addressing challenges faced by infants and young children in participating in vision tests independently and detecting vision abnormalities, thus aiding in the prevention of irreversible vision loss due to delayed diagnosis.

The third category of applications focuses on disease treatment, prognosis assessment, and rehabilitation. AI-based facial recognition technology is adept at capturing changes in patients' conditions and offering prompt treatment insights. Social challenges are at the crux of difficulties faced by children with autism spectrum disorders, as they often struggle with recognizing facial expressions. Early intervention plays a pivotal role in determining the prognosis of children's development. Nevertheless, therapeutic facilities frequently encounter therapist shortages, leading to rehabilitation delays that can negatively impact children's outcomes. Stanford University Voss, C et al. [78] conducted a study using a computer vision system integrated into Google Glass. This system facilitated activities like smile capture, emotion guessing, and free play, enabling real-time recognition of facial emotions of social partners and delivering emotion recognition feedback to the child. This innovative approach enhances children's emotional recognition capabilities and fosters improved facial interactions, demonstrating the promising applications of facial recognition in digital home-based rehabilitation therapy.

Moreover, facial recognition technology has also found utility in therapeutic drug administration. As individuals age, managing multiple medications becomes increasingly challenging, particularly with cognitive and memory decline. Over half of older adults struggle to adhere to their medication routines [79]. Crisóstomo et al. [80] addressed this issue by employing computer vision to identify older adults' faces and medication packages, ensuring timely medication administration and mitigating the risks associated with non-adherence. Li, YJ et al. [81] developed a convolutional neural network model for screening people with drug use disorders (PDUD) by utilizing transfer learning from a large dataset comprising 9870 images of individuals with PDUD and 19567 images of the general population. Their analysis of the facial features of PDUD revealed distinctive patterns in the left cheek, right cheek, and nose regions compared to the general population. The model effectively mitigated misdiagnoses resulting from inaccurate patient information, aiding in the early detection of substance use disorders and facilitating interventions before the onset of drug addiction.

The fourth category of applications is the comprehensive category, including psychological assessment, emotional state evaluation, clinical indicator monitoring, pain assessment, doctor-patient interactions, and clinical teaching. Anxiety and depression are growing mental health problems and are on the rise worldwide. According to the World Health Organization (WHO), over 700,000 individuals die by suicide annually, with mental disorders, particularly depression, being a major contributing factor to suicide [82]. WHO prioritizes suicide as a critical public health concern and has set the goal of reducing premature mortality from non-communicable diseases by one third by 2030 through prevention, treatment, and the promotion of mental health. Timely recognition of abnormal emotional states and provision of psychological counseling are essential in this context. Cohen, J et al. [83] employed Tina, a multimodal dialogue system (MDS) agent for cloud-based structured interviews, to assess participants' depression, anxiety, and suicide risk, analyzing their mental states through facial features, language, and speech data to develop a prediction model for remote mental health monitoring. Their study revealed that facial features were most effective in identifying anxiety, language in recognizing depression, and an integrated model combining facial features, language, and speech excelled in predicting suicidal risk.

Additionally, facial recognition technology finds application in predicting clinical indicators. Zhang, AX et al. [84] developed a deep learning model to identify anemic status by analyzing facial videos of patients, enabling rapid screening for anemia in emergency settings and facilitating timely decisions regarding emergency blood transfusions. Cai, TA et al. [85] analyzed facial video and speech audio data from real emergency room stroke patients to create the DeepStroke model using a multimodal deep learning approach. This model successfully detects subtle facial muscle coordination issues and speech impairments, conducting stroke assessments in under six minutes. The DeepStroke model demonstrates significantly higher sensitivity and accuracy compared to traditional stroke triage methods, enhancing patient outcomes by expediting treatment initiation and improving survival rates and prognoses, circumventing delays associated with conventional stroke screening processes involving imaging.

The culmination of the aforementioned studies shows the significant potential of facial recognition in various medical domains. Advancements in AI and computer vision technology have paved the way for applications in early disease screening, expedited diagnosis, tailored treatment delivery, continuous disease monitoring, and optimization of healthcare resource allocation. This addresses the challenge of limited clinical diagnostic and therapeutic resources, substantially improving diagnostic and treatment efficiency while enhancing patient survival rates and overall quality of life.

With the ongoing advancements in AI and computer vision technology, the integration of facial recognition technology within the medical domain is evolving as a promising interdisciplinary field. Utilizing bibliometric methods, we aim to conduct a systematic and objective analysis of the current research landscape and technological frontiers of AI-based facial recognition in healthcare. Our goal is to explore application trends and future directions within this domain. AI-driven facial recognition technology offers an objective and rapid means of capturing subtle disease-related changes, circumventing delays in diagnosis and treatment attributed to subjective factors. This technology finds pervasive use across disease prevention, early screening, diagnosis, treatment, and psychological state assessment, establishing itself as a crucial area for future research within the medical field.

However, the implementation of facial recognition technology in the medical field encounters certain challenges. The primary issue pertains to datasets. AI models rely heavily on extensive data sets, necessitating factors such as data availability, volume, diversity in patients' ethnic and cultural backgrounds, image quality, and algorithm precision for model development. Currently, much of the research in this field is limited to specific geographic regions or single countries. Encouraging international collaboration to broaden the pool of cases, establish high-quality databases, and validate large-sample, multi-country, multi-center models is a crucial area for future focus.

Another significant consideration is the privacy aspect associated with facial image capture, causing patient concerns regarding potential confidentiality breaches in diagnosis and treatment information compared to conventional methods [86]. Researchers have started exploring optical models and deep feature extraction techniques to directly extract confidential but pathological signals for disease diagnosis, minimizing privacy risks [87]. Nonetheless, addressing privacy and security concerns in medical ethics related to facial recognition applications and the formulation of pertinent laws and regulations are essential tasks [88]. Additionally, fostering effective communication and collaboration mechanisms between medical experts and AI specialists is crucial for advancing technological applications within this realm.

5. Limitations

There are some limitations to this study. The data sources are exclusively from English literature in the WoSCC database, which may result in the omission of relevant studies from other databases or in languages other than English. While integrating different databases is limited by bibliometric software and WoSCC covers the majority of high-quality studies, the overall results remain reliable. The specific reasons for choosing WoSCC as the data source have been clarified in the methodology section.

Additionally, due to the dynamic nature of the database, recently published high-quality studies may not receive immediate attention due to citation delays. Despite these shortcomings, our study encompasses most of the literature on AI-based facial recognition applications in medicine, providing valuable insights and guidance for researchers to stay informed about evolutionary processes, research hotspots, frontiers, and emerging trends in the field.

6. Conclusion

In recent years, intelligent image recognition technology has flourished. With the increasing demand for precise medical treatment, early disease screening, and prevention, the interdisciplinary research between facial recognition technology and the medical field has emerged as a significant research area. Compared to traditional diagnostic and treatment methods, AI-based facial recognition can capture subtle real-time details that the naked eye may miss, enabling more accurate, objective, and rapid patient analysis. This technology significantly contributes to the advancement of precision medicine. Nonetheless, future development must enhance international cooperation, building extensive high-quality facial image databases, fostering interdisciplinary collaboration between medicine and AI, and addressing ethical concerns associated with this technology.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Yalun Tang: Conceptualization, Data curation, Formal Analysis, Software, Writing – original draft, Writing – review & editing, Validation. **Tangke Gao:** Data curation, Software, Methodology, Formal Analysis, Visualization, Writing – review & editing. **Lei Gao:** Resources, Project administration, Methodology, Funding acquisition. **Dianna Liu:** Resources, Funding acquisition, Project administration. **Zexing Li:** Investigation, Data curation, Visualization. **Ruikang Zhong:** Investigation, Methodology, Formal Analysis. **Kaiwen Hu:** Conceptualization, Funding acquisition, Writing – review & editing, Validation.

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