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Kidney medicine meets computer vision: a bibliometric analysis

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Abstract

Background and objective Rapid advances in computer vision (CV) have the potential to facilitate the examination, diagnosis, and treatment of diseases of the kidney. The bibliometric study aims to explore the research landscape and evolving research focus of the application of CV in kidney medicine research.

Methods The Web of Science Core Collection was utilized to identify publications related to the research or applications of CV technology in the field of kidney medicine from January 1, 1900, to December 31, 2022. We analyzed emerging research trends, highly influential publications and journals, prolific researchers, countries/regions, research institutions, co-authorship networks, and co-occurrence networks. Bibliographic information was analyzed and visualized using Python, Matplotlib, Seaborn, HistCite, and Vosviewer.

Results There was an increasing trend in the number of publications on CV-based kidney medicine research. These publications mainly focused on medical image processing, surgical procedures, medical image analysis/diagnosis, as well as the application and innovation of CV technology in medical imaging. The United States is currently the leading country in terms of the quantities of published articles and international collaborations, followed by China. Deep learning-based segmentation and machine learning-based texture analysis are the most commonly used techniques in this field. Regarding research hotspot trends, CV algorithms are shifting toward artificial intelligence, and research objects are expanding to encompass a wider range of kidney-related objects, with data dimensions used in research transitioning from 2D to 3D while simultaneously incorporating more diverse data modalities.

Conclusion The present study provides a scientometric overview of the current progress in the research and application of CV technology in kidney medicine research. Through the use of bibliometric analysis and network visualization, we elucidate emerging trends, key sources, leading institutions, and popular topics. Our findings and analysis are expected to provide valuable insights for future research on the use of CV in kidney medicine research.

Keywords Bibliometric analysis · Computer vision · Artificial intelligence · Kidney medicine

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Introduction

The kidney plays a pivotal role in maintaining homeostasis within the human body through various physiological processes, including filtration of blood, excretion of metabolic wastes, and regulation of electrolyte balance. Regrettably, kidney diseases have become a global health issue that causes widespread morbidity and mortality [1, 2]. For instance, chronic kidney disease (CKD) affects approximately 700 million people globally [3]. The incidence of acute kidney injury can reach 10–60% in hospitalized individuals [4]. More than 250 million cases of urologic cancer in latest Global Cancer Statistics [5]. Kidney diseases can lead to severe conditions, including premature deaths, cardiovascular diseases, electrolyte disorders, anemia, and bone and mineral disorders, among others, therefore posing a significant threat to human health. This emphasizes the need for efficient diagnosis and treatment in clinical practice, particularly when the health system is overloaded [6].

Computer vision (CV) is the science dedicated to enabling machines to perceive visual information. It entails utilizing imaging equipment and computational methods in lieu of human eyes to detect, track, and measure targets. Moreover, it involves image processing and analysis, wherein computer algorithms enhance images for human observation or transmit them for instrument-based detection. Leveraging advanced image processing and artificial intelligence (AI) algorithms, CV provides a noninvasive, rapid, and precise approach to diagnosing and analyzing kidney diseases using medical images. Consequently, it enhances diagnostic and therapeutic efficiency [6, 7]. These benefits have spurred a burgeoning interest among researchers to utilize CV technology for kidney disease-related applications. Furthermore, the rapid development of CV techniques and the continuous improvement of computing power in recent years have brought new researchers into the field of kidney medicine, resulting in substantial breakthroughs and setting off an upsurge of research with unprecedented attention. However, it is noteworthy that no bibliometric analyses have been conducted on the subject to date.

Bibliometric analysis is a quantitative research methodology that aims to examine the utilization, dissemination, and influence of publications [8]. It reveals the developmental tendencies and patterns of academic fields, research topics, and researchers by statistical analyses of particular indicators within publications [9–11]. Consequently, bibliometric analysis serves as a basis for scientific research, academic evaluation, and management decision-making [12]. Our study aims to reveal the research trends and current and evolving focus of CV in the field of kidney medicine through bibliometric analysis.

Methods

Search strategy and inclusion of publications

Relevant publications were sought from the Web of Science (WOS) Core Collection (Clarivate Analytics, USA) [13], one of the most influential and comprehensive international scientific literature databases [10, 11]. We established inclusion criteria as follows: (1) publications published between January 1, 1900, and December 31, 2022; (2) publications categorized as original articles, review articles, or clinical trials; (3) publications limited to the English language; and (4) publications with a thesis of the kidney (i.e., examination and testing of the kidney, and diagnosis and treatment of diseases involving the kidney) and CV techniques (Appendix A). We restricted the search query to the "Topic" field. The search was performed on March 1, 2023.

Following data collection using the search strategy, 5371 records were originally obtained. Subsequently, two authors independently and manually reviewed the titles, abstracts, and full texts of the retrieved publications. The third author was consulted for a final decision when disagreements occurred. Finally, a total of 1322 records were selected. A depiction of the screening process can be found in Fig. 1.

Bibliometric analysis

The WOS [13] was utilized to acquire fundamental publication details comprising the year of publication, the institution of authors, titles of publications, research areas, and the countries/regions where the research was conducted. Furthermore, to facilitate summarizing publication trends, we utilized Matplotlib [14] and Seaborn [15], Python-based tools, for visual analysis of the aforementioned data.

We utilized Histcite software [16] to conduct citation analysis for publications. The software assesses the significance of a publication by measuring various metrics, including global citation score (GCS), global citation score per year (GCS/t), local citation score (LCS), local citation score per year (LCS/t), local cited references (LCR), and cited references (CR). Specifically, GCS shows the citation frequency based on the total count in the WOS, while LCS is the number of times a paper is cited by other papers in the local collection, such as the 1322 included publications in our study. Notably, it is important to consider that publications typically attract attention progressively, potentially

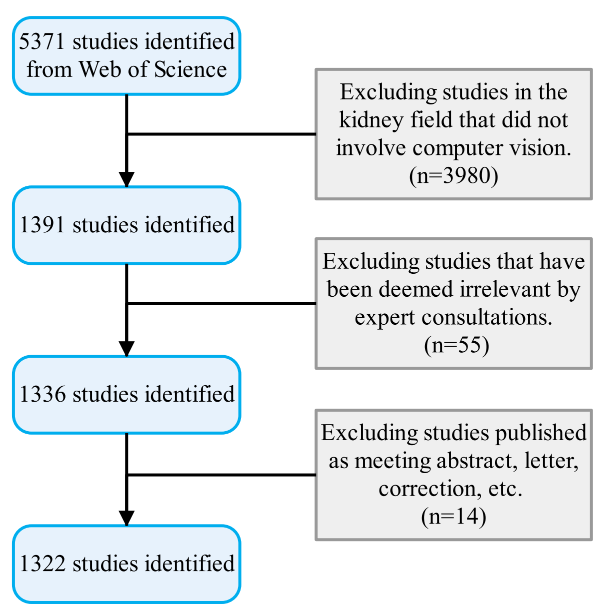


Fig. 1 Flow diagram of the publications screening process used in the study

limiting widespread recognition during their initial years of publication. To mitigate this problem, we averaged the GCS and LCS based on the number of years. Consequently, our study employs not only GCS and LCS but also incorporates GCS/t and LCS/t as benchmark metrics, aiming to facilitate a comparably equitable assessment. Furthermore, to expose the reciprocal citation relationships between scientific publications, facilitate researchers' quick and in-depth comprehension of the evolution of scientific research themes, and provide insights into past developments, present status, and future prospects, we employed LCS values sorting to plot a citation map for the foremost 30 publications via Histcite software. The citation map displays references as circles, with each circle corresponding to a reference number. The size of the circle reflects the LCS size. Arrows signify the connections between references and facilitate contextual organization within this field.

Moreover, our study employs VOSviewer software [17], Python, and R software to create a visual representation of a co-authorship network for authors, a chord diagram for cooperation between countries, and a co-occurrence network for keywords. In the co-authorship network, the relatedness of items is determined based on the number of co-authored publications, with larger nodes signifying a greater number of publications by those authors. This analysis was restricted to authors with at least three publications in the co-authorship network. The co-occurrence network determines the relatedness of keywords by analyzing the number of publications where they occur together, utilizing edges between nodes to represent word co-occurrence, and identifying research hotspots within a field. A minimum of five occurrences of a keyword was set as a threshold for inclusion in this study. The size of a node is indicative of its relative significance. Shorter distances between nodes correspond with stronger relationships. Thicker appearing lines are indicative of greater co-occurrence between two keywords [18]. Specifically, the original keywords and keywords plus provided by the author were extracted as keywords. Where author keywords are absent, we substituted them for a keyword plus, which is deemed to be comparably efficacious to author keywords [19]. Notably, in the initial co-occurrence network, we observed certain keywords with synonymous meanings (e.g., "kidney cancer" versus "renal cancer") or differing singular and plural forms (e.g., "convolutional neural network" versus "convolutional neural networks"). We analyzed the top 500 co-occurring keywords and combined them appropriately (Appendix B). Furthermore, to enhance the network's visual clarity and brevity, we narrowed our focus to the top 100 keywords with the strongest associations and restructured the co-occurrence network accordingly. Remarkably, the core concept of the vos layout technique and vos clustering technique [17] for the co-authorship network of authors and the co-occurrence network of keywords revolves around "co-occurrence clustering." This principle implies that the concurrent presence of two items signifies their correlation. This clustering methodology is predominantly utilized for analyzing literature data, specifically tailored for the examination of undirected one-mode networks, with a key emphasis on the visualization of scientific knowledge.

Results

Publication analysis

Figure 2 illustrates the annual publication count of the included publications. CV has been applied in the field of kidney medicine since 1990, with only a small number of publications each year until the late 2000s, when there was a general increase in the annual publication rate. The rate of growth regarding the annual publication count has experienced a substantial boost since 2016. The annual publication count exceeded 200 in 2021 and 2022.

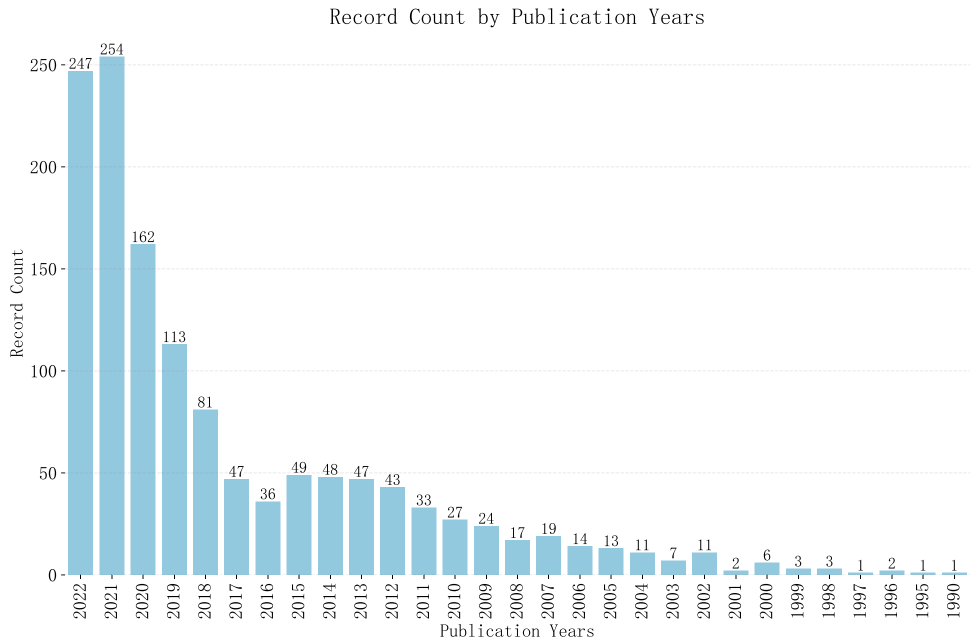
Figure 3 depicts top 25 across the various fundamental research information categories (author's institution, the publication title, the research area, and the countries/regions). The top five institutions that had the highest number of publications were all from the US. The National Institutes of Health USA (NIH), with 42 publications, ranked first, followed by Harvard University, University of California System, Mayo Clinic, and Harvard Medical School. The United States (US, $n = 470$), China ($n = 296$), and Germany ($n = 127$) ranked at the top in terms of countries/regions. Proceedings of SPIE, Lecture Notes In Computer Science (LNCS), IEEE Transactions on Medical Imaging (TMI), IEEE Engineering in Medicine and Biology Society Conference Proceedings (EMBC), and Medical Physics were among the journals that published the highest number of included papers. Regarding research areas, Radiology Nuclear Medicine Medical Imaging has the highest number of publications exceeding 100, followed by Engineering, Computer Science, Optics, and Imaging Science Photographic Technology.

Citation analysis

Influence of included publications

Considering that early published papers are innately more likely to have higher LCS and GCS values than later published papers, in citation analysis, we prioritized the LCS/t and GCS/t metrics to ensure the proper assessment of recent publications. When evaluating the citation frequency in the 1322 included publications denoting the field of computer-vision-based kidney medicine, five [6, 20–22, 25] of the top ten publications with the highest LCS/t scores pertained

Fig. 2 Annual publication numbers by year



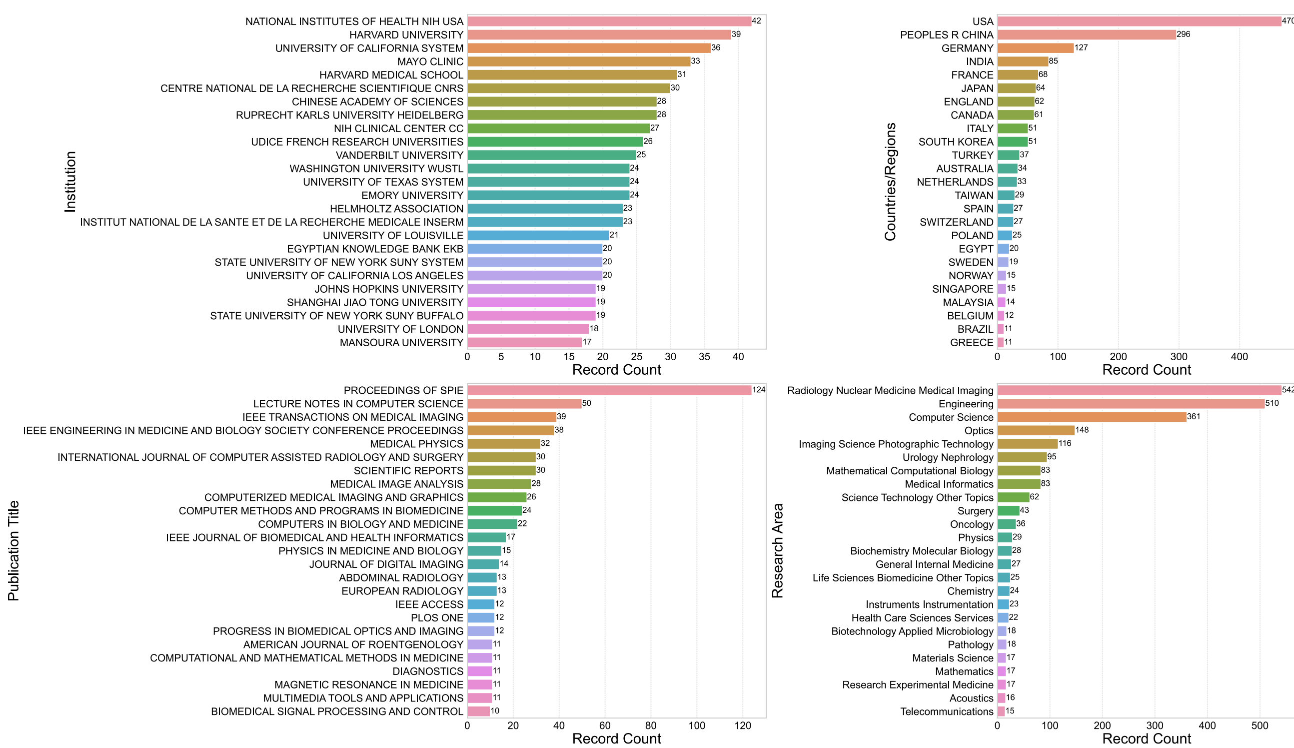


Fig. 3 Top 25 across the various fundamental research information categories (author's institution, the publication title, the research area, and the countries/regions)

to deep learning-based segmentation, and three publications [24, 26, 28] pertained to machine learning-based texture analysis (Table 1). When evaluating the overall impact of the included publications in WOS, similarly, half of the top publications with the highest GCS/t involve image segmentation, while texture analysis accounts for only one publication (Table 1).

Table 1 Top 10 publications according to the LCS/t and GCS/t values, respectively

#	Document	Year	LCS	LCS/t ↑	GCS	GCS/t	LCR	CR
1	**Deep Learning-Based Histopathologic Assessment of Kidney Tissue** [6]	2019	53	10.60	135	27.00	2	21
2	**Computational Segmentation and Classification of Diabetic Glomerulosclerosis** [20]	2019	38	7.60	88	17.60	3	32
3	Development and evaluation of deep learning-based segmentation of histologic structures in the kidney cortex with multiple histologic stains [21]	2021	20	6.67	43	14.33	8	53
4	**Automatic Multi-Organ Segmentation on Abdominal CT With Dense V-Networks** [22]	2018	36	6.00	304	50.67	3	54
5	**Region-Based Convolutional Neural Nets for Localization of Glomeruli in Trichrome-Stained Whole Kidney Sections** [23]	2018	34	5.67	59	9.83	0	24
6	**Machine learning-based quantitative texture analysis of CT images of small renal masses: Differentiation of angiomyolipoma without visible fat from renal cell carcinoma** [24]	2018	33	5.50	131	21.83	1	40
7	Deep Learning-Based Segmentation and Quantification in Experimental Kidney Histopathology [25]	2021	15	5.00	37	12.33	5	31
8	Textural differences between renal cell carcinoma subtypes: Machine learning-based quantitative computed tomography texture analysis with independent external validation [26]	2018	28	4.67	67	11.17	1	35
9	Association of Pathological Fibrosis With Renal Survival Using Deep Neural Networks [27]	2018	27	4.50	83	13.83	0	51
10	Clear Cell Renal Cell Carcinoma: Machine Learning-Based Quantitative Computed Tomography Texture Analysis for Prediction of Fuhrman Nuclear Grade [28]	2019	21	4.20	81	16.20	1	46
#	Document	Year	LCS	LCS/t	GCS	GCS/t ↑	LCR	CR
1	*Data-efficient and weakly supervised computational pathology on whole-slide images* [29]	2021	4	1.33	172	57.33	1	44
2	*Automatic Multi-Organ Segmentation on Abdominal CT With Dense V-Networks* [22]	2018	36	6.00	304	50.67	3	54
3	*Data augmentation using generative adversarial networks (CycleGAN) to improve generalizability in CT segmentation tasks* [30]	2019	0	0.00	211	42.20	0	19
4	*Virtual histological staining of unlabelled tissue-autofluorescence images via deep learning* [31]	2019	34	0.80	206	41.20	0	40
5	Pathomic Fusion: An Integrated Framework for Fusing Histopathology and Genomic Features for Cancer Diagnosis and Prognosis [32]	2022	2	1.00	75	37.50	0	81
6	The state of the art in kidney and kidney tumor segmentation in contrast-enhanced CT imaging: Results of the KiTS19 challenge [33]	2021	0	0.00	95	31.67	0	67
7	Unified Focal loss: Generalizing Dice and cross entropy-based losses to handle class imbalanced medical image segmentation [34]	2022	0	0.00	55	27.50	2	71
8	Deep Learning-Based Histopathologic Assessment of Kidney Tissue [6]	2019	53	10.60	135	27.00	2	21
9	PhaseStain: the digital staining of label-free quantitative phase microscopy images using deep learning [35]	2019	0	0.00	126	25.20	0	48
10	Machine learning-based quantitative texture analysis of CT images of small renal masses: Differentiation of angiomyolipoma without visible fat from renal cell carcinoma [24]	2018	33	5.50	131	21.83	1	40

The publications were sorted in descending order based on their LCS/t values (i.e., LCS/t ≥ 4.20) and GCS/t values (i.e., GCS/t ≥ 21.83), respectively

The bold font and italic font highlight those publications that also appear in the top 10 of the LCS value (i.e., LCS ≥ 32) and GCS value (i.e., GCS ≥ 150) in descending order, respectively

Author influence

A total of 5802 authors were identified for the included publications. Table 2 displays the top ten authors with the highest number of publications. Summers RM was the most productive author and remained research active between 2009 and 2022 (Table 2). Ronald Summers [36], Ayman El-Baz [37], and Marius George Linguraru [38] ranked at the top and have been active in this field since 2005. For the evaluation by citation frequency, publications by Ozgur Kilickesmez [46], with the highest total local citation score per year (TLCS/t), had been cited most in the local dataset of the current study, which included 1322 papers. Ming Y. Lu [50] turned out to be the top influential author in terms of TGCS/t in WOS.

Table 2 Top 10 authors according to the publication volume, TLCS/t and TGCS/t values, respectively

#	Author	RPY	Volume ↑	TLCS	TLCS/t	TGCS	TGCS/t
1	Summers RM (Summers, Ronald M.) [36]	[2009, 2022]	21	105	10.09	581	79.73
2	El-Baz A (El-Baz, Ayman) [37]	[2005, 2022]	19	58	5.37	309	35.23
3	Linguraru MG (Linguraru, Marius George) [38]	[2009, 2016]	19	117	10.90	375	35.46
4	Sarder P (Sarder, Pinaki) [39]	[2016, 2021]	19	71	15.83	268	56.393
5	Tomaszewski JE (Tomaszewski, John E.) [40]	[2016, 2021]	13	55	11.00	227	43.72
6	Yao JH (Yao, Jianhua) [41]	[2009, 2017]	13	54	5.33	261	23.62
7	Chen XJ (Chen, Xinjian) [42]	[2011, 2019]	12	77	7.85	326	30.05
8	Fogo AB (Fogo, Agnes B.) [43]	[2019, 2022]	12	56	13.77	146	38.27
9	Ginley B (Ginley, Brandon) [44]	[2016, 2021]	11	65	14.33	205	44.58
10	Huo YK (Huo, Yuankai) [45]	[2018, 2022]	11	8	2.83	65	17.50
#	Author	RPY	Volume	TLCS	TLCS/t ↑	TGCS	TGCS/t
1	**Kilickesmez O (Kilickesmez, Ozgur)** [46]	[2018, 2020]	8	83	16.07	361	74.02
2	**Kocak B (Kocak, Burak)** [46]	[2018, 2020]	8	83	16.07	361	74.02
3	**Sarder P (Sarder, Pinaki)** [39]	[2016, 2021]	19	71	15.83	268	56.393
4	Ginley B (Ginley, Brandon) [44]	[2016, 2021]	11	65	14.33	205	44.58
5	Jain S (Jain, Sanjay) [44]	[2016, 2021]	8	65	14.33	225	47.13
6	Jen KY (Jen, Kuang-Yu) [47]	[2018, 2021]	11	65	14.33	219	52.47
7	Fogo AB (Fogo, Agnes B.) [43]	[2019, 2022]	12	56	13.77	146	38.27
8	Boor P (Boor, Peter) [48]	[2017, 2022]	9	53	13.65	166	46.23
9	Kers J (Kers, Jesper) [49]	[2019, 2022]	3	60	13.43	157	36.33
10	Florquin S (Florquin, Sandrine) [49]	[2019, 2022]	2	56	12.10	147	33.00
#	Author	RPY	Volume	TLCS	TLCS/t	TGCS	TGCS/t ↑
1	Lu MY (Lu, Ming Y.) [50]	[2021, 2022]	3	6	2.33	260	101.33
2	Mahmood F (Mahmood, Faisal) [50]	[2021, 2022]	3	6	2.33	260	101.33
3	Chen RJ (Chen, Richard J.) [51]	[2021, 2022]	2	6	2.33	247	94.83
4	Williamson DFK (Williamson, Drew F. K.) [51]	[2021, 2022]	2	6	2.33	247	94.83
5	*Summers RM (Summers, Ronald M.)* [36]	[2009, 2022]	21	105	10.09	581	79.73
6	*de Haan K (de Haan, Kevin)* [52]	[2019, 2021]	3	4	0.80	369	78.73
7	*Ozcan A (Ozcan, Aydogan)* [52]	[2019, 2021]	3	4	0.80	369	78.73
8	*Rivenson Y (Rivenson, Yair)* [52]	[2019, 2021]	3	4	0.80	369	78.73
9	Kilickesmez O (Kilickesmez, Ozgur) [46]	[2018, 2020]	8	83	16.07	361	74.02
10	Kocak B (Kocak, Burak) [46]	[2018, 2020]	8	83	16.07	361	74.02

The authors were sorted in descending order based on their publication volume (i.e., Volume ≥ 11), TLCS/t values (i.e., TLCS/t ≥ 12.10), and TGCS/t values (i.e., TGCS/t ≥ 74.02), respectively

The bold font and italic font highlight those authors that also appear in the top 10 of the TLCS value (i.e., TLCS ≥ 67) and TGCS value (i.e., TGCS ≥ 369) in descending order, respectively

Journal influence

The total number of articles published in TMI peaked at 39 by 2022 (Table 3), indicating that TMI is one of the pioneering journals in publishing kidney medical research utilizing CV technology, which also had the highest TLCS/t based on data collected from WOS. The following journals with the highest volume of publications were Medical Physics (32) and International Journal of Computer Assisted Radiology and Surgery (IJCARS) (30). When restricted to the local dataset of the 1322 included publications, the TLCS/t value of the Journal of the American Society of Nephrology (JASN) was 33.20, at the top among all the journals (Table 3).

Citation map

Figure 4 shows the inter-citation relationships among the included publications based on LCS. The largest connected graph (see the upper left part of Fig. 4) primarily studies medical image segmentation of kidney organs, while the second-largest connected graph (see the lower right part

Table 3 Top 10 journals according to the publication volume, TLCS/t and TGCS/t values, respectively

#	Journal	RPY	Volume ↑	TLCS	TLCS/t	TGCS	TGCS/t
1	IEEE Transactions on Medical Imaging	[2002, 2022]	39	263	26.74	2030	239.77
2	Medical Physics	[2005, 2022]	32	108	18.08	616	101.65
3	International Journal of Computer Assisted Radiology and Surgery	[2006, 2022]	30	51	7.47	459	63.54
4	Scientific Reports	[2012, 2022]	30	0	0.00	894	162.63
5	Medical Image Analysis	[2005, 2022]	28	98	10.69	1100	162.64
6	Computerized Medical Imaging and Graphics	[2004, 2022]	26	107	9.14	510	83.69
7	Computer Methods and Programs in Biomedicine	[2002, 2022]	24	45	5.94	206	45.09
8	Computers in Biology and Medicine	[2007, 2022]	22	23	3.36	296	66.43
9	IEEE Journal of Biomedical and Health Informatics	[2013, 2022]	17	22	4.22	231	35.88
10	Physics in Medicine and Biology	[2012, 2022]	15	9	1.02	111	19.01
#	Journal	RPY	Volume	TLCS	TLCS/t ↑	TGCS	TGCS/t
1	**Journal of the American Society of Nephrology**	[2018, 2022]	8	152	33.20	354	79.93
2	**IEEE Transactions on Medical Imaging**	[2002, 2022]	39	263	26.74	2030	239.77
3	**Medical Physics**	[2005, 2022]	32	108	18.08	616	101.65
4	**European Radiology**	[2012, 2022]	13	85	17.42	398	81.62
5	Kidney International	[2017, 2021]	6	37	11.42	130	34.71
6	**Journal of Digital Imaging**	[2010, 2022]	14	75	11.16	256	40.41
7	**Medical Image Analysis**	[2005, 2022]	28	98	10.69	1100	162.64
8	**Computerized Medical Imaging and Graphics**	[2004, 2022]	26	107	9.14	510	83.69
9	**American Journal of Roentgenology**	[2008, 2022]	11	57	8.98	241	43.49
10	Abdominal Radiology	[2017, 2022]	13	32	8.24	103	23.81
#	Journal	RPY	Volume	TLCS	TLCS/t	TGCS	TGCS/t ↑
1	*IEEE Transactions on Medical Imaging*	[2002, 2022]	39	263	26.74	2030	239.77
2	*Medical Image Analysis*	[2005, 2022]	28	98	10.69	1100	162.64
3	*Scientific Reports*	[2012, 2022]	30	0	0.00	894	162.63
4	*Nature Biomedical Engineering*	[2019, 2021]	4	9	2.47	419	111.87
5	*Medical Physics*	[2005, 2022]	32	108	18.08	616	101.65
6	*Computerized Medical Imaging and Graphics*	[2004, 2022]	26	107	9.14	510	83.69
7	*European Radiology*	[2012, 2022]	13	85	17.42	398	81.62
8	Journal of the American Society of Nephrology	[2018, 2022]	8	152	33.20	354	79.93
9	Computers in Biology and Medicine	[2007, 2022]	22	23	3.36	296	66.43
10	*International Journal of Computer Assisted Radiology and Surgery*	[2006, 2022]	30	51	7.47	459	63.54

The journals were sorted in descending order based on their publication volume (i.e., Volume ≥ 15), TLCS/t values (i.e., TLCS/t ≥ 8.24), and TGCS/t values (i.e., TGCS/t ≥ 63.54), respectively

The bold font and italic font highlight those journals that also appear in the top 10 of the TLCS value (i.e., TLCS ≥ 51) and TGCS value (i.e., TGCS ≥ 379) in descending order, respectively

of Fig. 4) mainly focuses on the medical image analysis of kidney-related structures, including glomeruli and the renal cortex. The connected graph comprising node 70, node 103, and node 142 has publications involving two-dimensional segmentation and three-dimensional segmentation. Last, the connected graph consisting of Node 516, Node 547, and Node 602 is primarily focused on texture analysis based on machine learning.

Co-authorship analysis

Authors. The collaboration relationships among authors who have coauthored at least three articles are presented in Fig. 5. Some of the 395 items in the co-authorship network for authors are not connected to each other. The largest set of connected items consists of 58 items (Fig. 5(b)). In summary, Summers [36], Linguraru [38], Yao [41] appeared to be the most collaborative authors.

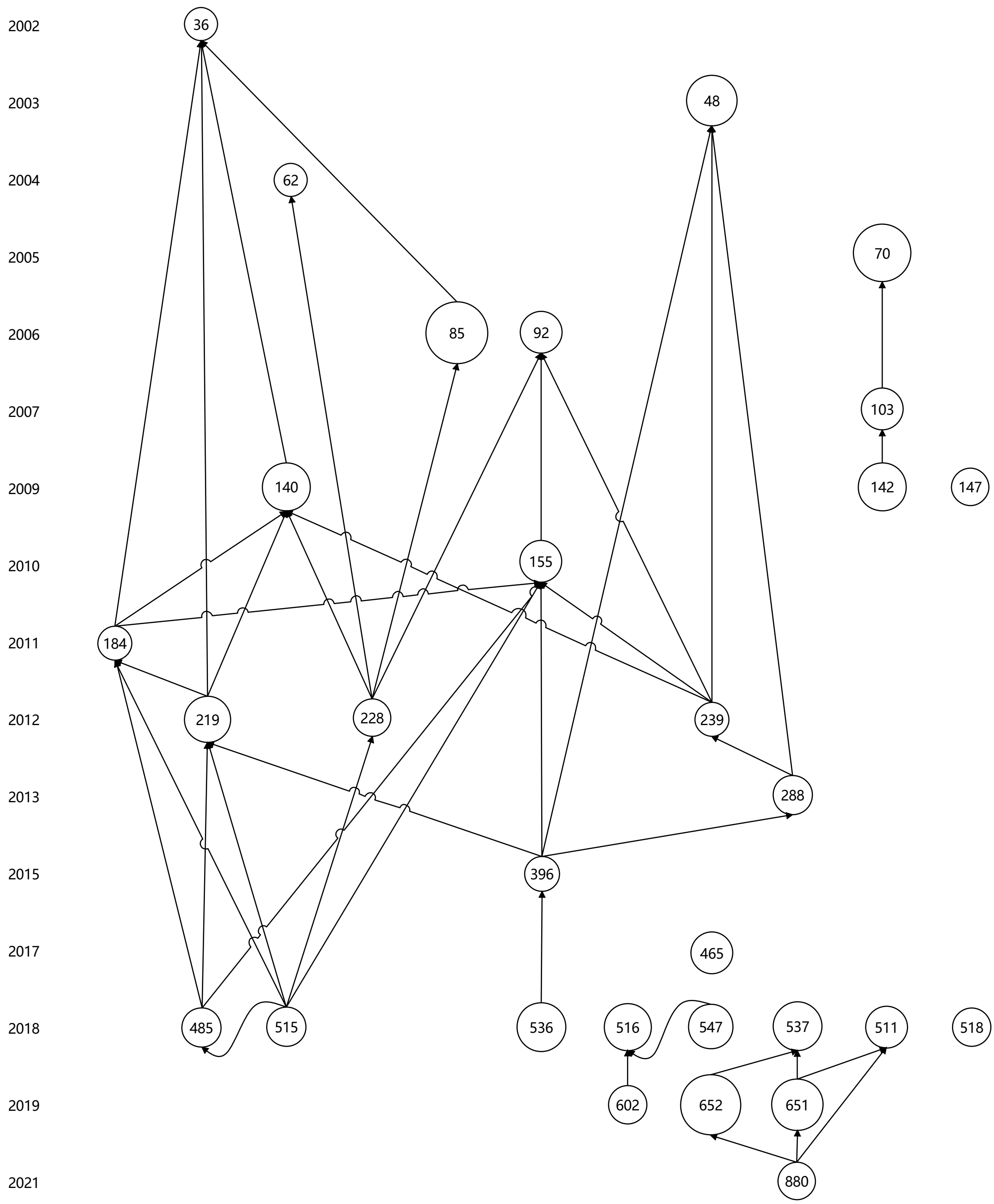
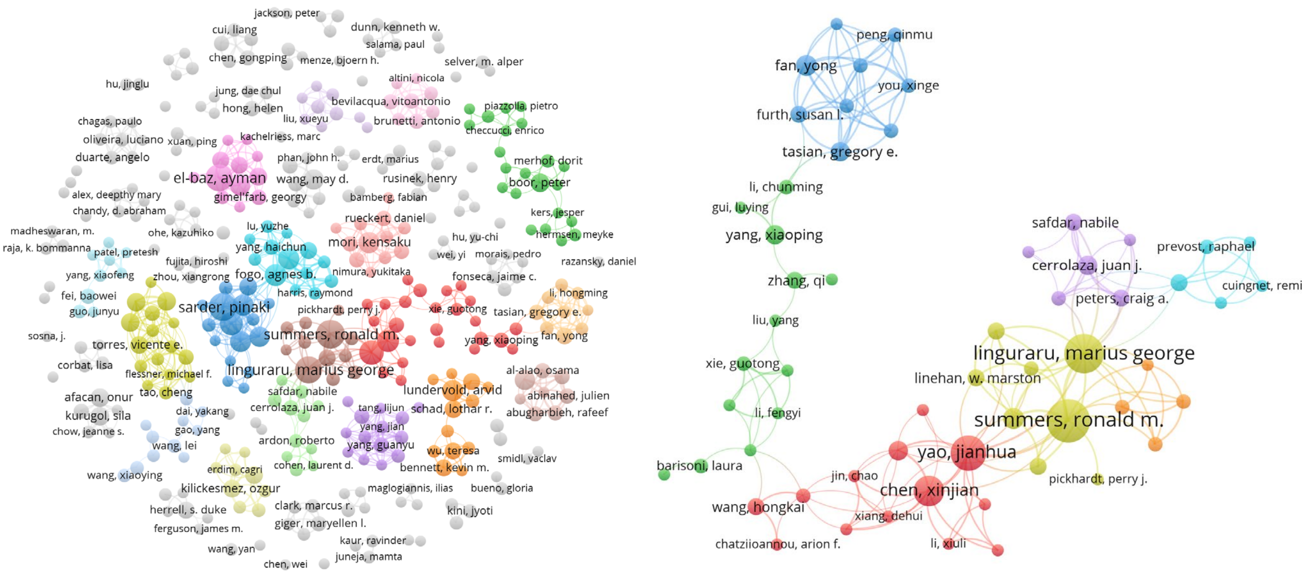


Fig. 4 Citation map. The size of a node is proportional to the LCS value computed by HistCite software for the corresponding document. For more details about the nodes, please refer to Appendix C. The Histcite software was utilized to visualize a citation map from the 30 highest-ranking publications, which were sorted in descending order based on their LCS values (i.e., LCS ≥ 18). An arrow emitted by a node signifies that the document it represents references the document represented by the pointed node

Countries. As listed in Fig. 6, the United States collaborated with numerous countries, including China, Germany, Canada, France, India, and Egypt. China was the leading country in terms of publications produced in cooperation with the United States.

Co-occurrence analysis

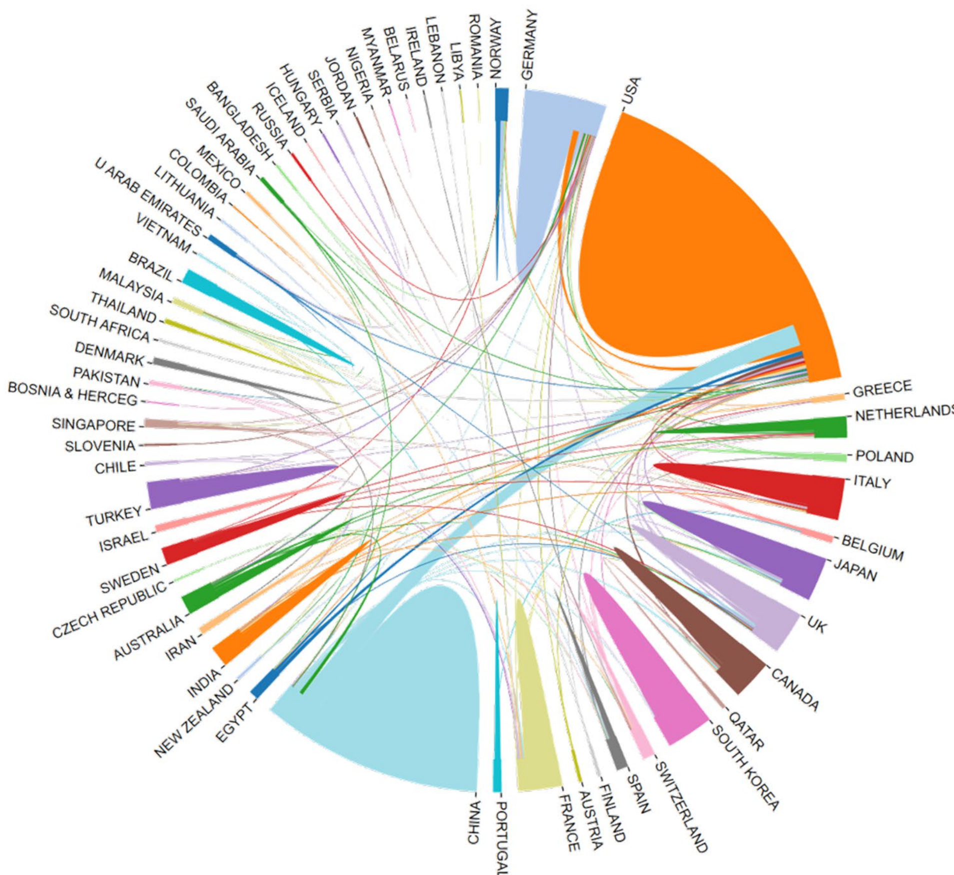
Of the 4206 keywords of the included publications, 281 had a minimum of five occurrences and were included for further analysis. To enhance the clarity of the visualization,

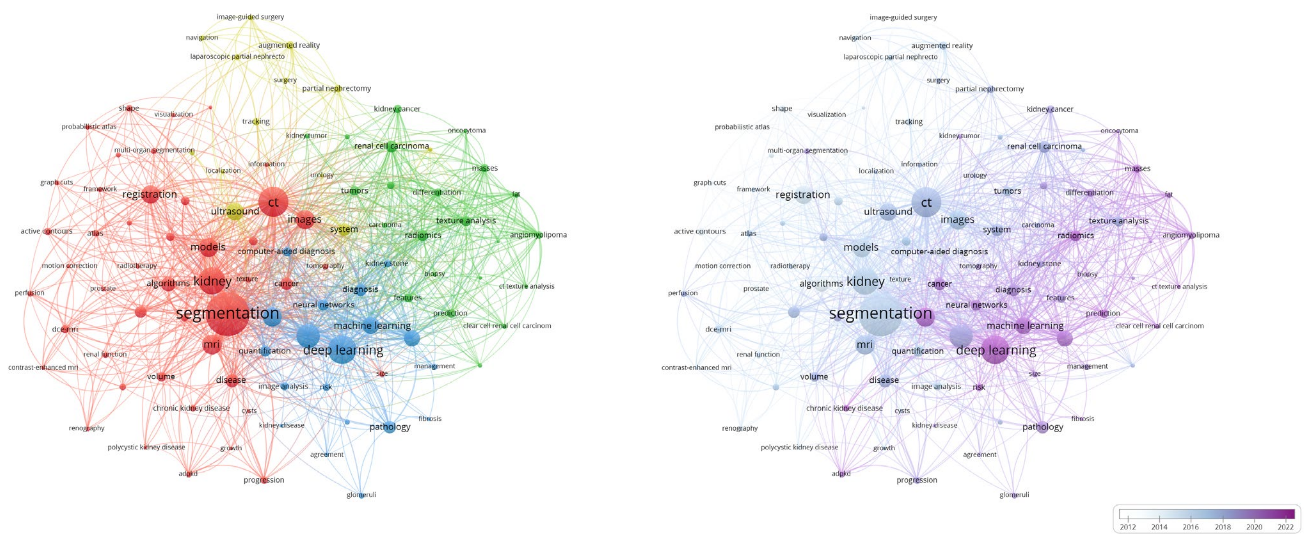


(a) Set of connected and unconnected items
(b) The largest set of connected items

Fig. 5 Network visualization map of the co-authorship network for authors. The collaborative relationships between all items (i.e., 395 authors) are depicted in subgraph (**a**). Subgraph (**b**) displays the largest set of connected items within subgraph (**a**)

Fig. 6 Chord diagram for cooperation between countries. The thicker the arc, the more cooperation.





(a) Network visualization map

(b) Overlay visualization map according to the average publication time

Fig. 7 Network visualization map of the keyword co-occurrence network

we utilized VOSviewer software to display the top 100 keywords based on their frequency (Fig. 7).

In Figure 7(a) of the keyword co-occurrence, "segmentation" had the highest frequency node, followed by "CT", "deep learning", "kidney", and others. This suggests that these keywords were frequently mentioned, and the focus of research in CV-based kidney medicine was primarily on using deep learning techniques for segmentation tasks from CT images. Furthermore, the keywords can be divided into four clusters to better reflect research topics (Fig. 7(a)). The red cluster included main keywords such as "segmentation", "kidney", "models", "CT", "MRI", "registration", "motion correction", "volume", and "shape". This cluster showed the relationship between the keywords in medical image processing tasks. The yellow cluster included main keywords such as "ultrasound", "system", "image-guided surgery", "surgery", "augmented reality", "tracking", and "partial nephrectomy", presenting the relationship between keywords in surgical treatment tasks, and featured the application of ultrasound technology. The green cluster includes main keywords such as "texture analysis", "features", "tumors", "fat", "kidney cancer", "angiomyolipoma", "clear cell renal cell carcinoma", and "prediction". This cluster indicates the relationship between keywords in medical image analysis/diagnosis tasks related to diseases in kidney medicine, especially tumors. Finally, the blue cluster consists of main keywords including "deep learning", "machine learning", "neural networks", "convolutional neural networks", "computer-aided diagnosis", and "pathology". This cluster demonstrated the relationship between keywords regarding the technology and the application and innovation of CV technology in medical images such as pathology.

In addition, we visualize the keywords based on the average publication time. Figure 7(b) depicts the frequency of keyword occurrences between 2012 and 2022, enabling the assessment of research focus trends over time. The nodes' color shifts gradually from white to bold to italic, signifying the earliest to the most recent periods of keywords utilized in publications. This analysis can reflect the popular keywords in recent years and infer future hotspot trends. We found that before 2012, traditional CV techniques, including "graph cuts", "motion correction", "active contours" and "shape", were the preferred methods for image processing tasks. Around 2016, the kidney medicine field started studying surgical treatment tasks that utilized CV technology, utilizing keywords such as "surgery", "laparoscopic partial nephrectomy", "tracking", and "augmented reality". From 2016 to 2018, mainstream research shifted toward kidney-related segmentation tasks from medical images such as CT, MRI, and ultrasound. We found that from 2018 to 2022, cutting-edge CV technologies such as "machine learning", "deep learning" and "convolutional neural networks" emerged as research hotspots.

Methodological analysis

We analyzed the CV-based methodologies involved in the publications included in this study and classified them into three categories: manual feature-based methodologies, machine learning-based methodologies, and deep learning-based methodologies. Methodologies utilizing manual features involve the manual design and selection of features, in conjunction with traditional CV techniques such as the watershed algorithm, Gabor filters, scale-invariant feature transform (SIFT), and Fourier transform for medical image feature extraction and analysis [53–58]. They often require domain expertise and professional experience, with feature selection potentially guided by domain experts. Machine learning-based methodologies extract feature representations or patterns from medical images using algorithms like k-means, k-nearest neighbor (K-NN), support vector machines (SVM), bayesian, and random forests, leveraging acquired knowledge to perform medical image tasks [24, 26, 28, 59, 60]. Deep learning-based methodologies employ deep neural networks and their variations to autonomously learn high-level feature representations from medical images in an end-to-end manner [6, 21, 22, 25, 61]. It's noteworthy that these data-driven deep learning approaches excel in handling extensive datasets and intricate tasks.

Discussion

In the current study, we conducted a bibliometric analysis to reveal the research and application of CV in the field of kidney medicine. Our study not only analyzed highly regarded publications and journals and prolific researchers but also uncovered focal points of the research and application of CV in the kidney medicine field. These findings are expected to provide beneficial insights for upcoming clinical practices and research directions.

We noticed that the volume of publications addressing CV in the kidney field rose in several stages, which might correspond to the technological improvements at the same time points. For instance, the increasing trend of publication volume after 2000 suggests a growing interest among researchers in CV technology. The annual publication volume exceeded 40 in 2012, suggesting an increase in research activity. This might be attributed to the breakthrough in artificial intelligence-based CV technology around 2012 when the victory of AlexNet [62] in the ImageNet [63] competition prompted a surge of research on convolutional neural networks in the field of CV. Our finding that the annual growth rate of publication volume further surged after 2016 indicated that CV has been a hot topic in the field of kidney medicine research. From the point of view of computer science, at this stage, the UNet [64] model began to play a crucial role in promoting the development of medical image segmentation, with numerous variants being researched and applied in the field of medical image analysis or processing [65–67]. The annual publication volume exceeding 200 between 2021 and 2022 signifies the increased attention given to CV technology in recent years.

We found that the United States is currently at the forefront of research and application of CV technology in the field of kidney medicine. In addition, the most prominent research institutions and countries, mainly originate from developed nations, such as the USA and CNRS in France. This observation suggests a more dynamic engagement in the field by developed nations and their institutions compared to developing countries, where studies with high impact are less prevalent. The variation in academic publication output between developing and developed countries and their respective institutions may stem from multiple factors, such as inadequate research resources in developing countries [68], generous funding, and leading researchers in developed nations [69], linguistic and writing hurdles, and editorial prejudice [70]. Notably, developing countries, such as China and India which rank high in publication volume, have also made great contributions to the field of CV-based renal medicine. As a result, collaboration between developed and developing countries is essential.

The Proceedings of SPIE collect the most recent research findings in a range of fields, including physics, electronics and electrical engineering, computer and control engineering, information technology, and mechanical and manufacturing engineering, with the largest number of published works at present. This finding suggests that the principal application of CV technology in kidney medicine, currently, is for clinical imaging, particularly for supporting research on renal cells [24]. TMI and Medical Image Analysis (MedIA) are globally considered the most renowned and favored journals in the artificial intelligence field, with high publication rankings. This reflects the growing popularity of CV technology based on artificial intelligence. Our analysis reveals that the cause of the relatively low publication volume of TMI and MedIA is twofold: the rise of CV technology based on artificial intelligence since 2012 and the lower annual publication volume of TMI and MedIA. Regarding research areas, we found that the vast majority of publications on CV-based kidney medicine are in the fields of radiology nuclear medicine medical imaging, engineering, and computer science, suggesting that such research thrives in interdisciplinary domains of medical engineering.

Through citation analyses, we found that publications using deep learning-based methodologies exert more influence than machine learning-based methodologies. Based on our analyses, machine learning algorithms excel in texture analysis, while deep learning methods are commonly employed for more complex tasks such as semantic segmentation. We hypothesize that the effectiveness of deep learning methods in these tasks stems from their capability to extract high-dimensional and complex features. We noticed that deep learning approaches are held in high esteem in CV-based kidney medicine [6], whereas weakly supervised learning methods are highly regarded across all fields [29]. We attribute this phenomenon to the fact that although deep learning algorithms yield outstanding results, medical images requiring extensive manual annotations heavily rely on expert experience, making data annotation labor-intensive. Weakly supervised learning has garnered attention across diverse fields due to its capability to mitigate the rigorous data labeling process. Notably, three publications [6, 22, 24] had high scores in Table 1 (i.e., LCS/t ≥ 4.20 and GCS/t ≥ 21.83), indicating that a current focus of research in the field of kidney medicine and other related fields is the segmentation of multiple organs [22], including the kidneys, from CT images and that CV techniques utilizing machine learning and deep learning are playing a significant role [6, 21, 28]. These findings imply that influential publications in CV-based renal medicine research can also enjoy recognition across other research domains.

Our findings confirm that CV technology has recently received more emphasis in top journals in the nephrology field, including JASN and Kidney International, demonstrating the embracement of CV technology by the nephrology society. Furthermore, we discovered that the TMI and MedIA journals have a significant influence in all areas of study. This is because the research topics covered by TMI and MedIA relate to the expansive and prevalent area of artificial intelligence. In addition, Nature Biomedical Engineering, Medical Physics, European Radiology, and Computerized Medical Imaging and Graphics have been listed as some of the most popular journals, indicating that the topic being discussed is predominantly associated with the interdisciplinary realm of computer science, biomedical engineering, and medicine.

We examined the trends in CV-based kidney medical research by analyzing the citation map, as shown in Figure 4. In particular, we found that expert-based methods are evolving toward fully automatic deep learning-based methods [21]. It is noteworthy that texture analysis is currently popular and uses machine learning techniques [26, 28]. Additionally, we observed that the objects for segmentation are becoming increasingly varied. Furthermore, the segmentation of kidney organs is shifting toward kidney-related objects such as renal cells [24], glomeruli [20], and the renal cortex [21]. We also noted that the dimension of kidney-related segmentation has shifted from 2D to 3D [71]. However, despite this shift, 2D image data remain prevalent in current research. We speculate that this may be due to challenges in acquiring data sources and concerns related to privacy and ethics. Finally, we found that the mode of data used in current research is also becoming increasingly diverse, such as computed tomography (CT) images [72] and ultrasound images [73], magnetic resonance (MR) images [73], and pathological images [27].

Based on the findings depicted in Figure 5, we observe a numerous and dispersed research community in CV-based kidney medicine. We attribute this dispersion partly to the isolation among various research groups, with the privacy and confidentiality of medical data emerging as one potential contributing factor. Notably, visualizing the co-authorship network for authors can assist researchers in pinpointing bridges for direct or indirect communication with specific authors. Nevertheless, the isolation of research groups within the co-authorship network for authors implies that while it fosters diverse study, it also requires researchers to strengthen cooperation and communication for mutually beneficial results.

Based on the outcomes presented in Figure 6, it is evident that almost all countries exhibit a preference for intra-country collaboration. We find that the United States has established collaborations with numerous nations and suggests a high degree of expertise in CV-based kidney medicine research. Additionally, China demonstrates a keen interest in cooperating with other countries. Of particular interest is the observation that the Netherlands, Norway, and several other countries collaborate more frequently with Germany than with the United States. One plausible explanation for this trend may be their geographical proximity and shared membership in the European continent. In the current transnational cooperation, the collaboration between China and the United States holds a predominant position. Unlike many European countries, this cross-continental collaboration has been facilitated by the robust presence of China and the United States in the realm of CV-based kidney medicine, alongside their sustained collaborative endeavors aimed at fostering ongoing advancements in the field. We posit that these findings may serve as inspiration for other nations to engage in greater transnational collaboration, particularly with countries such as China and the United States, to foster mutually beneficial outcomes.

The keyword co-occurrence analysis indicates that CV-based kidney medical research can be classified into four research directions (Fig. 7(a)), namely, medical image processing tasks, surgical treatment tasks, medical image analysis/diagnosis tasks, and the application and innovation of CV technology in medical images. Image processing methods and algorithms, such as deep learning, in CV technology are believed to form the basis for the analysis/diagnosis and surgical treatment of medical images related to the kidneys. Additionally, the most frequent keywords, such as "segmentation", "ct", "deep learning", and "kidney", indicate that CV-based kidney medical research primarily concentrates on segmentation tasks from medical images utilizing deep learning techniques. The color-coding of these nodes in Fig. 7(b) signifies that they emerged after 2016. We speculate that one potential explanation for this trend is the surge in the volume of publications after 2016 following the introduction of the UNet model [64], which initiated a research surge. These results indicate that modern CV technologies, including machine learning and deep learning, are extensively employed for the analysis and diagnosis of medical images relevant to the kidney [20, 24]. Furthermore, the co-occurrence analysis of keywords reveals that CV-based kidney medical research is trending toward analyzing and diagnosing medical images (e.g., renal cell pathology analysis) rather than just processing them (e.g., segmentation). This analysis also highlights the shift in CV technology from traditional feature engineering methods, which rely on hands-on design, to deep learning techniques, which utilize automated feature extraction.

Through citation analysis (see Table 1 and Fig. 4) and co-occurrence analysis (see Fig. 7), we observe the transition of CV algorithms towards artificial intelligence (AI). To delve deeper into this transformation, we categorize AI algorithms into machine learning [59, 60] and deep learning [22, 25, 61]. Machine learning facilitates intelligent decision-making by discerning patterns and laws from data, while deep learning extends this capability further by enabling more intricate and abstract feature learning through deep neural networks, leading to significant advancements in medical image tasks. Due to their ability to learn complex feature representations in a data-driven manner without expert intervention, AI algorithms have been extensively utilized in CV-based kidney medicine research over the past decade. Generally, deep learning exhibits superior feature representation capabilities compared to machine learning, making it widely adopted for complex tasks such as medical segmentation. However, as deep learning heavily relies on high-quality data, it is not the only solution, and many studies still employ machine learning methods, particularly for tasks like texture analysis. Given the challenges in acquiring and labeling pathological images compared to CT or MRI images, the use of machine learning algorithms, such as weak supervision, to address data quality issues has garnered widespread attention across various domains. With the increase in both data quantity and quality, deep learning often surpasses machine learning in performance. We anticipate that deep learning will continue to dominate in the future as data quality improves further.

In order to delve deeper into the development and constraints of deep learning-based CV technology in kidney medicine, we conducted an exhaustive review of the publications identified in this study, scrutinizing it across three dimensions: algorithms, data, and applications. Regarding algorithms, we observe a predominant reliance on convolutional neural networks (CNNs) [62], including UNet and its variants [74]. This preference is driven by CNNs' robust inductive bias, enabling the effective capture of local information vital for medical image feature extraction. Nonetheless, CNNs struggle with long-range information due to their limited local receptive field, resulting in a suboptimal representation of global features. Addressing this, vision transformer (ViT) [75] employs a self-attention mechanism to enhance awareness of global information, offering promising avenues for future research and application. Although ViT is excellent at global modeling, its implementation incurs a high computational overhead, particularly in tasks like medical image segmentation. To mitigate this, the state spaces model-based (SSM) vision mamba [76] emerges as a potential solution, offering innovative solutions by establishing distant dependencies while maintaining linear complexity. Regarding data, the scarcity of high-quality kidney medicine images persists, hindering progress. Fundamental models like the medical segmentation large model (e.g., MedSAM [77]) demonstrate promise, yet their direct applicability remains limited due to data distribution inconsistencies. Sustained efforts in large model research are imperative, alongside continued exploration of semi-supervised and weakly supervised learning. Regarding applications, in limited-resource settings, deploying models with high complexity poses challenges for health equity. We have examined the publications identified in this study and posit that they offer novel insights into the domain of CV-based kidney medicine. We anticipate that forthcoming research in renal medicine will emphasize the development of robust models to enhance their usability in embedded surgical devices and to improve the real-time performance of medical image tasks.

This study presents the first bibliometric analysis of CV-based kidney medicine research. Although our study has several advantages, it also has certain limitations. First, only English literature was included in the study. While English is widely used globally, this limitation may have resulted in missing critical articles published in other languages. Second, all data used in this study were obtained from the Web of Science Core Collection, which is a comprehensive literature database that provides publication indicators ideal for bibliometric analysis. However, the limited coverage of the Web of Science Core Collection restricts access to publications found in other databases, such as Scopus and PubMed. Finally, citation analysis was primarily used to determine the extent of influence of publications, authors, and journals based on the number of citations. However, this approach may not fully reflect their actual influence, as some publications, authors, or journals can have a significant influence despite having few citations. On the other hand, self-citation may also introduce bias into the analysis [10, 78]. Furthermore, employing GCS/t and LCS/t as evaluation metrics in citation analysis could lead to inaccuracies when assessing recently published works, given that some publications may require several years to gain traction. Hence, in forthcoming studies, we will differentiate between early movers, mid movers, and late movers regarding publications to facilitate a more equitable comparison. To our knowledge, this advancement would be the inaugural endeavor at bibliometric analysis.

Conclusion

CV has achieved significant progress in the field of kidney medicine, providing robust assistance in kidney medicine for image processing, analysis/diagnosis, and surgeries associated with kidney diseases. We conducted a comprehensive investigation of the research trends and focal points in this field using bibliometric analysis methods for the first time, analyzing highly influential publications and journals, prolific researchers, countries/regions, research institutions, a citation map, a co-authorship network, and a co-occurrence network. CV-based kidney medicine research is on the rise, especially in medical imaging, surgery, and analysis/diagnosis. Journals like TMI and MedIA are pivotal not only in renal medicine but also in computer science and artificial intelligence. The USA leads in terms of publications and collaborations, with China closely following behind. Deep learning segmentation and machine learning texture analysis are key techniques. CV algorithms are advancing towards AI, focusing on kidney-related topics. Data used in the research is transitioning from 2D to 3D, with more diverse modalities. Our research findings and analysis are expected to contribute to the development and advancement of future CV-based kidney medicine research. With the advancing intersection of medical science and engineering and the expanding range of application scenarios, CV research and application in the field of kidney medicine will continue to encounter both challenges and opportunities.

Appendix A: Search query

Following thorough deliberations between computer and clinical medical experts specialized in nephrology, the resulting retrieval search query is presented below: (TS=(kidney* OR nephr* OR glomerul* OR renal)) AND (TS=("Computer Vision" OR "Object Detection" OR "Lesion Detection" OR Segmentation OR "Image Classification" OR "Image Recognition" OR "Image Reconstruction" OR "Image Registration" OR "Image-to-image Translation" OR "Image Fusion" OR "Image Denoising" OR Medical-Image-Analysis) OR TS=(Neural-Network* OR Federated-Learning OR Transfer-Learning OR Supervised-Learning OR Unsupervised-Learning OR Semi-Supervised OR Weakly-Supervised OR Self-Supervised OR "Active Learning" OR Domain-Adaptation OR Meta-Learning OR Few-shot-Learning OR One-Shot-Leaning OR Zero-Shot-Learning OR AutoEncoder OR Auto-encoder OR Recursive-Neural-Network* OR "Long-Short-Term Memory" OR Recurrent-Neural-Network* OR Convolutional-Neural-Network* OR LeNet OR AlexNet OR VGG OR GoogLeNet OR InceptionV* OR ResNet OR DenseNet OR MobileNet OR ShuffleNet OR Generative-Adversarial-Network* OR UNet OR U-Net OR YOLOv* OR Single-Shot-MultiBox-Detector OR Region-CNN OR RCNN OR R-CNN OR Vision-Transformer* OR Diffusion-Model))

Appendix B: Thesaurus terms

See Table 4.

Table 4 Thesaurus terms for the top 500 co-occurring keywords

#	Keyword	Replaces by	#	Keyword	Replace by	#	Keyword	Replace by	#	Keyword	Replace by	#	Keyword	Replace by
1	iImage		17	Generative adversarial network	Generative adversarial networks	33	Neural network		49	cad		65	Movement correction	Motion correction
2	Medical image		18	Active contour model	Active contour models	34	Neural-network		50	Computer aided diagnosis		66	Dynamic contrast enhanced mri	dce-mri
3	Medical images	Images	19	Multiorgan segmentation	Multi-organ segmentation	35	Neural-net-works	Neural networks	51	Computer-aided diagnosis (cad)	Computer-aided diagnosis	67	Image guided surgery	Image-guided surgery
4	Medical image analysis		20	Nonrigid registration	Non-rigid registration	36	Renal-cell carcinoma	Renal cell carcinoma	52	Computed tomography		68	Mutual-information	Mutual information
5	Image-analysis	Image analysis	21	Augmented-reality	Augmented reality	37	Dynamic mr	Dynamic mri	53	Computed tomography (CT)		69	Renal-function	Renal function
6	Kidney-disease	Kidney disease	22	Feature-selection	Feature selection	38	Chronic kidney-disease	Chronic kidney disease	54	Computed-tomography		70	3d reconstruction	3-dimensional reconstruction
7	Network	Networks	23	Graph cut	Graph cuts	39	pca	Principal component analysis	55	CT images	CT	71	Glomerulus	Glomeruli
8	Artificial neural network	Artificial neural networks	24	Tumor	Tumors	40	Autosomal dominant polycystic kidney disease	adpkd	56	Renal tumor		72	Automated segmentation	Automatic segmentation
9	Convolutional neural network		25	Algorithm	Algorithms	41	Cyst	Cysts	57	Renal tumors	Kidney tumor	73	Ultrasound image	
10	Convolutional neural-net-works		26	Model	Models	42	Active contour	Active contours	58	Kidneys		74	Ultrasound images	
11	Convolutional neural-net-work		27	Magnetic-resonance		43	Active shape model	Active shape models	59	Renal	Kidney	75	Ultrasound imaging	Ultrasound

Table 4 (continued)

#	Keyword	Replaces by	#	Keyword	Replace by	#	Keyword	Replace by	#	Keyword	Replace by	#	Keyword	Replace by
12	Convolutional neural network (cnn)		28	mr		44	Digital pathology		60	Kidney stones		76	Surface	Surfaces
13	cnn	Convolutional neural networks	29	Magnetic resonance imaging		45	Renal pathology	Pathology	61	Kidney-stones	Kidney stone	77	Mass	Masses
14	ccrc	Clear cell renal cell carcinoma	30	MR-images	MRI	46	Image segmentation	Segmentation	62	Edge detection	Boundary detection	78	Visible fat	Fat
15	Cell-carcinoma	Cell carcinoma	31	Prostate-cancer	Prostate cancer	47	Renal cancer	Kidney cancer	63	Image registration	Registration	79	Glomerular-filtration-rate	Glomerular filtration rate
16	Random forest	Random forests	32	Artificial-intelligence	Artificial intelligence	48	Predict	Prediction	64	Simulation	Simulations	80	Diseases	Disease

Appendix C: Nodes details for the citation map

Table 5 shows the details of the nodes in Fig. 4.

Table 5 Nodes details for the citation map (i.e., Fig. 4.)

NodeID	Document	Year	LCS	LCS/t	GCS	GCS/t	LCR	CR
36	An automated segmentation method of kidney using statistical information	2002	19	0.86	29	1.32	0	14
48	Construction of an abdominal Probabilistic atlas and its application in segmentation	2003	39	1.86	259	12.33	1	55
62	Computer-aided detection of kidney tumor on abdominal computed tomography scans	2004	18	0.90	33	1.65	0	14
70	Segmentation of kidney from ultrasound images based on texture and shape priors	2005	49	2.58	146	7.68	0	41
85	Computer-aided kidney segmentation on abdominal CT images	2006	56	3.11	97	5.39	1	24
92	Graph cuts framework for kidney segmentation with prior shape constraints	2007	25	1.47	62	3.65	0	12
103	Performance of an automated segmentation algorithm for 3D MR renography	2007	25	1.47	62	3.65	3	30
140	Segmentation of kidneys using a new active shape model generation technique based on non-rigid image registration	2009	32	2.13	49	3.27	1	21
142	Assessment of 3D DCE-MRI of the kidneys using non-rigid image registration and segmentation of voxel time courses	2009	34	2.27	91	6.07	1	45
147	Augmented Reality: A New Tool To Improve Surgical Accuracy during Laparoscopic Partial Nephrectomy? Preliminary In Vitro and In Vivo Results	2009	20	1.33	133	8.87	0	21
155	Non-parametric Iterative Model Constraint Graph min-cut for Automatic Kidney Segmentation	2010	25	1.79	31	2.21	3	17
184	3D Kidney Segmentation from CT Images Using a Level Set Approach Guided by a Novel Stochastic Speed Function	2011	19	1.46	42	3.23	4	14
219	Automatic Detection and Segmentation of Kidneys in 3D CT Images Using Random Forests	2012	32	2.67	107	8.92	4	17
228	Prior Shape Level Set Segmentation on Multistep Generated Probability Maps of MR Datasets for Fully Automatic Kidney Parenchyma Volumetry	2012	20	1.67	38	3.17	8	36
239	Statistical 4D graphs for multi-organ abdominal segmentation from multiphase CT	2012	18	1.50	85	7.08	5	62
288	Automated Abdominal Multi-Organ Segmentation With Subject-Specific Atlas Generation	2013	24	2.18	190	17.27	6	39
396	Abdominal multi-organ segmentation from CT images using conditional shape-location and unsupervised intensity priors	2015	19	2.11	99	11.00	11	59
465	Performance of an Artificial Multi-observer Deep Neural Network for Fully Automated Segmentation of Polycystic Kidneys	2017	27	3.86	77	11.00	2	30
485	Convolutional networks for kidney segmentation in contrast-enhanced CT scans	2018	23	3.83	57	9.50	5	24
511	Association of Pathological Fibrosis With Renal Survival Using Deep Neural Networks	2018	27	4.50	83	13.83	0	51
515	Kidney segmentation in ultrasound, magnetic resonance and computed tomography images: A systematic review	2018	22	3.67	45	7.50	31	114
516	Machine learning-based quantitative texture analysis of CT images of small renal masses: Differentiation of angiomyolipoma without visible fat from renal cell carcinoma	2018	33	5.50	131	21.83	1	40
518	Deep feature classification of angiomyolipoma without visible fat and renal cell carcinoma in abdominal contrast-enhanced CT images with texture image patches and hand-crafted feature concatenation	2018	21	3.50	46	7.67	1	32
536	Automatic Multi-Organ Segmentation on Abdominal CT With Dense V-Networks	2018	36	6.00	304	50.67	3	54
537	Region-Based Convolutional Neural Nets for Localization of Glomeruli in Trichrome-Stained Whole Kidney Sections	2018	34	5.67	59	9.83	0	24
547	Textural differences between renal cell carcinoma subtypes: Machine learning-based quantitative computed tomography texture analysis with independent external validation	2018	28	4.67	67	11.17	1	35
602	Clear Cell Renal Cell Carcinoma: Machine Learning-Based Quantitative Computed Tomography Texture Analysis for Prediction of Fuhrman Nuclear Grade	2019	21	4.20	81	16.20	1	46
651	Computational Segmentation and Classification of Diabetic Glomerulosclerosis	2019	38	7.60	88	17.60	3	32
652	Deep Learning-Based Histopathologic Assessment of Kidney Tissue	2019	53	10.60	135	27.00	2	21
880	Development and evaluation of deep learning-based segmentation of histologic structures in the kidney cortex with multiple histologic stains	2021	20	6.67	43	14.33	8	53

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Data and code availability All data generated or analyzed during this study are included in this published article [and its supplementary information files].

Declarations

Conflict of interest Lei Zhang reports financial support was provided by Science and Technology plan transfer payment project of Sichuan province. Lei Zhang reports financial support was provided by Sichuan University and Yibin Municipal People's Government University and City strategic cooperation special fund project. Lei Zhang reports financial support was provided by Key Research and Development Program of Science and Technology Department of Sichuan Province.

References

1. Koye DN, Magliano DJ, Nelson RG, Pavkov ME (2018) The global epidemiology of diabetes and kidney disease. Adv Chronic Kidney Dis 25(2):121–132
2. Peek JL, Wilson MH (2023) Cell and gene therapy for kidney disease. Nat Rev Nephrol 1–12
3. Levey AS, Coresh J (2012) Chronic kidney disease. Lancet 379(9811):165–180
4. Jager KJ, Kovesdy C, Langham R, Rosenberg M, Jha V, Zoccali C (2019) A single number for advocacy and communication—worldwide more than 850 million individuals have kidney diseases
5. Jacques Ferlay ME, Siegel RL, Isabelle Soerjomataram MD, Ahmedin Jemal DVM (2024) Global cancer statistics 2022: Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries
6. Hermsen M, de Bel T, Den Boer M, Steenbergen EJ, Kers J, Florquin S, Roelofs JJTH, Stegall MD, Alexander MP, Smith BH et al (2019) Deep learning-based histopathologic assessment of kidney tissue. J Am Soc Nephrol 30(10):1968–1979
7. Lin D-T, Lei C-C, Hung S-W (2006) Computer-aided kidney segmentation on abdominal ct images. IEEE Trans Inf Technol Biomed 10(1):59–65
8. Ellegaard O, Wallin JA (2015) The bibliometric analysis of scholarly production: how great is the impact? Scientometrics 105:1809–1831
9. Diéguez-Santana K, González-Díaz H (2023) Machine learning in antibacterial discovery and development: a bibliometric and network analysis of research hotspots and trends. Comput Biol Med 155:106638
10. Poly TN, Islam MM, Bruno AW, Ming CL, Li Y-C (2023) Artificial intelligence in diabetic retinopathy: Bibliometric analysis. Comput Methods Progr Biomed 231:107358
11. Yin T, Chen Y, Tang L, Yuan H, Zeng X, Ping F (2022) Relationship between modifiable lifestyle factors and chronic kidney disease: a bibliometric analysis of top-cited publications from 2011 to 2020. BMC Nephrol 23(1):120
12. Shah SHH, Lei S, Ali M, Doronin D, Hussain ST (2020) Prosumption: bibliometric analysis using histcite and vosviewer. Kybernetes 49(3):1020–1045
13. Pranckutė R (2021) Web of science (wos) and scopus: the titans of bibliographic information in today's academic world. Publications 9(1):12
14. Ari N, Makhamadsulton U (2014) Matplotlib in python. In: 2014 11th international conference on electronics, computer and computation (ICECCO). IEEE, pp 1–6
15. Bisong E, Bisong E (2019) Matplotlib and seaborn. In: Building machine learning and deep learning models on google cloud platform: a comprehensive guide for beginners, pp 151–165
16. Garfield E (2009) From the science of science to scientometrics visualizing the history of science with histcite software. J Informet 3(3):173–179
17. Van Eck N, Waltman L (2010) Software survey: Vosviewer, a computer program for bibliometric mapping. Scientometrics 84(2):523–538
18. Liao H, Tang M, Luo L, Li C, Chiclana F, Zeng X-J (2018) A bibliometric analysis and visualization of medical big data research. Sustainability 10(1):166
19. Zhang J, Qi Yu, Zheng F, Long C, Zuxun L, Duan Z (2016) Comparing keywords plus of wos and author keywords: a case study of patient adherence research. J Am Soc Inf Sci 67(4):967–972
20. Ginley B, Lutnick B, Jen K-Y, Fogo AB, Jain S, Rosenberg A, Walavalkar V, Wilding G, Tomaszewski JE, Yacoub R et al (2019) Computational segmentation and classification of diabetic glomerulosclerosis. J Am Soc Nephrol 30(10):1953–1967
21. Jayapandian CP, Chen Y, Janowczyk AR, Palmer MB, Cassol CA, Sekulic M, Hodgin JB, Zee J, Hewitt SM, O'Toole J et al (2021) Development and evaluation of deep learning-based segmentation of histologic structures in the kidney cortex with multiple histologic stains. Kidney Int 99(1):86–101
22. Gibson E, Giganti F, Yipeng H, Bonmati E, Bandula S, Gurusamy K, Davidson B, Pereira SP, Clarkson MJ, Barratt DC (2018) Automatic multi-organ segmentation on abdominal ct with dense v-networks. IEEE Trans Med Imaging 37(8):1822–1834
23. Bukowy JD, Dayton A, Cloutier D, Manis AD, Staruschenko A, Lombard JH, Woods LCS, Beard DA, Cowley AW (2018) Region-based convolutional neural nets for localization of glomeruli in trichrome-stained whole kidney sections. J Am Soc Nephrol 29(8):2081–2088
24. Feng Z, Rong P, Cao P, Zhou Q, Zhu W, Yan Z, Liu Q, Wang W (2018) Machine learning-based quantitative texture analysis of ct images of small renal masses: differentiation of angiomyolipoma without visible fat from renal cell carcinoma. Eur Radiol 28:1625–1633
25. Bouteldja N, Klinkhammer BM, Bülow RD, Droste P, Otten SW, Freifrau S, von Stillfried J, Moellmann SM, Sheehan RK, Menzel S et al (2021) Deep learning-based segmentation and quantification in experimental kidney histopathology. J Am Soc Nephrol 32(1):52–68
26. Kocak B, Yardimci AH, Bektas CT, Turkcanoglu MH, Erdim C, Yucetas U, Koca SB, Kilickesmez O (2018) Textural differences between renal cell carcinoma subtypes: machine learning-based quantitative computed tomography texture analysis with independent external validation. Eur J Radiol 107:149–157
27. Kolachalama VB, Singh P, Lin CQ, Mun D, Belghasem ME, Henderson JM, Francis JM, Salant DJ, Chitalia VC (2018) Association of pathological fibrosis with renal survival using deep neural networks. Kidney Int Rep 3(2):464–475
28. Bektas CT, Kocak B, Yardimci AH, Turkcanoglu MH, Yucetas U, Koca SB, Erdim C, Kilickesmez O (2019) Clear cell renal cell carcinoma: machine learning-based quantitative computed tomography texture analysis for prediction of fuhrman nuclear grade. Eur Radiol 29:1153–1163
29. Lu MY, Williamson DFK, Chen TY, Chen RJ, Barbieri M, Mahmood F (2021) Data-efficient and weakly supervised

computational pathology on whole-slide images. Nat Biomed Eng 5(6):555–570
30. Sandfort V, Yan K, Pickhardt PJ, Summers RM (2019) Data augmentation using generative adversarial networks (cyclegan) to improve generalizability in ct segmentation tasks. Sci Rep 9(1):16884
31. Rivenson Y, Wang H, Wei Z, de Haan K, Zhang Y, Yichen W, Günaydın H, Zuckerman JE, Chong T, Sisk AE et al (2019) Virtual histological staining of unlabelled tissue-autofluorescence images via deep learning. Nat Biomed Eng 3(6):466–477
32. Chen RJ, Lu MY, Wang J, Williamson DFK, Rodig SJ, Lindeman NI, Mahmood F (2020) Pathomic fusion: an integrated framework for fusing histopathology and genomic features for cancer diagnosis and prognosis. IEEE Trans Med Imaging 41(4):757–770
33. Heller N, Isensee F, Maier-Hein KH, Hou X, Xie C, Li F, Nan Y, Guangrui M, Lin Z, Han M et al (2021) The state of the art in kidney and kidney tumor segmentation in contrast-enhanced ct imaging: results of the kits19 challenge. Med Image Anal 67:101821
34. Yeung M, Sala E, Schönlieb C-B, Rundo L (2022) Unified focal loss: generalising dice and cross entropy-based losses to handle class imbalanced medical image segmentation. Comput Med Imaging Graph 95:102026
35. Rivenson Y, Liu T, Wei Z, Zhang Y, de Haan K, Ozcan A (2019) Phasestain: the digital staining of label-free quantitative phase microscopy images using deep learning. Light Sci Appl 8(1):23
36. Elton Daniel C, Turkbey Evrim B, Pickhardt Perry J, Summers Ronald M (2022) A deep learning system for automated kidney stone detection and volumetric segmentation on noncontrast ct scans. Med Phys 49(4):2545–2554
37. Moumen E-M, Rasha K, Abou E-GM, Mohamed S, Fahmi K, Ayman E-B (2022) Kidney segmentation from dce-mri converging level set methods, fuzzy clustering and markov random field modeling. Sci Rep 12(1):18816
38. Cerrolaza Juan J, Nabile S, Elijah B, James J, Peters Craig A, George LM (2016) Renal segmentation from 3d ultrasound via fuzzy appearance models and patient-specific alpha shapes. IEEE Trans Med Imaging 35(11):2393–2402
39. Brandon G, Kuang-Yu J, Seok HS, RodriguesLuís JS, Fogo Agnes B, Jonathan Z, Vighnesh W, Miecznikowski Jeffrey C, Yumeng W et al (2021) Automated computational detection of interstitial fibrosis, tubular atrophy, and glomerulosclerosis. J Am Soc Nephrol 32(4):837–850
40. Shashiprakash AK, Lutnick B, Ginley B, Govind D, Lucarelli N, Jen K-Y, Rosenberg AZ, Urisman A, Walavalkar V, Zuckerman JE et al (2021) A distributed system improves inter-observer and ai concordance in annotating interstitial fibrosis and tubular atrophy. In: Medical imaging 2021: digital pathology, vol 11603. SPIE, pp 208–213
41. Xiang D, Bagci U, Jin C, Shi F, Zhu W, Yao J, Sonka M, Chen X (2017) Cortexpert: a model-based method for automatic renal cortex segmentation. Med Image Anal 42:257–273
42. Tian H, Chen G, Xiang D, Chen X (2019) Simultaneous and automatic two surface detection of renal cortex in 3d ct images by enhanced sparse shape composition. In: Medical imaging 2019: image processing, vol 10949. SPIE, pp 613–618
43. Yao T, Yuzhe L, Long J, Jha A, Zhu Z, Asad Z, Yang H, Fogo AB, Huo Y (2022) Glo-in-one: holistic glomerular detection, segmentation, and lesion characterization with large-scale web image mining. J Med Imaging 9(5):052408–052408
44. Ginley B, Jen K-Y, Han SS, Rodrigues L, Jain S, Fogo AB, Zuckerman J, Walavalkar V, Miecznikowski JC, Wen Y et al (2021) Automated computational detection of interstitial fibrosis, tubular atrophy, and glomerulosclerosis. J Am Soc Nephrol 32(4):837–850
45. Yao T, Yuzhe L, Long J, Jha A, Zhu Z, Asad Z, Yang H, Fogo AB, Huo Y (2022) Glo-in-one: holistic glomerular detection, segmentation, and lesion characterization with large-scale web image mining. J Med Imaging 9(5):052408–052408
46. Erdim C, Yardimci AH, Bektas CT, Kocak B, Koca SB, Demir H, Kilickesmez O (2020) Prediction of benign and malignant solid renal masses: machine learning-based ct texture analysis. Acad Radiol 27(10):1422–1429
47. Jen K-Y, Murali LK, Lutnick B, Ginley B, Govind D, Mori H, Gao G, Sarder P (2021) In silico multi-compartment detection based on multiplex immunohistochemical staining in renal pathology. In: Medical imaging 2021: digital pathology, vol 11603. SPIE, pp 294–301
48. Büllow RD, Marsh JN, Joshua Swamidass S, Gaut JP, Boor P (2022) The potential of artificial intelligence-based applications in kidney pathology. Curr Opin Nephrol Hypertens 31(3):251–257
49. Kers J, Bülow RD, Klinkhammer BM, Breimer GE, Fontana F, Abiola AA, Hofstraat R, Corthals GL, Peters-Sengers H, Djudjaj S et al (2022) Deep learning-based classification of kidney transplant pathology: a retrospective, multicentre, proof-of-concept study. Lancet Digit Health 4(1):e18–e26
50. Laleh NG, Muti HS, Loeffler CML, Echle A, Saldanha OL, Mahmood F, Lu MY, Trautwein C, Langer R, Dislich B et al (2022) Benchmarking weakly-supervised deep learning pipelines for whole slide classification in computational pathology. Med Image Anal 79:102474
51. Chen RJ, Lu MY, Wang J, Williamson DFK, Rodig SJ, Lindeman NI, Mahmood F (2022) Pathomic fusion: an integrated framework for fusing histopathology and genomic features for cancer diagnosis and prognosis. IEEE Trans Med Imaging 41(4):757–770
52. de Haan K, Zhang Y, Zuckerman JE, Liu T, Sisk AE, Diaz MFP, Jen K-Y, Nobori A, Liou S, Zhang S et al (2021) Deep learning-based transformation of h &e stained tissues into special stains. Nat Commun 12(1):4884
53. Tsagaan B, Shimizu A, Kobatake H, Miyakawa K (2002) An automated segmentation method of kidney using statistical information. In: International conference on medical image computing and computer-assisted intervention. Springer, pp 556–563
54. Lapeer RJ, Tan AC, Aldridge R (2002) Active watersheds: combining 3d watershed segmentation and active contours to extract abdominal organs from mr images. In: Medical image computing and computer-assisted intervention–MICCAI 2002: 5th international conference Tokyo, September 25–28, 2002 Proceedings, Part I 5. Springer, pp 596–603
55. Xie J, Jiang Y, Tsui H (2005) Segmentation of kidney from ultrasound images based on texture and shape priors. IEEE Trans Med Imaging 24(1):45–57
56. Dettori L, Bashir A, Hasemann J (2007) Texture classification of normal tissues in computed tomography using gabor filters. In: Medical imaging 2007: image processing, vol 6512. SPIE, pp 253–262
57. Xuesong L, Zhang S, Yang W, Chen Y (2010) Sift and shape information incorporated into fluid model for non-rigid registration of ultrasound images. Comput Methods Programs Biomed 100(2):123–131
58. Valentin B, Stabinska J, Reurik F, Tell C, Mewes AD, Müller-Lutz A, Antoch G, Rump LC, Wittsack HJ, Ljimani A (2022) Feasibility of renal perfusion quantification by fourier decomposition mri. Magn Reson Imaging 85:3–9

59. Mrukwa G, Polanska J (2022) Divik: divisive intelligent k-means for hands-free unsupervised clustering in big biological data. BMC Bioinform 23(1):538
60. Kaur R, Juneja M, Mandal AK (2021) Machine learning based quantitative texture analysis of ct images for diagnosis of renal lesions. Biomed Signal Process Control 64:102311
61. Goel A, Shih G, Riyahi S, Jeph S, Dev H, Hu R, Romano D, Teichman K, Blumenfeld JD, Barash I et al (2022) Deployed deep learning kidney segmentation for polycystic kidney disease mri. Radiol Artif Intell 4(2):e210205
62. Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, vol 25
63. Deng J, Dong W, Socher R, Li L-J, Li K, Fei-Fei L (2009) Imagenet: a large-scale hierarchical image database. In: 2009 IEEE conference on computer vision and pattern recognition. IEEE, pp 248–255
64. Ronneberger O, Fischer P, Brox T (2015) U-net: convolutional networks for biomedical image segmentation. In: Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, October 5–9, 2015, Proceedings, Part III 18. Springer, pp 234–241
65. Wang Z, Zou N, Shen D, Ji S (2020) Non-local u-nets for biomedical image segmentation. In: Proceedings of the AAAI conference on artificial intelligence, vol 34, pp 6315–6322
66. Kundu S, Karale V, Ghorai G, Sarkar G, Ghosh S, Dhara AK (2022) Nested u-net for segmentation of red lesions in retinal fundus images and sub-image classification for removal of false positives. J Digit Imaging 35(5):1111–1119
67. Yin X-X, Sun L, Fu Y, Lu R, Zhang Y (2022) U-net-based medical image segmentation. J Healthc Eng 2022
68. Block MAG, Anne M (2003) Assessing capacity for health policy and systems research in low and middle income countries. Health Res Policy Syst 1:1–20
69. Manchanda R, Varma R (2004) Representation of authors and editors from poor countries: observed publication bias may reflect who is funding research. BMJ 329(7457):110
70. Horton R (2000) North and south: bridging the information gap. Lancet 355(9222):2231–2236
71. Zöllner FG, Sance R, Rogelj P, Ledesma-Carbayo MJ, Rørvik J, Santos A, Lundervold A (2009) Assessment of 3d dce-mri of the kidneys using non-rigid image registration and segmentation of voxel time courses. Comput Med Imaging Graph 33(3):171–181
72. Thong W, Kadoury S, Piché N, Pal CJ (2018) Convolutional networks for kidney segmentation in contrast-enhanced ct scans. Comput Methods Biomech Biomed Eng Imaging Vis 6(3):277–282
73. Torres HR, Queirós S, Morais P, Oliveira B, Fonseca JC, Vilaça JL (2018) Kidney segmentation in ultrasound, magnetic resonance and computed tomography images: a systematic review. Comput Methods Programs Biomed 157:49–67
74. Siddique N, Paheding S, Elkin CP, Devabhaktuni V (2021) U-net and its variants for medical image segmentation: a review of theory and applications. IEEE Access 9:82031–82057
75. Xie E, Wang W, Zhiding Yu, Anandkumar A, Alvarez JM, Luo P (2021) Segformer: simple and efficient design for semantic segmentation with transformers. Adv Neural Inf Process Syst 34:12077–12090
76. Zhu L, Liao B, Zhang Q, Wang X, Liu W, Wang X (2024) Vision mamba: efficient visual representation learning with bidirectional state space model. arXiv:2401.09417
77. Ma J, He Y, Li F, Han L, You C, Wang B (2024) Segment anything in medical images. Nat Commun 15(1):654
78. Dickersin K (1990) The existence of publication bias and risk factors for its occurrence. JAMA 263(10):1385–1389