IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 16 May 2024, accepted 9 June 2024, date of publication 12 June 2024, date of current version 26 June 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3413595

TOPICAL REVIEW

Automation and Decision Support in the Area of Nephrology Using Numerical Algorithms, Artificial Intelligence, and Expert Approach: Review of the Current State of Knowledge

DAWID PAWUŚ[1], **TOMASZ PORAŻKO**[2,3], **AND SZCZEPAN PASZKIEL**[1]
[1]Faculty of Electrical Engineering, Automatic Control and Informatics, Opole University of Technology, 45-758 Opole, Poland
[2]Department of Internal Medicine and Nephrology, Institute of Medical Sciences, University of Opole, 45-052 Opole, Poland
[3]Department of Nephrology with Dialysis Unit, Opole University Hospital, 46-020 Opole, Poland

Corresponding author: Dawid Pawuś (dawid.pawus@student.po.edu.pl)

ABSTRACT This study explores the contemporary landscape of integrating numerical algorithms, artificial intelligence (AI), and expert methodologies within the domain of nephrology. Focusing on automation and decision support, we scrutinize the impact of numerical algorithms on the precise evaluation of kidney function. Furthermore, we delve into the transformative potential of artificial intelligence, particularly in the realms of machine learning and deep learning applications, elucidating its role in early disease detection and the formulation of personalized treatment strategies. The synergy between computer-based tools and expert-driven approaches is examined, underscoring their collaborative role in enhancing the accuracy and dependability of diagnoses. Additionally, we address the ethical considerations and challenges associated with the incorporation of automation in nephrology. The paper provides a concise overview of in-depth analysis while illustrating the promising prospects of these innovative methodologies for reshaping nephrology research and patient care.

INDEX TERMS Expert system, artificial intelligence, neural networks, classification, numerical algorithms, automation system, machine learning, algorithms in nephrology, kidney disease, AI in medicine.

I. INTRODUCTION

Nephrology, at the forefront of medical science, undergoes a profound transformation fueled by advanced technologies. This shift, driven by numerical algorithms, artificial intelligence (AI), and expert methodologies, promises to redefine decision support and automation in kidney care.

The kidneys, crucial regulators of physiological equilibrium, present diagnostic and treatment challenges. Traditionally, nephrology relied on manual analyses, posing challenges due to complex datasets. However, the convergence of numerical algorithms and AI offers unprecedented insights into renal health, enhancing diagnostic accuracy and treatment precision. This synergy with expert insights heralds a dynamic system poised to navigate nephrological complexities efficiently.

Complementing these technological advancements, the expert approach brings the seasoned insights of nephrologists into the fold. The nuanced understanding of renal pathophysiology, when integrated with numerical algorithms and AI, establishes a collaborative synergy where human expertise refines and guides the outputs of automated systems. This harmonious partnership ensures the clinical relevance and reliability of decision support tools in nephrology.

In this article, we review the latest literature on automation, numerical algorithms, artificial intelligence and expert approaches in nephrology and related fields. We analyze the state of knowledge in the use of modern algorithms in issues related to kidney diseases. It was checked what algorithms are used in this field of research, and the Scopus database

The associate editor coordinating the review of this manuscript and approving it for publication was Yizhang Jiang.

was explored to check the distribution of publications over the years. Based on the review, we propose possible future paths for the development of nephrology-engineering cooperation. The article also lays the foundation for a series of future research by the authors on this topic, allowing us to find trends that should be followed.

The importance of this study lies in its endeavor to elucidate the pivotal role of technological integration in nephrology and its potential to reshape clinical practice. With kidney diseases posing significant challenges due to their complexity and variability, there is an urgent need for innovative approaches that can enhance diagnostic accuracy, treatment efficacy, and patient management.

By harnessing the power of numerical algorithms and AI, we can unlock insights from vast datasets, enabling clinicians to make informed decisions with greater confidence and efficiency. As we delve into an analysis of the current state of knowledge, this article also introduces a groundbreaking conceptual framework for a new system in nephrological care.

Moreover, this article explores the contemporary landscape of transformative technologies in nephrology, highlighting potential synergies and challenges. By focusing on specific applications, our goal is to show how these improvements can impact standards of patient care and automate decision-making and treatment.

When proposing the topic of the article, it was necessary to review related works and compare them with our research. By examining publication databases, several dozen articles were found closely related to review works related to AI and nephrology. Their popularity began to grow in 2020, with the maximum number in 2022. However, this topic is very poorly recognized and requires further development, especially due to the very rapid development of technology and new algorithms. Therefore, our work offers the latest, broad, professional and multi-topic review of research progress. The authors believe that it will contribute to the selection of further development paths in the discussed fields.

Researchers discuss advances in artificial intelligence [1], innovation [2], and transformation [3] in nephrology and dialysis [4]. Other studies worth mentioning include a review of work in the context of the future of artificial intelligence and modern technologies in kidney diseases [5], [6]. Research on numerical models and machine learning is also of interest [7], [8], [9].

An essential element of review work related to nephrology is the combination of acute kidney injury and prediction using AI and related algorithms [10], [11], [12]. Another group of reviews are works related to predictive models in personalized medicine [13]. In turn, discussions supported by a collection of works on AI-based clinical applications in nephrology are included in the works [14] and [15]. Works related to ethical issues are reviewed in [16] and [17].

To sum up, it should be said that most of these publications are characterized by a review focused on a specific narrow field, and thus not fully exhausting the topic. Our work, in turn, offers a broad overview of the latest trends.

The next section will feature articles and research related to the topics covered in this article.

II. KIDNEY DISEASES AND THEIR DIAGNOSIS

Kidney diseases according to registries affect around 850 million people around the world [18]. Moust of them are diagnosed in advanced stages of the disease causing life threating state requiring dialysis or a kidney transplantation. Therefore specific and sensitive evaluation of the patient with kidney disease is necessary. Thorough patient evaluation with suspicion of a kidney disease plays a pivotal role in early diagnosis, prognosis and effective treatment.

The process typically consists of taking a history of the disease, onset, its symptoms, their duration and severity, triggering conditions i.e. infection, stress, surgery, medications and concomitant pathologies i.e. hypertension, diabetes, obesity inflammatory and autoimmune diseases. The next step is a physical examination of vital parameters as blood pressure, heart rate, respiratory rate, blood saturation, temperature as well as body weight, followed by BMI calculation. Then searching for possible kidney disease consequences as fluid overload like oedema, specific respiratory sounds, than anaemia i.e. pallor of skin, and finally uremic toxins retention causing specific oral smell or skin rash, scratches or deposits.

Afterwords patient has his blood and urine tested. Laboratory work out of a blood includes kidney function measured with serum creatinine followed by calculation of glomerular flirtation rate (GFR) using specific equations i.e. Cocroft – Gault formula, MDRD or EPI-CKD. Full blood count, serum concentration of ions as sodium, kalium, calcium, inflammatory markers (i.e. C-reative protein), total protein and albumin, glucose and glycated haemoglobin (HbA1C), lipids, with coagulation tests are also done. Urine test are crucial with urine sediment protein and glucose content as well as protein excretion using albumin to creatinine urine concertation ratio (ACR), protein to creatinine urine concertation ratio (PCR) or 24 hour urine collection for protein amount. Urine can be also testet for precents specific kidney stones formatting substances. There are also specific immunology tests detecting particular diseases as anti-nuclear antibodies (ANA) common in lupus, anti-cytoplasmatic antibodies (ANCA) common in vasculitis or anti-phospholipase antibodies (anti-PLAR) specific for membranous nephropathy. To estimate activity of autoimmune disease complement parameters as C3, C4 are measured. Pivotal role plays specific procedure as kidney biopsy to collect small piece of kidney tissue for histopathology examination using specific test with light and electron microscopy. The method is used to calculate number of glomeruli, structures filtrating blood, their specific disease changes as necrosis, inflammation, protein deposits as well as scarring with condition of surrounding tissue.

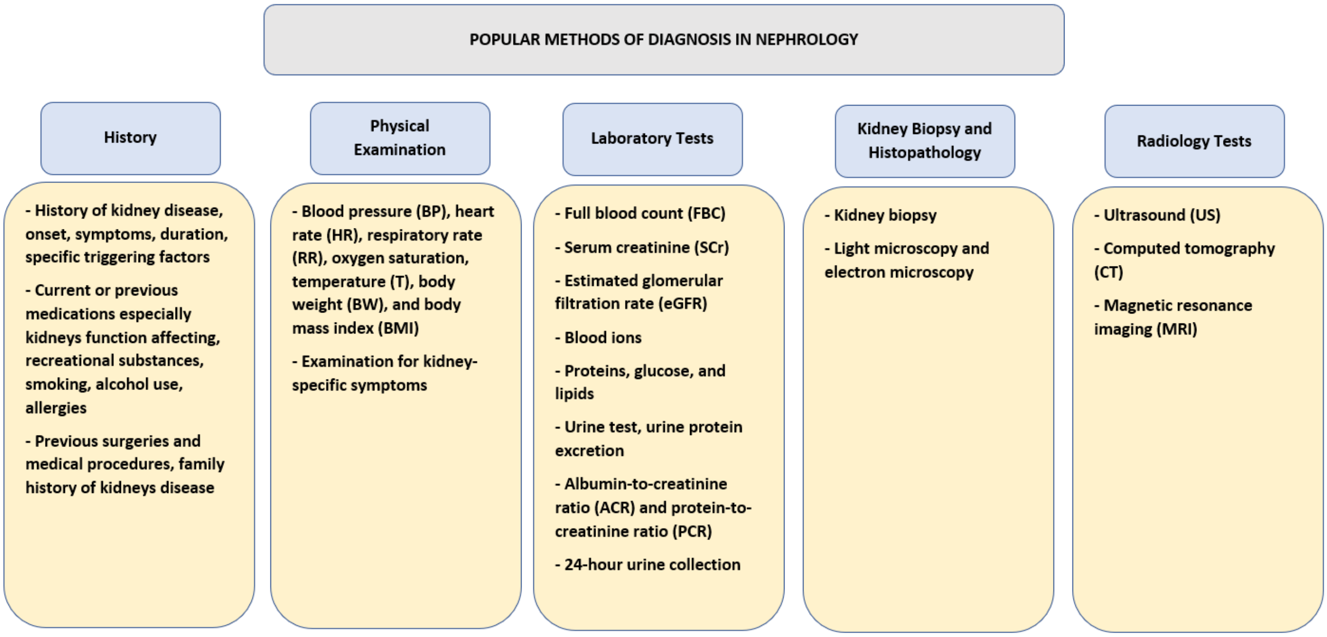

FIGURE 1. The most popular methods of diagnosis in nephrology.

Finally kidneys and urine colleting systems must be visualised with ultrasonography, enhanced or unenhanced computer tomography (CT), magnetic resonance imaging (MRI) or CT or MRI based urography. These methods are also used to detect characteristic pathologies to body organs caused by kidney disease. Whole diagnostic patient evaluation is used not only to detect particular type of a kidney disease but also to monitor its activity throughout treatment course.

Figure 1 provides an illustrative overview of the most widely used diagnostic methods in nephrology. These methods play a crucial role in the field, contributing significantly to the identification and assessment of kidney-related conditions. The figure encompasses various diagnostic techniques, reflecting the diverse approaches employed by nephrologists to diagnose and understand different aspects of kidney diseases.

A. BLOOD TESTS

Blood tests stand as fundamental pillars in the comprehensive evaluation of kidney health, providing valuable insights into the intricate processes of filtration, excretion, and overall renal function. These diagnostic analyses are instrumental in detecting early signs of dysfunction, guiding clinicians in the formulation of precise diagnoses and tailored treatment plans. In this subsection, we will explore the significance of blood tests in renal assessment, unraveling the key parameters and biomarkers that illuminate the health and vitality of these essential organs. From assessing filtration rates to identifying markers of kidney injury, blood tests offer a dynamic and informative window into the complex landscape of renal well-being [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].

- Serum creatinine - creatinine, a byproduct of muscle metabolism and dietary protein breakdown, is a vital kidney function indicator. The kidneys filter creatinine from the blood, expelling it in urine. Serum creatinine levels, measured through a blood test, indicate renal efficiency. Elevated levels suggest compromised kidney function, indicative of acute kidney injury or chronic kidney disease. Urine tests for creatinine provide complementary insights into the kidneys' ability to eliminate waste. Regular assessment of both blood and urine creatinine levels is crucial for a comprehensive evaluation of kidney health [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].
- Estimated glomerular filtration rate (eGFR) - the estimated glomerular filtration rate (eGFR) is a key metric for assessing kidney function, derived from factors like serum creatinine, age, and sex. It provides an estimate of the kidneys' efficiency in eliminating waste from the blood. Represented visually, a pie chart categorizes GFR levels: 0-15 indicates kidney failure, 15-60 signifies kidney disease, 60-90 represents early-stage kidney disease, and 90-120 is considered normal [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].

  While eGFR is widely reliable, specific situations may require a more precise assessment, leading to measured GFR (mGFR) tests. Notably, eGFR may be less accurate for individuals under 18, pregnant individuals, those very overweight, or with significant muscle mass. In such cases, additional tests like ultrasound or kidney biopsy might be advised for a comprehensive evaluation, ensuring targeted interventions when needed [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].

- Blood urea nitrogen (BUN) - urea nitrogen, a byproduct of protein breakdown, is eliminated by the kidneys. Elevated levels, measured through a blood test called Blood Urea Nitrogen (BUN), may indicate impaired kidney function. Unlike creatinine and eGFR, BUN alone is less informative. Healthcare providers assess BUN alongside creatinine and eGFR to comprehensively evaluate kidney health. The correlation of these measures offers a nuanced understanding, enabling timely interventions for potential kidney issues [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].
- Cystatin C - is a protein produced by cells, is an alternative to creatinine for estimating kidney function. While less common and potentially pricier, it provides valuable insights into kidney health. A lower cystatin C level is favorable. When combined with other tests, it enhances the diagnostic capability, offering a nuanced evaluation of kidney function. Regular monitoring of both creatinine and cystatin C levels contributes to a comprehensive assessment of renal health [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].
- The measured glomerular filtration rate (mGFR) - mGFR provides a direct and accurate measurement of kidney function by assessing how efficiently the kidneys remove waste products from the blood. While it is a more complex and less commonly used test compared to estimated GFR (eGFR), it may be recommended by healthcare providers when a precise evaluation of kidney function is essential. The test methods can vary, including 24-hour urine collection or multiple blood samples taken over several hours [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].

B. URINE TESTS

A urine test, conducted by examining a small urine sample, serves as a diagnostic tool for detecting signs of kidney disease and various health issues. When kidneys are impaired, they may allow the leakage of protein into the urine, an early indicator of kidney disease. These tests help doctors assess kidney function, determine the stage of kidney disease, monitor conditions like diabetes that can lead to kidney problems, and check for complications such as anemia and metabolic acidosis. Additionally, urine tests are valuable for identifying other issues like kidney or urinary tract infections. Regular urine testing is essential for early detection and management of kidney-related concerns [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].

- Urine test - a dipstick urine test is a quick and common method often included in a comprehensive urinalysis. It specifically aims to detect albumin, a liver-produced protein, in the urine. While not providing an exact measurement, the dipstick changes color if albumin levels are above normal. If abnormalities are detected, further tests may be recommended by your doctor [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].
  A broader urinalysis involves a visual examination of the urine sample, considering aspects like color and cloudiness. Additionally, a dipstick, a chemically treated test strip, is used to identify abnormalities such as high acid levels, albumin, bacteria, blood, pus, or sugar. The color changes on the strip indicate these irregularities. In some cases, the urine sample may undergo microscopic examination for a more detailed analysis [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].
  Together, these tests offer a comprehensive evaluation of urine composition and can signal potential issues related to kidney function, infections, or other health concerns. The results guide healthcare providers in determining the need for further investigations or interventions based on the identified abnormalities [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].
- Urine Albumin-to-Creatinine Ratio (UACR) - test assesses kidney health by measuring albumin (a protein) in comparison to creatinine (a muscle waste product) in urine. It provides insights into the amount of albumin passing into urine over 24 hours. Results showing a urine albumin level of 30 or above may indicate kidney disease [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].
  Key points to note include the potential repetition of the test for result confirmation and the significance of albumin levels in guiding treatment decisions for kidney disease. A consistent or decreasing urine albumin level indicates the effectiveness of the treatment. The UACR test calculates the ratio by dividing urine albumin by urine creatinine, aiming for a "normal" UACR level below 30 mg/g, where a lower number is considered better. A UACR level of 30 mg/g or higher suggests albuminuria, signaling a potential issue with kidney health. Regular monitoring of UACR is crucial for assessing treatment effectiveness and managing kidney-related concerns [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].

C. OTHER TESTS

There are also several other important studies that stand out and are quite diverse. They are presented appropriately.

- Kidney biopsy - a kidney biopsy involves examining tiny kidney samples to gather additional information after blood tests, urine tests, or imaging. It aids in diagnosing conditions like nephrotic syndrome, guiding treatment decisions, and assessing kidney transplant functionality. The two main types are percutaneous and laparoscopic. Percutaneous biopsies use a thin needle through a small cut, with patients awake and under local anesthesia. Laparoscopic biopsies, reserved for specific cases, involve a camera-equipped tube and anesthesia. The procedure helps identify the cause and severity of kidney problems, assess irreparable damage, and provide insights for effective patient care [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].

- Kidney ultrasound - a kidney ultrasound, also known as a renal ultrasound, is a non-invasive and painless procedure that employs sound waves to create images of the kidneys. It is a safe diagnostic tool used by doctors to assess various aspects of kidney health. The ultrasound can reveal abnormalities in the size or shape of the kidneys, assess blood flow to the kidneys, detect signs of injury or damage, identify kidney stones, cysts, or tumors, and examine the bladder [4], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].

D. FAMILY MEDICAL HISTORY AND GENERAL CONDITION OF THE PATIENT

- Heredity of kidney diseases - some kidney diseases, such as chronic kidney disease, polycystic kidney disease or some types of nephropathy, may be inherited. If there is a family history of kidney disease, your doctor may pay special attention to possible genetic risk factors.
- Impact of general health - a patient's overall health affects kidney function. Cardiovascular diseases, diabetes, hypertension and even infections can negatively affect the kidney. It is important that the doctor takes these aspects into account when diagnosing and assessing the risk of kidney disease.
- Risk factors - some risk factors for kidney disease, such as smoking, substance abuse, unhealthy diet and obesity, may be related to a patient's overall lifestyle. Family history and overall health help your doctor identify these risk factors.
- Impact of treatment - family history of disease may influence the approach to treatment and monitoring of the patient. If there is a family history of a predisposition to certain kidney diseases, your doctor may recommend more intensive monitoring or earlier diagnostic tests.

In summary, both family history and the patient's overall health are key to fully assessing the risk, diagnosis, and treatment planning of kidney disease. It is important to have an open conversation with your doctor about your health history to enable comprehensive patient care.

E. SUMMARY OF CLINICAL TESTS FOR DIAGNOSING KIDNEY DISEASES

The laboratory tests and indicators listed in this chapter are included in Table 1. It lists the corresponding risk thresholds and possible accompanying diseases.

The next section will effectively discuss the state of knowledge in the use of modern algorithms and artificial intelligence in nephrology and related fields.

III. THE STATE OF KNOWLEDGE IN THE USE OF MODERN ALGORITHMS AND ARTIFICIAL INTELLIGENCE IN NEPHROLOGY AND RELATED FIELDS

In search of the state of knowledge about scientific works on the use of artificial intelligence, neural algorithms or expert approaches in nephrology, the authors examined the resources of the Scopus database. Tried to find different combinations of keywords. The results showed that the first publications on the use of numerical algorithms in nephrology and the broad scope of kidney diseases appeared already in the 1980s. We can only single out a handful of important and valuable publications from those times. The current state of knowledge is still being developed and is probably not in its prime time. Table 2 contains the results of the Scopus database search according to the combination of selected words in publications. The status of this information is current as of December 29, 2023.

Analysis of the presented table suggests interesting conclusions. The topic of artificial intelligence and machine learning enjoys considerable interest among researchers, as illustrated by the growing number of publications over the years. The year 2023 seems to be particularly active in terms of the number of publications and citations. In the context of nephrology, research focused on "kidney" appears to outweigh "nephrology" in terms of volume. This suggests specific interest in the organ within artificial intelligence research.

The number of publications related to "membranous nephropathy" is relatively low compared to other areas, which may indicate a more limited interest in this particular aspect of nephrology. Expert systems and decision-making systems are also present in research, but the number of publications in these areas is smaller compared to artificial intelligence and machine learning.

The category "classification" or "prediction" using "algorithm" in the context of nephrology shows a significant number of publications, which suggests interest in creating prognostic and classification models in this field. Overall, the table shows the development of research in the field of artificial intelligence and machine learning, with particular emphasis on applications in nephrology, while pointing out differences in research intensity in different subcategories.

Analysis of the list of publications from the Scopus database allows us to conclude that research and research areas can be divided into several key categories, in the following order: Medical, Computer Science, Biochemistry, Genetic, Engineering and Mathematics. This sequence of categories reflects the diversity of research perspectives and interdisciplinarity in the context of artificial intelligence, machine learning and nephrology, as evidenced by available publications in the Scopus database. Researchers from the fields of medicine, computer science, biochemistry,

TABLE 1. Summary of clinical tests for diagnosing kidney diseases.

Clinical test	Risk thresholds	Possible diseases
Creatinine	0.6 to 1.3 mg/dl	Acute kidney injury, Chronic kidney disease
Estimated Glomerular Filtration Rate	Below 60 ml/min/1.73m^2	Early-stage kidney disease, Kidney disease, Kidney failure
Blood Urea Nitrogen	15 to 40 mg/dl	Impaired kidney function, Kidney disease
Cystatin C	Higher levels suggest reduced kidney function	Impaired kidney function, Chronic kidney disease
Urine Albumin-to-Creatinine Ratio	>30 mg/g	Kidney disease, Albuminuria
Body Mass Index	Overweight: >25 kg/m^2, Obese: >30 kg/m^2	Increased risk of kidney disease
Blood Pressure	>140/90 mmHg	Hypertension, Kidney disease
Pulse Rate	Abnormal range	Cardiovascular conditions, Kidney disease
Oxygen Saturation	Below 95%	Respiratory or circulatory issues, Kidney disease
Urine Test (Proteinuria)	Positive result	Kidney disease, Urinary tract infection
Full Blood Count	Abnormal values	Anemia, Infections, Kidney disease complications
Kidney Biopsy	Histopathological findings	Nephrotic syndrome, Glomerulonephritis, Kidney transplant assessment
Glucose	70 to 99 mg/dl	Diabetes, Kidney disease complications
Blood Ions (Sodium, Potassium, Calcium)	136 to 144 mmol/L, 3.7 to 5.1 mmol/L, 8.5 to 10.2 mg/dL	Electrolyte imbalances, Kidney disease

TABLE 2. Number of individual publications in the Scopus database according to selected criteria.

Searched words	Number of works	First publication year	Year with most papers	Year with most citations
"artificial intelligence" and "nephrology" or "nephrologist"	174	1987	2022	2023
"artificial intelligence" and "kidney"	1867	1976	2023	2023
"artificial intelligence" and "membranous nephropathy"	6	1992	2021	2023
"machine learning" and "nephrology" or "nephrologist"	191	2010	2022	2023
"machine learning" and "kidney"	4097	1992	2023	2023
"machine learning" and "membranous nephropathy"	26	1992	2023	2023
"expert system" or "decision system" and "nephrology" or "nephrologist"	240	1987	2022	2023
expert system" or "decision system" and "kidney"	2191	1981	2021	2022
expert system" or "decision system" and "membranous nephropathy"	8	2000	2014	2023
"classification" or "prediction" and "algorithm" and "nephrology" or "nephrologist"	99	1993	2022	2022
"classification" or "prediction" and "algorithm" and "kidney"	4012	1979	2023	2022
"classification" or "prediction" and "algorithm" and "membranous nephropathy"	26	1997	2021	2023

genetics, engineering and mathematics seem to be actively participating in this research, which indicates a wide range of applications and cooperation between different fields of science.

Analyzing the available data, it can be noticed that research on the discussed issue is in the development phase. Compared to more developed fields such as cardiology, this field of research has been found to be relatively narrow. This indicates

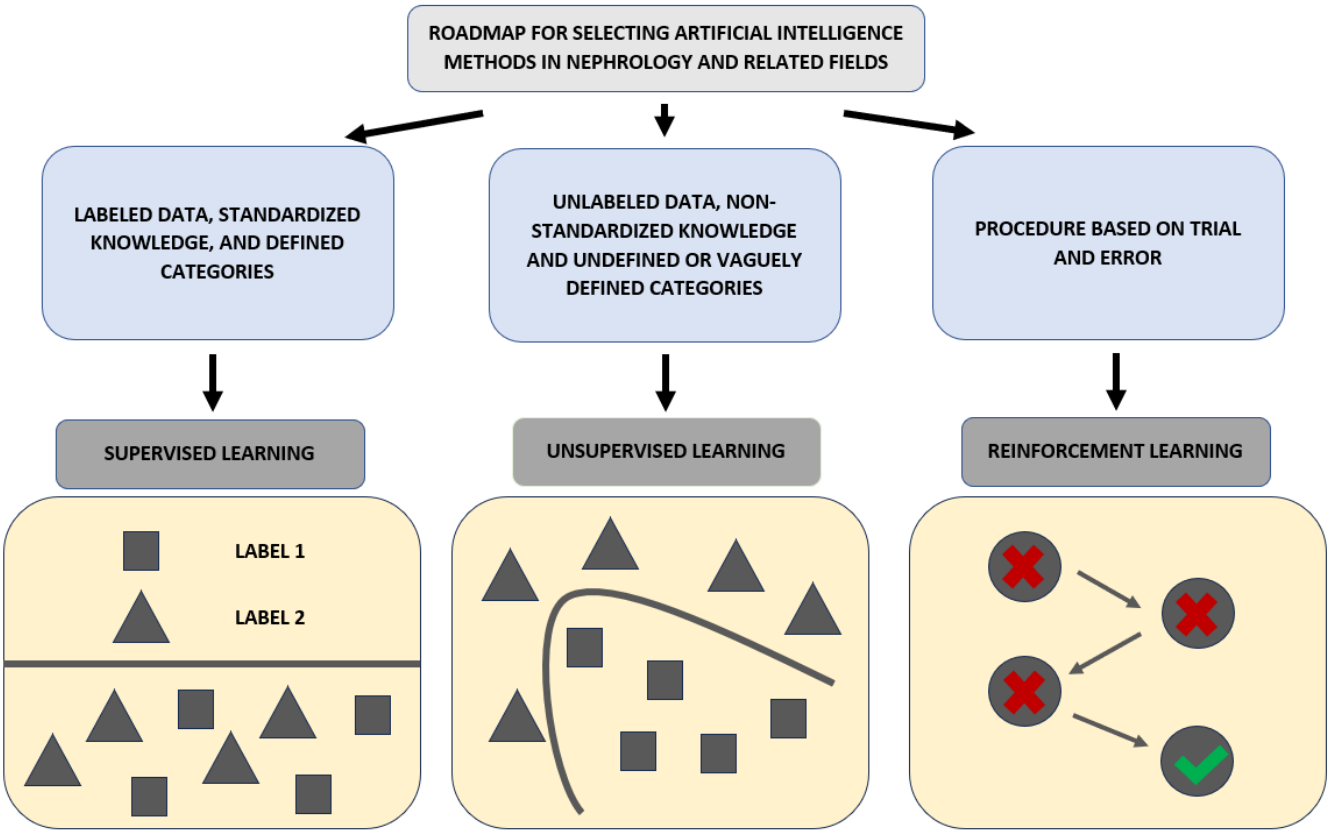

FIGURE 2. **Procedure for selecting an artificial intelligence-based system in nephrology.**

the need to further develop research in this area to better understand its specificity and potential implications.

Figure 2 shows the procedure for selecting an artificial intelligence-based system in nephrology. Typically, designers of such systems find themselves in three positions. They can use supervised learning for labeled data, standardized knowledge, and defined categories. However, another case is access to unlabeled data, non-standardized knowledge, and undefined or vaguely defined categories. Then unsupervised learning turns out to be a good solution. The third, not so common option is the trial and error method, which is associated with an approach based on, for example, reinforcement learning.

In recent years, the field of nephrology has witnessed a paradigm shift with the integration of modern algorithms and artificial intelligence into clinical practice. This transformative wave has ushered in a new era of personalized and efficient patient care, enabling healthcare professionals to harness the power of data-driven insights. In this section, we explore the current state of knowledge in the application of modern algorithms and AI technologies within the realm of nephrology.

Early Detection and Diagnosis: One of the primary areas where modern algorithms and AI have made significant strides is in the early detection and diagnosis of renal diseases. Machine learning models, fueled by vast datasets of patient information, can analyze complex patterns and identify subtle indicators that may elude human observation. This capability holds the potential to diagnose conditions such as chronic kidney disease (CKD) at an earlier stage, allowing for timely intervention and improved patient outcomes.

Predictive Modeling for Progression and Complications: Predicting the progression of renal diseases and anticipating potential complications is a critical aspect of nephrology. Advanced algorithms can analyze diverse patient factors, including laboratory results, genetic markers, and lifestyle data, to generate predictive models. These models help clinicians anticipate disease trajectories, enabling them to tailor treatment plans and interventions to individual patient needs.

A. GENERAL OUTLINE AND STATE OF THE ART REVIEW

The article [33] discusses the potential of AI to revolutionize healthcare, particularly in nephrology. It highlights the various benefits of AI, such as personalized medicine, early disease detection, and improved drug discovery. The economic aspects of using AI for predicting patient outcomes, readmission rates, and hospital stays are also emphasized. Despite these advancements, the article emphasizes that AI cannot replace the crucial patient-doctor relationship in healthcare. It underscores the need for considering risks and challenges associated with AI, advocating for education within the nephrology community to effectively integrate AI into daily practice. The article acknowledges that while AI won't replace nephrologists, those who use it effectively can enhance patient care. However, it emphasizes the necessity for a shift in traditional healthcare roles, coupled with ongoing training and education to ensure ethical and effective AI usage in clinical practice.

The work [34] stresses the importance of robust experimental design in preclinical studies for medical imaging analysis in nephropathology, emphasizing the need for representative data, proper validation, and comprehensive analysis. It highlights the potential bias without these elements. The concluding remarks discuss advances in photonics, the future role of AI in clinical diagnosis, and the necessity of integrating engineering and clinical domains for effective collaboration. The article concludes with a debate on the reliability of AI systems in clinical practice, suggesting a deep dive into real-world data, validation, analysis, reporting, and sharing to ensure trustworthy experimental designs and conclusions.

The authors of articles [35], [36], [37], [38] describe in turn the integration of artificial intelligence, deep learning, and digital health in nephrology. It emphasizes the importance of clinicians and scientists understanding the basics and terminology of these technologies. The American Society of Nephrology has established the Augmented Intelligence and Digital Health (AIDH) task force to guide kidney health in this era. The article introduces a series covering fundamental concepts like bias in clinical AI, deep learning, natural language processing, reinforcement learning, transformer models, and risk prediction. Subsequent articles focus on potential clinical applications of AI in nephrology, including its role in diagnosis, prognosis, treatment, subphenotyping for acute kidney injury (AKI), continuous kidney replacement therapy (KRT), maintenance dialysis, and nephrology research. The collection aims to provide a comprehensive understanding of both the fundamentals and practical applications of AI in nephrology, stressing the need for interdisciplinary collaboration and ethical considerations. The term "augmented intelligence" is favored over "artificial intelligence" to highlight its potential to enhance, rather than replace, healthcare providers' abilities.

Interesting and very important information is contained in work [39]. The scoping review discusses actionable guidelines and quality criteria for the development, evaluation, and implementation of Artificial Intelligence Prediction Models (AIPMs) in healthcare. The review identifies six phases in the AIPM cycle: data preparation, AIPM development, AIPM validation, software development, AIPM impact assessment, and AIPM implementation into daily healthcare practice. The provided framework offers practical recommendations for those involved in AIPM projects. The review acknowledges potential biases in data sources and language limitations, emphasizing the need for comprehensive quality assessment before widespread adoption of AIPMs in healthcare. The scoping review aims to serve as a foundation for a structured quality assessment framework, highlighting gaps in the existing literature that require further research and practical experience with AIPM implementation.

Another publication - [40], discusses the rapid evolution of clinical artificial intelligence in nephrology, highlighting its potential in predicting conditions such as AKI, CKD, renal cell carcinoma, and kidney allograft failure. Emphasis is placed on the transformative impact of deep learning transformer models, particularly in analyzing longitudinal electronic health record data. The advantages of transformers, such as enhanced computational efficiency and the ability to capture complex relationships in high-dimensional EHR data, are outlined. The article also addresses the societal and ethical implications of integrating AI frameworks into clinical practice, stressing the importance of establishing common vocabulary and guiding principles within the nephrology community for equitable outcomes. The key message is the need for awareness and engagement among clinical stakeholders to shape the positive evolution of AI models in nephrology.

The article [41] conducts a cross-sectional bibliometric analysis to assess the utilization of machine learning in kidney research compared to other organs. The article examines the prevalence and utilization of machine learning in medical research, specifically focusing on the kidney within the context of five organ systems. Findings reveal that machine learning-based articles related to the kidney constitute a small percentage (3.2%) of the total relevant articles compared to other organs, notably the brain. Furthermore, conventional statistical methods, such as the Cox proportional hazard model, are more commonly employed in kidney research. The study highlights a lower adoption of machine learning in organ-specific specialty journals compared to interdisciplinary journals. Additionally, the funding landscape indicates a lower number of applications proposing machine learning approaches in kidney-related study sections compared to those focused on neurology and neuropathology. The study concludes that there is a need to enhance awareness and adoption of machine learning in the kidney research community.

In the next set of articles ([1], [42]), the authors emphasize the increasing role of AI in medicine, specifically within nephrology. They explore fundamental AI and ML concepts, including neural networks and deep learning, and highlight their applications in clinical care, hemodialysis prescriptions, and transplant recipient follow-up. The articles discuss how AI can predict conditions like progressive immunoglobulin A nephropathy, foreseeing a transformative impact on clinical nephrology.

Article [43] focuses on the underutilization of machine learning as a research tool in nephrology, comparing it with other organ-specific research areas. The authors advocate for increased awareness and education within the nephrology community, emphasizing the potential advantages of AI research tools. They discuss the need for collaboration, the creation of large disease consortiums, and the importance of funding to advance machine learning research in nephrology. Article [44], in turn, provides a specific application of machine learning in predicting proteinuria classification in kidney transplant patients. By combining data related to blood glucose values and the use of immunosuppressive drugs, the study aims to enhance the prediction of proteinuria severity, showcasing the potential of ML in personalized medicine within nephrology. Another publication [45], explores the historical influence of technology on nephrology, emphasizing the recent impact of machine learning. It describes ML as a collection of computationally intensive statistical learning techniques and discusses its applications in predicting outcomes such as acute kidney injury, allograft loss, and specific histologic features in kidney biopsies. In [7] the scope has been expanded to include mathematical models in nephrology. It distinguishes between mechanistic dynamical systems, which represent causal relationships among variables, and AI/ML predictive tools, noting their respective strengths and weaknesses. The authors propose that the intersection of these seemingly antagonistic frameworks could provide better care in addressing chronic kidney disease and dialysis parameters. The publication [46] discusses challenges in nephrology, emphasizing the global unmet needs in chronic kidney disease. It explores the potential of leveraging big data and artificial intelligence to enhance kidney health care. The article reviews the applications of big data in nephrology research, focusing on population-based disease surveillance and air pollution-related studies. It highlights initiatives like the United States Renal Data System (USRDS) and China Kidney Disease Network (CK-NET). Overall, the publication emphasizes the role of big data and AI in addressing gaps in nephrology, improving disease surveillance, and understanding environmental factors affecting kidney health.

The chapter [47] explores the rapid growth of artificial intelligence in applied statistics, particularly in clinical applications. AI, a broad term, mimics intelligent behavior using computational models. Machine learning, a subset of AI, employs algorithms to identify patterns in datasets and generate inferences. The synergy of large biomedical datasets, statistical methodologies, and hardware advances offers significant opportunities for AI to impact patient care. Common ML/AI applications include decision support, early disease progression detection, patient subtyping, and image analysis in pathology/radiology, as well as genotype-to-phenotype analyses. Notably, neurology, cardiology, and pulmonology have surpassed nephrology in the adoption of ML techniques. The entire work [47] provides related, very valuable issues in the field of the use of artificial intelligence in medicine. The publication [48] discusses the pervasive role of artificial intelligence in various aspects of daily life and academic disciplines, including medicine. Rather than replacing clinicians, AI is seen as enhancing their intelligence in areas such as diagnosis, prognosis, and treatment decisions. Focusing on kidney disease, a significant global health burden, the article emphasizes the need for further research and applied works to improve prediction accuracy and understanding of histologic pathology. It highlights the importance of AI applications in diagnostics and prognostics, particularly in resource-inadequate areas, and stresses the necessity of collecting high-volume, high-quality data. Additionally, the publication calls for building a consensus on ethics and safety in the use of AI technologies in the medical field.

B. NATURAL PROCESSING LANGUAGE, ANALYSIS OF DESCRIPTIVE TEXTS, EXTRACTING KNOWLEDGE FROM MEDICAL TEXTS, AND RELATED ISSUES

The publication [49] discusses the use of Natural Language Processing (NLP) in nephrology research. It focuses on NLP's role in extracting patient symptoms from unstructured progress notes in electronic health records (EHR) and sentiment analysis during home hemodialysis sessions. The text also highlights NLP's contribution to improving risk prediction models for kidney disease progression and acute kidney injury. Examples include predicting chronic kidney disease progression using clinical documents and identifying AKI onset by analyzing both structured and unstructured data. Additionally, NLP is mentioned in predicting the probability of delay or discard for deceased kidney donors. The article concludes by noting the potential of NLP in nephrology education and acknowledges limitations such as physician bias and the need for external validation. Despite challenges, the article sees promising applications for NLP in nephrology. Issues related to NLP are also discussed by the authors of [50]. The study examines Natural Language Processing approaches in nephrology research, focusing on rule-based and machine learning models. Rule-based models are computationally simpler but require extensive programming effort, while ML-based systems automatically learn from data, offering deeper insights with sufficient information. The use of comprehensive medical terminologies enhances NLP in medicine, aiding in clustering patient data and identifying high-level concepts. The collaboration between medical experts and computer scientists is crucial for the success of NLP studies in nephrology. The interdisciplinary approach ensures clinically relevant and biologically plausible goals, mitigates biases, and addresses ethical considerations in applying ML to healthcare.

The work [51] provides a comprehensive survey of text classification in natural language processing from 1961 to 2021. It covers traditional and deep learning models, proposing a taxonomy based on text characteristics and models for feature extraction and classification. The review includes technical developments, benchmark datasets, and a thorough comparison of techniques and evaluation metrics. The conclusion summarizes key implications, outlines future research directions, and highlights challenges in the field of text classification.

Article [52] investigates the challenges and opportunities in applying NLP to extract clinical insights from Electronic Health Records (EHRs). The systematic review of 127 papers covers seven categories, including medical note classification, clinical entity recognition, text summarization, deep learning, transfer learning architecture, information extraction, medical language translation, and other NLP applications. The findings indicate a widespread use of unstructured EHR data, with common applications such as International Classification of Diseases, Ninth Revision (ICD-9) classification, clinical note analysis, and named entity recognition for psychiatric disorders. The study emphasizes the need for better evaluation of adopted ML models and addressing data imbalance issues. Future studies should focus on specific challenges in areas like Lupus Nephritis, Suicide Attempts, perinatal self-harm, and ICD-9 classification.

Review article [53] examines recent advancements in chatbot technology in the medical field, particularly focusing on cancer therapy. It covers the historical background, developmental progress, and design characteristics of chatbots. The study explores their applications in various aspects of cancer care, such as diagnosis, treatment, monitoring, patient support, workflow efficiency, and health promotion. Addressing concerns like ethical, moral, security, technical, and regulatory standards, the article emphasizes that while chatbots cannot replace human elements in healthcare, they can integrate into clinical practice to reduce costs, streamline workflows, and enhance patient outcomes. The potential applications in pandemic support, global health, and education are also discussed. The authors advocate for further research and interdisciplinary collaboration to advance chatbot technology and enhance the quality of patient care.

Pharmacovigilance, focusing on adverse drug event (ADE) detection, sees advancements in two articles. Article [54] explores natural language processing in analyzing electronic health record narratives since 2000, emphasizing statistical analysis and machine learning for enhanced ADE detection. Challenges include accurately characterizing ADE context and distinguishing recommended from off-label therapies. Article [55], in turn, proposes a unified neural network architecture for diverse natural language processing tasks, emphasizing versatility through learning from extensive unlabeled data. Both articles highlight engineering aspects and the potential of machine learning in improving ADE detection and processing of clinical narratives. Paper [56] explores the integration of ChatGPT, an advanced language model, in the field of nephrology. It highlights the rapid progress of artificial intelligence, particularly machine learning, and its potential applications in managing kidney diseases. The review discusses ChatGPT's role in dataset management, diagnostics, treatment planning, patient communication, education, and medical research in nephrology. It also addresses ethical and legal considerations associated with AI in medical practice. While emphasizing the promise of AI models like ChatGPT in healthcare innovation, the article underscores the need for thorough evaluation and validation before real-world implementation. This review serves as a valuable resource for nephrologists and healthcare professionals interested in leveraging AI for personalized nephrology care.

C. DEEP LEARNING IN NEPHROLOGY: PREDICTION, ESTIMATION, CLASSIFICATION, OPTIMIZATION, DECISION SUPPORTING, AND ANALYSIS

Authors of work [57] introduces reinforcement learning in the context of healthcare decision-making, using treatment prescription as an example. It explains fundamental concepts like Markov Decision Processes and reinforcement learning methods. Clinical applications are explored, with a focus on nephrology, including optimizing erythropoietin dosage and potential applications in treating complications of AKI or CKD. The article highlights challenges such as the complexity of human biology and ethical concerns, emphasizing the need for clinical validation and clinicians' oversight.

The work [58] includes the application of deep learning in medicine, focusing on its potential to analyze large biomedical datasets like electronic health records, -omics biobanks, clinical images, and wearable measurements. Deep learning, particularly neural networks, can automatically learn representations from raw data, allowing for the extraction of meaningful patterns. The article explores different types of neural networks, supervised and unsupervised learning methods, and their applications in medicine, including patient stratification and disease subtype identification. It addresses challenges such as data aggregation, deidentification, and model validation for clinical use. The article emphasizes the need for multidisciplinary collaboration and adherence to regulatory frameworks for successful integration of deep learning into healthcare practices.

The article [59] introduces a novel automated model, Hyperparameter Tuning Inception-v4 (HPTI-v4), for detecting and classifying Diabetic Retinopathy (DR) from color fundus images. DR is a major cause of global visual loss, particularly among individuals aged 25-74, impacting both health and economic systems. The proposed model enhances contrast using contrast limited adaptive histogram equalization (CLAHE) during preprocessing, followed by histogram-based segmentation. The HPTI-v4 model extracts features and employs a multilayer perceptron (MLP) for classification. Experiments on the MESSIDOR DR dataset demonstrate the superior performance of HPTI-v4 over other compared methods.

The articles [60], [61], [62], [63] focus on technical and engineering aspects within the context of diagnosing and predicting kidney-related disorders. The first article utilizes machine learning and survival analysis to develop a model for predicting long-term outcomes in Immunoglobulin A nephropathy (IgAN). The second introduces the innovative iBox risk prediction score for assessing the risk of kidney allograft loss, integrating eight prognostic factors from various medical domains. The third article introduces a nomogram based on preoperative data to predict acute kidney injury following cardiac surgery. The last article presents an early-risk score for predicting AKI in patients with acute decompensated heart failure, offering a simple and accurate risk assessment system. All articles underscore the role of advanced analytical and technological tools in diagnostics, risk stratification, and optimizing the management of patients with kidney-related diseases.

The articles [64], [65], [66], [67], [68], [69] collectively delve into the integration of advanced computational techniques, particularly machine learning and deep learning models, in the domain of renal medicine. Covering diverse aspects such as genetic polymorphisms' impact on tacrolimus bioavailability, continuous risk prediction for patient deterioration, artificial neural network models for end-stage kidney disease prognosis, convolutional neural networks for histopathologic assessment of kidney tissue, monitoring of arteriovenous access aneurysms through cloud-based deep learning, and predicting intradialytic hypotension using recurrent neural networks, these studies underscore the technical intricacies and engineering innovations in renal healthcare. The emphasis lies in leveraging sophisticated algorithms to enhance diagnostic accuracy, prognostic capabilities, and personalized treatment approaches, showcasing the significant role of technology in advancing the understanding and management of renal conditions.

The articles [70], [71], [72], [73], [74], [75] collectively delve into the realm of clinical prediction models, emphasizing their pivotal role in contemporary healthcare. The first two articles establish a foundational understanding of diagnostic and prognostic prediction models, highlighting the challenges and underscoring the importance of transparent reporting for assessing their quality. The third article focuses on the critical issue of sample size determination in model development, stressing the need for larger, representative datasets to enhance model robustness. Article four introduces an adaptive sample size calculation method, offering a dynamic approach to tailor sample sizes based on evolving model performance. The fifth and sixth articles extend the discourse to external validation, proposing methodologies to determine minimum sample sizes for robust evaluation of predictive performance, whether for binary or continuous outcomes. Collectively, these articles address technical aspects such as model development, validation, and sample size considerations, presenting valuable insights for advancing the precision and reliability of clinical prediction models in the complex landscape of healthcare decision-making.

The publication [76] presents a diagnostic program employing convolutional neural networks (CNNs) for the immunofluorescence (IF) diagnosis of common glomerular diseases, Immunoglobulin A nephropathy (IgAN) and idiopathic membranous nephropathy (IMN). The program includes modules for glomeruli detection, IF intensity comparison, and a dual-CNN (D-CNN) for deposition appearance and location classification. Trained on glomerular IF images, the program demonstrated high accuracy in recognizing deposition patterns, outperforming inexperienced nephropathologists. Its stable performance, even with images from different hospitals, underscores its potential as an effective diagnostic tool for IgAN and IMN. The study [77] addresses diagnostic challenges in membranous nephropathy (MN), a serious kidney condition. The research proposes a new approach using Raman spectra of serum and urine combined with deep learning for rapid and non-invasive diagnosis. Three models, ResNet, AlexNet, and GoogleNet, are employed, with data amplification using Gaussian white noise. Results show high accuracy in classifying patient serum data and strong discrimination in urine data. AlexNet emerges as the most effective model. This innovative use of Raman spectroscopy and deep learning suggests a promising method for swift and accurate membranous nephropathy identification. In [78] authors introduce MN-Net, a CNN-based method for efficient detection and classification of glomeruli in whole slide images (WSIs) related to membranous nephropathy. MN-Net, divided into glomerulus detection and weakly supervised classification networks, achieves high precision (99.66% for detection, 99.53% for MN glomeruli classification) using PASM-stained WSIs from multiple centers. The method is lauded for its speed, accuracy, robustness, and cost-effective data annotation. Additionally, the study suggests potential extensions to classify other glomerular diseases under a light microscope, with proposed improvements through glomerular basement membrane segmentation and measurement models for enhanced reliability. The study [79] develops a highly accurate non-invasive fluid biopsy-assisted diagnosis model for glomerular diseases using hyperspectral analysis of 65 urine samples. Significant spectral differences were identified, and an artificial intelligence model achieved a 96% accuracy in early diagnosis of four glomerular diseases. This non-invasive diagnostic method shows promise for clinical application.

Study [80] investigates the use of an artificial intelligence-based analytic renal pathology system (ARPS) in primary membranous nephropathy (PMN) patients. Examining biopsy-proven PMN cases, ARPS effectively identified and quantified glomerular lesions and intrinsic cell types. The system demonstrated high accuracy in lesion identification and showed significant correlations between intra-glomerular characteristics assessed by ARPS and PMN prognosis. Notably, the study suggests the potential of ARPS for predicting urinary protein remission based on renal phospholipase A2 receptor (PLA2R) and podocyte numbers. The publication [81] introduces a predictive model for evaluating the prognosis of idiopathic membranous nephropathy, a major cause of chronic kidney disease. Using data from 266 patients, statistical analyses and regression techniques were employed to create a nomogram featuring key variables. The nomogram exhibits strong predictive accuracy and calibration in training and validation sets. It concludes that the nomogram serves as a valuable tool for clinicians in early-stage prognosis assessment and treatment decision-making for IMN patients. Interesting and valuable research can be found in [82]. This study focuses on rituximab treatment challenges in membranous nephropathy, particularly the risk of underdosing due to urinary drug loss in nephrotic syndrome patients. A machine learning algorithm is developed, utilizing patient characteristics at rituximab infusion, to predict the risk of underdosing. The algorithm, incorporating variables like age, gender, body surface area, and biomarkers, shows high accuracy, sensitivity, and specificity in training and testing sets. Importantly, patients with a higher predicted risk of underdosing require higher cumulative rituximab doses and experience a longer time to remission. The algorithm has the potential to guide early intensification of rituximab regimens in high-risk patients, improving the chances of achieving remission. Study [83] tackles the diagnostic challenges of membranous nephropathy, a common cause of nephrotic syndrome in adults. The conventional method involves time-consuming manual observation of kidney biopsy samples, leading to variability in results among physicians. The proposed framework uses whole-slide images (WSIs) from a light microscope and immunofluorescence images for patient classification. It integrates glomerular segmentation, confidence coefficient extraction, and multi-modal fusion modules. The approach significantly improves diagnostic accuracy, achieving a higher F1-score of 97.32% compared to 92.76% and 93.20% when using only light-microscopy-observed images or immunofluorescent images, respectively. This study underscores the effectiveness of combining both imaging modalities in enhancing membranous nephropathy diagnosis.

Paper [84] addresses challenges in the diagnosis of primary membranous nephropathy, often reliant on invasive renal biopsy and subject to variability among experts. To enhance reliability, a belief rule-based system is developed, integrating knowledge from different experts. The system utilizes 9 biochemical indicators as input variables, constructing a belief rule base layer for diagnosis. In a study involving 134 patients, the proposed method demonstrates high sensitivity (98.0%), specificity (96.9%), accuracy (97.8%), and area under the curve (AUC) of 0.93. The results suggest a novel and effective approach for PMN diagnosis without the need for renal biopsy, showcasing the potential of the developed system in providing accurate diagnoses based on biochemical indicators. The publication [85] focuses on developing a predictive model for long-term renal function impairment following minimally invasive partial nephrectomy (PN). The study, conducted on 381 patients with a median follow-up of 69 months, utilized a machine-learning algorithm called Classification and Regression Tree (CART). Key risk factors identified for chronic kidney disease stage migration included the progression of CKD stage after surgery, Age-Adjusted Charlson Comorbidity Index (ACCI), and baseline CKD stage. The algorithm generated four clusters with varying rates of CKD progression, providing a comprehensive prediction tool. The model demonstrated a concordance index (c-index) of 0.75, showcasing its efficacy in predicting long-term renal function outcomes. The findings emphasize the importance of perioperative renal function loss in predicting functional recovery and suggest the model's potential utility in intensifying follow-up for patients at risk of renal function deterioration after PN.

D. ARTIFICIAL INTELLIGENCE, AND MACHINE LEARNING

The article [86] explores the application of artificial intelligence and machine learning in dialysis. It discusses the potential uses in diagnosis, prognosis, and treatment recommendations. Dialysis, with its standardized and extensive patient data, is ideal for AI/ML applications. The article highlights specific models for predicting intradialytic hypotension, classifying vascular access aneurysms, anemia control, and reducing hospitalization rates. Despite promising research, routine implementation faces challenges like data privacy, model complexity, and portability issues. The need for rigorous evaluation, addressing biases, and training the medical workforce is emphasized to enhance AI/ML integration in dialysis care.

The article [87] addresses the increasing use of machine learning models in biomedical research, emphasizing the need for proper application and transparent reporting. A multidisciplinary panel of experts developed guidelines through the Delphi method, aiming to ensure accurate usage and comprehensive reporting of machine learning models in clinical settings. The guidelines include specific reporting items for research articles and a practical sequence of steps for developing predictive models. The overall objective is to promote reliable assessments of model validity and facilitate consistent interpretation of model outputs, thereby enhancing the adoption of machine learning in biomedical research.

Another valuable article is [88]. It explores the potential applications of artificial intelligence and machine learning in the context of continuous kidney replacement therapy (CKRT) within healthcare. With a focus on enhancing critical care for patients with acute kidney injury, the authors discuss AI/ML applications in risk classification, CKRT initiation, dosing, anticoagulation management, subphenotyping, and quality assurance. They highlight the significance of multimodal data from electronic health records and CKRT machines, emphasizing the need for accurate data management and quality. The article also addresses considerations such as model evaluation, interpretation, algorithm bias, ethical concerns, and the importance of prospective validation for successful implementation in CKRT.

The work [89] analyzes the emerging role of artificial intelligence in nephrology, particularly in the context of acute kidney injury. It explores the applications of AI, such as risk prediction and detection of AKI, identification of AKI phenotypes, and its integration into the Kidney Precision Medicine Project (KPMP). The discussion emphasizes the need for rigorous evaluation, including controlled clinical trials, to determine the clinical utility and impact of AI tools on patient outcomes. The authors highlight the potential of AI to reshape AKI care, improve risk assessment, and guide therapeutic interventions. The Kidney Precision Medicine Project aims to redefine AKI by integrating molecular phenotypes and utilizing AI for data analysis. The article calls for cautious optimism, emphasizing the importance of unbiased development and thorough validation of AI tools in reshaping AKI research and clinical care.

The next work is [90]. The authors list the challenges in developing and evaluating risk prediction models in clinical practice, using a case study on estimating the 10-year risk of CKD in patients over 45. It covers key aspects like framing the problem, data quality, model forms (including machine learning), and performance measurement strategies. The case study emphasizes defining outcomes, identifying at-risk populations, considering time frames, and addressing ethical concerns.

Publication [91] explores the impact of recent advances in machine learning and artificial intelligence on nephrology, emphasizing the potential benefits and challenges. It discusses instances where AI-driven decisions may introduce biases and exacerbate disparities in healthcare. The types of biases, spanning from data collection to model interpretation, are outlined. The article suggests various methods, including algorithmic debiasing and nonalgorithmic bias mitigation, to recognize and address biases in clinical AI applications. It underscores the importance of transparency, education, and continuous monitoring in ensuring fair and equitable AI utilization in nephrology and medicine.

The articles [92], [93], [94], [95] explore the integration of advanced technologies, including machine learning and artificial intelligence, in nephrology. The first article employs ML to identify metabolomic signatures in pediatric CKD patients, associating them with specific conditions. The second article reviews AI applications in nephropathology, emphasizing its supportive role for nephropathologists. The third article evaluates the successful clinical implementation of an AI algorithm for total kidney volume in autosomal dominant polycystic kidney disease (ADPKD). The fourth article provides a comprehensive narrative review of AI's potential in various nephrology aspects, acknowledging validation challenges. Together, these articles highlight the transformative impact of ML and AI in reshaping nephrology research and diagnostics.

The articles [96], [97], [98], [99] collectively highlight the integration of machine learning techniques in the realm of renal healthcare. Addressing diverse aspects such as dialysis adequacy prediction, fluid management in acute kidney injury, and optimization of dosing regimens for transplant patients, these studies showcase the versatile applications of machine learning. The emphasis is on leveraging advanced algorithms, including random forest, extreme gradient boosting, and others, to enhance diagnostics, prognostics, and personalized treatment strategies in kidney-related disorders. The overarching theme underscores the significant technical advancements and engineering aspects contributing to improved patient care and outcomes in the field of nephrology. Authors of [100] challenge in tacrolimus dosing for patients with kidney diseases by employing machine learning technology to predict tacrolimus blood concentration. Data from 913 hospitalized patients treated with tacrolimus were collected and utilized to construct six machine learning models. The XGBoost model demonstrated superior predictive performance, achieving an accuracy of 73.33%, F-beta of 91.24%, and AUC of 0.5531. While highlighting the potential of machine learning in predicting tacrolimus levels, the study acknowledges the need for further research to address model biases and enhance real-world applicability.

Authors of [101] introduce a fuzzy logic-based expert system for diagnosing and predicting chronic kidney disease. Parameters and risk factors were identified through literature review and nephrologist input, leading to fuzzy rules development using MATLAB and Mamdani Inference System. The system demonstrated high accuracy (92.13%), sensitivity (95.37%), and specificity (88.88%) on a dataset of 216 medical records. Notably, it exhibited robustness against noisy data, with minimal decreases in performance. The results suggest the system's potential utility in clinical settings for early CKD diagnosis and prediction.

Articles [102], [103], [104], [105], [106], [107], [108], [109], [110] revolve around the application of advanced technologies, particularly machine learning and artificial intelligence, in the domain of kidney diseases. The technical focus spans from investigating the seasonality of Acute Kidney Injury hospitalizations in England to the development and validation of machine-learned prognostic risk scores for diabetic kidney disease (DKD). Additionally, the articles delve into the early prediction of mortality in intensive care unit (ICU) patients with AKI, the use of machine learning algorithms to predict the histology type of primary nephrotic syndrome without the need for biopsy, and the identification of potential biomarkers for MN.

In the first article, the researchers employ unsupervised machine learning techniques, such as multiple correspondence analysis and k-means clustering, to analyze the seasonality of AKI hospitalizations and classify patients into distinct phenotypes based on underlying comorbidities. The second article focuses on the use of various machine learning approaches to provide early diagnoses of Chronic Kidney Disease. The study employs predictive modeling and evaluates different classifiers, highlighting the potential of recent advancements in machine learning for accurate prediction in the field of kidney disease. Next article emphasizes the role of machine learning algorithms in predicting CKD infection. Nine distinct machine learning algorithms are employed, and their performance is evaluated using multiple metrics, including F1-score, precision, accuracy, recall, and runtime. In the fourth article, in turn, a machine-learned prognostic risk score, KidneyIntelX™, is developed and validated using electronic health records and biomarkers for patients with diabetic kidney disease. The study demonstrates improved prediction of kidney outcomes compared to existing clinical models. Subsequently, the fifth article provides a brief overview of CKD, highlighting its impact on kidney function and the potential consequences, such as kidney failure. However, the article appears to be incomplete and lacks specific technical details. In the sixth article, the researchers use explainable artificial intelligence (XAI) approaches to develop an algorithm for the early prediction of mortality in ICU patients with AKI. The study employs machine learning methods, including eXtreme Gradient Boosting (XGBoost), and interprets the model using SHapley Additive exPlanation (SHAP) values and Local Interpretable Model-Agnostic Explanations (LIME) algorithm. Then, in the seventh article explores the possibility of predicting the histology type of primary nephrotic syndrome without renal biopsy using machine learning. The study trains and validates a machine learning algorithm on biopsy-confirmed data and tests it prospectively on another sample, achieving an overall accuracy of prediction. The eighth article focuses on bioinformatics analysis to explore potential biomarkers of MN. Differential expression analysis, weighted gene co-expression network analysis (WGCNA), and machine learning algorithms are employed to identify hub genes associated with MN. Next article investigates the risk factors associated with coronary heart disease in patients with idiopathic membranous nephropathy. The study utilizes statistical methods, such as the Mann-Whitney U test and LASSO regression, to screen factors and develop an effective clinical prediction model.

The articles [111], [112], [113], [114], [115] collectively explore the application of machine learning techniques for the early detection and diagnosis of Chronic Kidney Disease. Emphasizing the critical need for timely identification due to CKD's impact on mortality rates, the studies employ a variety of machine learning algorithms, including Support Vector Machine (SVM), AdaBoost (AB), Linear Discriminant Analysis (LDA), Gradient Boosting (GB), and ensemble methods. These articles showcase the potential of machine learning in healthcare, particularly in predicting kidney diseases. They highlight the importance of accurate and early diagnosis, given the asymptomatic nature of CKD. Various algorithms are evaluated, and ensemble methods prove to enhance predictive accuracy. The research collectively underscores the transformative role of machine learning in advancing the field of nephrology, offering promising outcomes for healthcare practitioners and contributing to improved patient care and outcomes in the context of Chronic Kidney Disease.

The Table 3 included in the Appendix is a detailed summary of the research achieved in the articles described in the III-C and III-D subsections.

E. ETHICS, GUIDELINES AND RECOMMENDATIONS

Articles [116], [117], [118], [119] collectively explore the multifaceted intersection of artificial intelligence, machine learning, and clinical research. They address the increasing use of ML in clinical settings for predictive performance and identifying specific patient subpopulations. The challenge of transparent reporting to facilitate communication between ML experts and clinical practitioners is emphasized. Ethical considerations, including the distinctions between robot ethics, machine ethics, and computational ethics, are discussed in the second article, highlighting the importance of the latter in ethical AI development. The third article introduces CONSORT-AI, extending reporting guidelines for clinical trials involving AI interventions to enhance transparency. The fourth article proposes the Checklist for AI in Medical Imaging (CLAIM) to ensure rigorous validation and reproducibility of AI applications in medical imaging, emphasizing detailed reporting for quality assessment. Together, these contributions provide a comprehensive guide for navigating the technical and ethical complexities of integrating AI and ML into clinical research.

Articles [16], [120], [121], [122], in turn, describe the application of artificial intelligence in nephrology, addressing various aspects from diagnostic and prognostic capabilities to ethical considerations. The first article emphasizes the potential of AI-enabled decision support systems in predicting kidney pathophysiology, offering insights into acute kidney injury, chronic kidney disease, and renal tumors. It stresses the need for multidisciplinary commitment to ensure fair algorithms and a competent AI workforce. The second article delves into the growing role of artificial intelligence, focusing on the ChatGPT AI chatbot in nephrology. It explores concerns about AI-generated abstracts resembling human-authored ones and emphasizes the need for a balanced examination of AI's pros and cons in healthcare. Findings from a 2023 paper highlight challenges in peer-reviewing ChatGPT-generated abstracts, underscoring the importance of establishing guidelines for AI use in medical disciplines. The perspective provides examples of ChatGPT's benefits in pediatric nephrology, showcasing its potential applications in answering medical queries. Overall, the article offers insights into the evolving landscape of AI integration in nephrology, acknowledging both promises and challenges while emphasizing the need for thoughtful implementation. The next article critically examines the ethical implications of integrating chatbots into nephrology, addressing concerns related to privacy, data security, bias mitigation, and the preservation of the doctor-patient relationship. The fourth article discusses the digitalization of nephrology, emphasizing the current state of AI/machine learning applications, ethical and regulatory challenges, and proposing an ethics and governance framework for their broader clinical application. Overall, these articles showcase the technical advancements, ethical considerations, and challenges in leveraging AI for improved diagnosis, treatment, and patient outcomes in nephrology.

F. THE IMPACT OF ARTIFICIAL INTELLIGENCE ON PROGRESS IN OTHER FIELDS

Artificial intelligence has widespread applications across various domains, including but not limited to biomedicine, robotics, data analysis, classification, industry, control systems, and automation [123], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138]. In biomedicine, AI is utilized for tasks such as medical image analysis, disease diagnosis, and drug discovery. In robotics, AI algorithms enhance the capabilities of robots, enabling them to perform complex tasks and adapt to dynamic environments. In data analysis and classification, AI algorithms excel in extracting patterns, trends, and insights from large datasets, facilitating informed decision-making. Moreover, AI plays a crucial role in industrial settings by optimizing processes, predictive maintenance, and quality control. In the realm of control systems, AI is employed for advanced control strategies, making systems more adaptive and efficient. Automation benefits from AI-driven technologies, leading to increased productivity and efficiency across various industries. Overall, the versatile applications of artificial intelligence contribute significantly to advancing and transforming diverse fields.

IV. DISCUSSION OF AN OVERVIEW OF RELATED WORKS

The subsection summarizes the information contained in this chapter, focusing on applications of artificial intelligence in nephrology and medicine. Key technologies include machine learning, deep learning, neural networks, expert systems, fuzzy logic, natural language processing, predictive analytics, feature engineering, data mining and classification. These tools support diagnosis, treatment and patient care by analyzing data, automating processes and providing decision support for a variety of medical tasks (Fig. 3).

Figure 4 presents the types of data that can be analyzed by AI in nephrology today. It also has a certain impact on the mutual development of research and science.

In nephrology, artificial intelligence is revolutionizing the approach to diagnosis, treatment and monitoring of kidney diseases by analyzing a variety of data. AI can efficiently process clinical data such as medical history, patient symptoms and physical examination results. In addition, laboratory data such as blood and urine test results are analyzed, allowing kidney problems to be identified more quickly.

Medical imaging, including imaging test results and histological images from kidney biopsies, are also being analyzed by AI to support more accurate diagnosis. Genetic data analysis allows us to identify genes associated with kidney diseases and assess the risk of their occurrence. Monitoring blood pressure with AI allows for a better understanding of the impact of blood pressure on kidney function.

Medical information systems and data from patient monitoring devices are integrated, enabling comprehensive analysis of the patient's history and current health parameters. Artificial intelligence can also use data from scientific research and medical literature to update and improve its algorithms.

As a result, AI makes it possible to identify patterns, predict outcomes, support diagnosis, optimize treatment plans, and monitor progress and response to therapy. This significantly improves the effectiveness of care for patients with kidney diseases, accelerating the diagnostic process and increasing the chances of effective treatment.

Most clinical data, particularly in the field of nephrology, is imbalanced in terms of the number of cases across different disease categories or patient conditions. For instance, cases of kidney diseases may constitute only a small percentage of overall medical data. In such situations, machine learning algorithms, especially those based on supervised learning, may tend to favor larger classes, leading to suboptimal outcomes for less frequent classes that are equally clinically significant.

In response to this issue, researchers in the presented papers use appropriate data pre-processing techniques that can help optimize data quality before using them in machine learning algorithms. Examples of such techniques include:

- **Data screening:** Identifying and eliminating outliers and incorrect data to remove undesired distortions.
- **Data balancing:** Applying techniques such as oversampling of smaller classes or undersampling of larger classes to balance the distribution of different data categories.
- **Normalization and standardization:** Transforming data to ensure consistency and facilitate comparisons between them.
- **Feature selection:** Choosing significant data features that have the most impact on the decision-making process, while eliminating unnecessary or less important features.

The next part of the article will examine future paths of transformation and development of systems in the discussed field.

V. POSSIBLE FUTURE PATHS OF DEVELOPMENT OF AUTOMATIC DECISION SUPPORT SYSTEMS FOR NEPHROLOGISTS

As the field of nephrology advances, the integration of automatic decision support systems powered by artificial intelligence holds immense promise for revolutionizing patient care. AI technologies, including machine learning algorithms, are poised to play a pivotal role in enhancing the diagnostic precision, prognostic capabilities, and

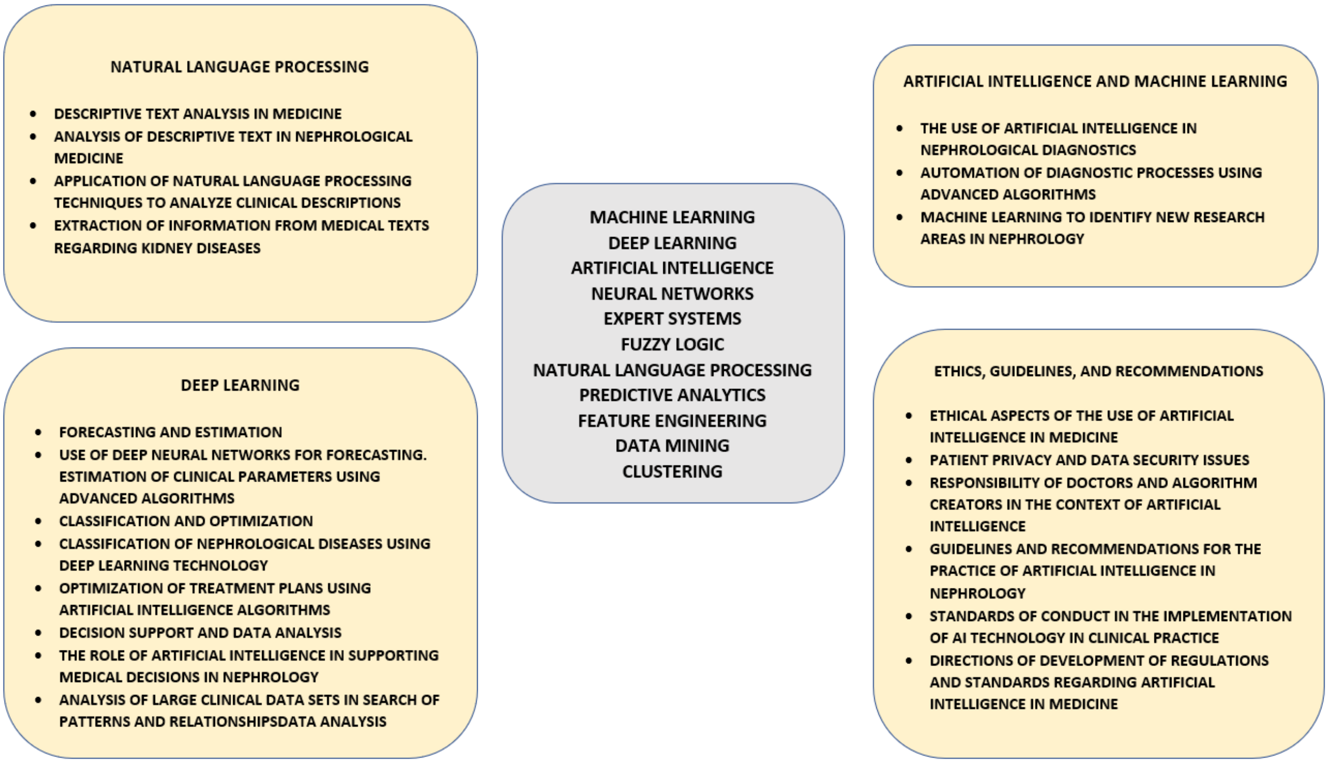

FIGURE 3. Artificial intelligence-based tools used in nephrology and medicine.

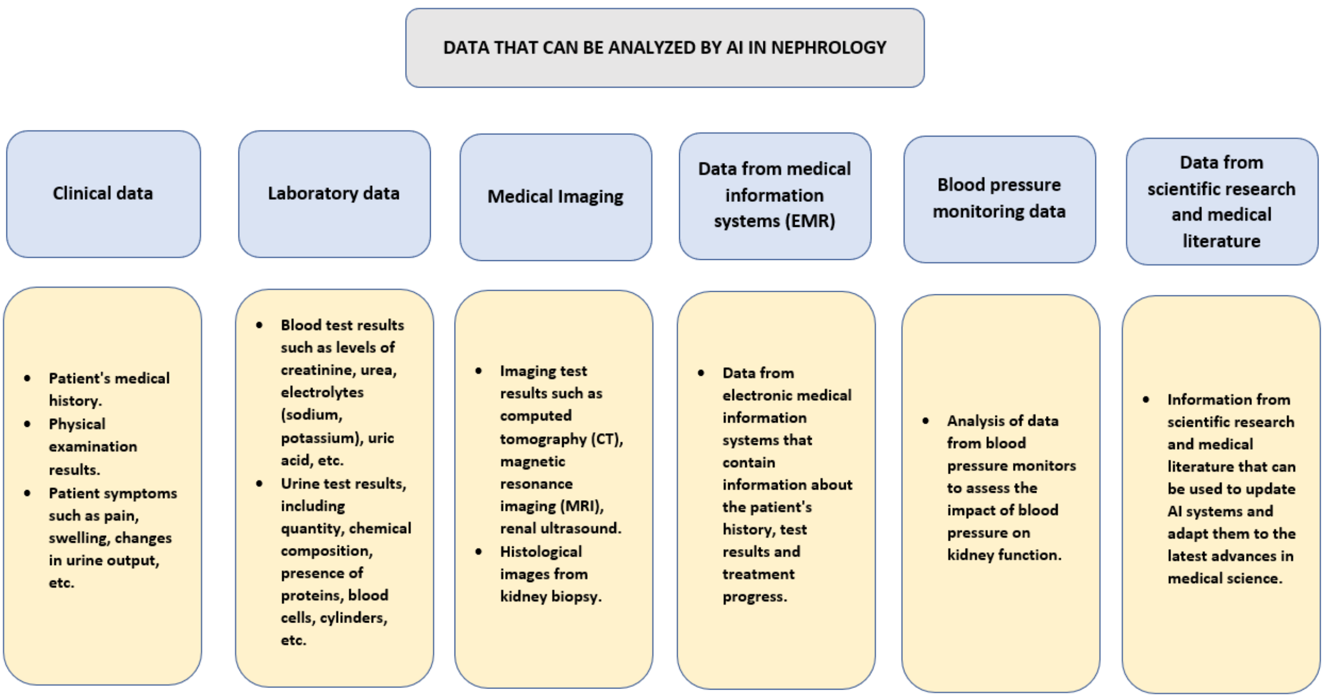

FIGURE 4. Types of data that can be analyzed by AI in nephrology.

overall decision-making processes in nephrology. This section explores the potential future paths of development for these automatic decision support systems, envisioning innovative avenues that could significantly impact the landscape

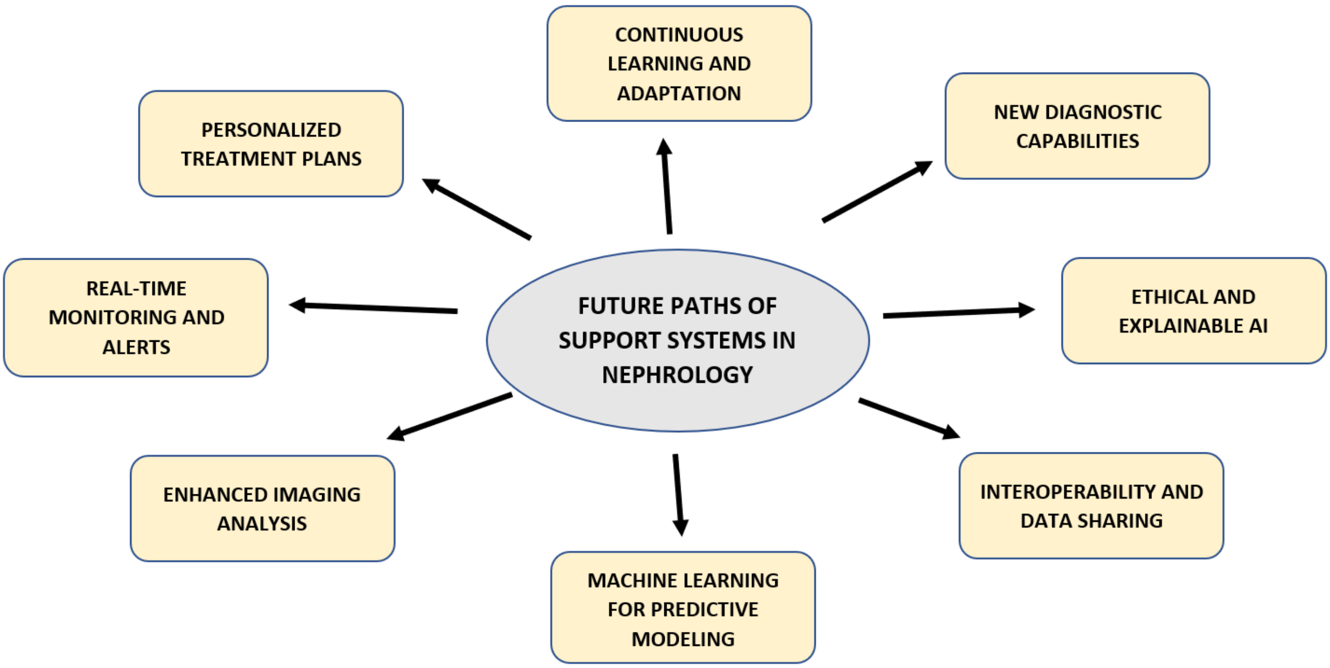

FIGURE 5. **Possible future paths of development of automatic decision support systems in nephrology.**

of nephrological practice. For this purpose, knowledge from the literature review presented in the previous section was used.

Figure 5 presents an overview of possible future paths of development of automatic decision support systems for nephrologists. This idea will be developed later in the chapter.

The intersection of burgeoning computing capabilities, refined algorithms, and the exponential growth of health data sets the stage for transformative applications in nephrology. The evolving role of AI is not intended to replace the expertise of nephrologists but rather to complement and amplify their capabilities. In the quest for more accurate predictions, personalized treatment strategies, and ethical deployment of these technologies, the future paths outlined herein aim to address the evolving needs of nephrology in the coming years. Here are some possible future paths of development:

- **Personalized Treatment Plans**: Future systems may leverage advanced algorithms to analyze a patient's genetic profile, lifestyle factors, and individual preferences. This personalized approach could lead to the development of tailored treatment plans, optimizing therapeutic interventions for better outcomes. Integration with electronic health records (EHRs) and continuous learning mechanisms would ensure that treatment recommendations evolve based on the patient's ongoing health status.
- **Real-time Monitoring and Alerts**: Future systems might incorporate real-time monitoring of vital signs, biomarkers, and other relevant parameters. Automated alerts could notify nephrologists of sudden changes or critical events, enabling timely interventions. Continuous monitoring could be particularly beneficial for patients with chronic kidney diseases, allowing for proactive management to prevent acute exacerbations.
- **Enhanced Imaging Analysis**: Advancements in imaging analysis may include the development of AI algorithms for more accurate interpretation of radiological and pathological images. Automated recognition of subtle changes or early signs of pathology could assist in early diagnosis and treatment planning. Integration with three-dimensional imaging and virtual reality technologies could enhance the visualization of complex renal structures.
- **Machine Learning for Predictive Modeling**: Machine learning algorithms could evolve to predict disease progression, treatment responses, and potential complications. Predictive models may incorporate a wide range of clinical, laboratory, and imaging data to provide nephrologists with insights into long-term patient outcomes. These models could be continuously updated with new data, improving their accuracy and reliability over time.
- **Interoperability and Data Sharing**: Efforts may focus on improving interoperability standards to facilitate seamless data sharing between healthcare systems and institutions. Access to a broader range of patient data could enhance decision support systems' capabilities, especially in cases where patients receive care from multiple providers. Secure data exchange protocols and standardized formats could ensure privacy and compliance with regulatory requirements.
- **Ethical and Explainable AI**: With the increasing complexity of AI algorithms, there will likely be a heightened emphasis on ethical considerations and

explainability. Transparent and interpretable AI models could provide clear justifications for their recommendations, addressing concerns related to trust and accountability. Ethical guidelines and frameworks may be developed to guide the responsible use of AI in nephrology practice.

- **Continuous Learning and Adaptation**: Decision support systems could adopt continuous learning mechanisms, adapting their algorithms based on real-world outcomes and feedback from clinicians. Integration with ongoing medical research and clinical trials could ensure that the systems stay abreast of the latest advancements in nephrology. Regular updates and maintenance protocols would be essential to prevent obsolescence and maintain the relevance of decision support tools. In conclusion, the envisioned future of automatic decision support systems in nephrology encompasses a spectrum of advancements, from personalized medicine to cutting-edge technologies. These developments aim to enhance the capabilities of nephrologists, improve patient outcomes, and contribute to the ongoing evolution of nephrology as a medical discipline.
- **New Diagnostic Capabilities**: The future holds the promise of novel diagnostic capabilities, with AI-driven systems enhancing the speed and accuracy of disease detection. Advanced algorithms may enable the identification of subtle biomarkers and patterns in diverse datasets, contributing to early and more precise diagnoses. Integration of AI in diagnostic processes could usher in a new era of comprehensive and efficient diagnostic approaches in nephrology.

Based on the literature and the future paths outlined for improving AI-enabled decision support systems in nephrology, several strategies can be proposed to address key challenges and enhance functionality:

- **Standardized Interoperability Protocols**: Implementing standardized data formats and interoperability protocols across healthcare systems is crucial. This involves developing common frameworks for data exchange, ensuring compatibility between different electronic health record (EHR) systems, and establishing secure protocols for data sharing.
- **Cloud-Based Solutions**: Leveraging cloud computing can facilitate seamless data sharing and collaboration among medical centers. Cloud platforms provide scalable storage and computing resources, enabling efficient data integration and analysis across diverse healthcare settings.
- **Privacy-Preserving Technologies**: Adopting privacy-preserving techniques such as federated learning and differential privacy can mitigate concerns about patient data confidentiality. These methods allow AI models to be trained on distributed data sources without directly accessing sensitive information.
- **Ethical Guidelines and Governance**: Establishing clear ethical guidelines and governance frameworks specific to AI applications in nephrology is essential. This includes ensuring transparency in AI algorithms, promoting patient consent and data anonymization, and addressing biases in AI-driven decision support systems.
- **Collaborative Research Networks**: Encouraging collaboration among researchers, clinicians, and data scientists through networks and consortia can facilitate data sharing while adhering to ethical standards. These networks can foster interdisciplinary approaches to solving complex problems in nephrology.
- **Data Harmonization and Quality Assurance**: Developing methods for harmonizing heterogeneous datasets and ensuring data quality is vital for enhancing the reliability and generalizability of AI models. This involves standardizing data collection methods, addressing missing data issues, and implementing quality assurance measures.
- **Patient-Centric Data Access**: Empowering patients with control over their health data through consent mechanisms and patient portals can enhance data access for research and AI development while respecting individual privacy preferences.
- **Continuous Education and Awareness**: Promoting education and awareness among healthcare professionals about the benefits and challenges of AI-enabled decision support systems is crucial. This includes training on data privacy, AI ethics, and the responsible use of AI in clinical practice.
- **Regulatory Compliance and Certification**: Ensuring compliance with regulatory requirements such as HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation) is essential for building trust and promoting widespread adoption of AI technologies in nephrology.

By implementing these strategies, researchers and practitioners can work towards overcoming the challenges associated with data interoperability, privacy, and ethics while maximizing the potential of AI-enabled decision support systems to improve patient care in nephrology.

The last section will summarize the papers review and draw appropriate conclusions.

VI. CONCLUSION AND POLICY IMPLICATIONS

In summary, the combination of numerical algorithms, artificial intelligence and expert approaches in the field of nephrology represents a promising frontier with significant potential to improve patient care and revolutionize research methodologies. Through comprehensive analysis, this work has shed light on various aspects of this integration.

Numerical algorithms play a key role in the precise assessment of kidney function. Their use allows for a more detailed understanding of kidney parameters, which allows for better diagnosis and treatment planning. Reliance on numerical algorithms provides the basis for objective, data-driven decision-making, thereby improving the overall effectiveness and reliability of nephrology assessments. The

TABLE 3. Literature on disease prediction using data analysis and image recognition.

Article	Type	Disease or field
[57]	Data Analysis	Clinical Applications
[58]	Data Analysis	Medicine
[59]	Image Recognition	Diabetic Retinopathy Fundus Image Classification
[60]	Data Analysis	IgA Nephropathy
[61]	Data Analysis	Kidney Transplants
[62]	Data Analysis	Acute Kidney Injury Following Cardiac Surgery
[63]	Data Analysis	Acute Kidney Injury in Patients with Acute Decompensated Heart Failure
[64]	Data Analysis	Bioavailability of Tacrolimus in Patients with Renal Transplantation
[65]	Data Analysis	Future Acute Kidney Injury
[66]	Data Analysis	End-Stage Kidney Disease in Patients with Immunoglobulin A Nephropathy
[67]	Image Recognition	Histopathologic Assessment of Kidney Tissue
[68]	Image Recognition	Arteriovenous Access Aneurysms in Hemodialysis Patients
[69]	Data Analysis	Intradialytic Hypotension
[70]	Data Analysis	Diagnosis vs. Prognosis
[71]	Data Analysis	Transparent Reporting of Multivariable Prediction Models
[72]	Data Analysis	Sample Size Calculation for Prediction Models
[73]	Data Analysis	Adaptive Sample Size Determination
[74]	Data Analysis	Minimum Sample Size for External Validation (Binary Outcome)
[75]	Data Analysis	Minimum Sample Size for External Validation (Continuous Outcome)
[76]	Image Recognition	Diagnostic Screening Program for Immunofluorescence Images
[77]	Image Recognition	Rapid Diagnosis of Membranous Nephropathy
[78]	Image Recognition	Glomeruli Classification with Membranous Nephropathy
[79]	Data Analysis	Non-Invasive Diagnosis Model for Common Glomerular Diseases
[80]	Image Recognition	Analytic Renal Pathology System in Membranous Nephropathy
[81]	Data Analysis	Probability of Remission in Patients with Membranous Nephropathy
[82]	Data Analysis	Rituximab Therapy Optimization in Membranous Nephropathy
[83]	Image Recognition	Kidney Pathological Image Classification
[84]	Image Recognition	Computer-Aided Diagnosis of Primary Membranous Nephropathy
[85]	Data Analysis	Predict Long-Term Renal Function Impairment
[86]	Data Analysis	Dialysis with AI and Machine Learning
[87]	Data Analysis	Guidelines for Developing and Reporting ML Predictive Models
[88]	Data Analysis	Continuous Kidney Replacement Therapy
[90]	Data Analysis	Risk Prediction and Machine Learning
[91]	Data Analysis	Bias in Artificial Intelligence
[92]	Data Analysis	Metabolomic Signatures of Pediatric CKD Etiology
[93]	Data Analysis	Machine Learning in Nephropathology
[94]	Data Analysis	AI Algorithm for Total Kidney Volume Measurement
[95]	Data Analysis	Artificial Intelligence in Glomerular Diseases
[96]	Data Analysis	Machine Learning in Medicine
[97]	Data Analysis	Dialysis Adequacy Predictions
[98]	Data Analysis	Volume Responsiveness in AKI Patients
[99]	Data Analysis	Therapeutic Effect and Adverse Events Prediction
[100]	Data Analysis	Tacrolimus Blood Concentration Prediction
[101]	Data Analysis	Predict Chronic Kidney Disease
[102]	Data Analysis	Seasonality of AKI Phenotypes
[103]	Data Analysis	Chronic Kidney Disease Prediction
[104]	Data Analysis	Chronic Kidney Disease Classification
[105]	Data Analysis	Risk Score for Diabetic Kidney Disease Progression
[106]	Data Analysis	Chronic Renal Disease Prediction
[107]	Data Analysis	Prognosis in Acute Kidney Injury
[108]	Data Analysis	Pathologic Type Prediction of Primary Nephrotic Syndrome
[109]	Data Analysis	Hub Genes Identification in Membranous Nephropathy
[110]	Data Analysis	Risk Factors and Prediction of Atherosclerosis Complications in Membranous Nephropathy
[111]	Data Analysis	Chronic Kidney Disease Prediction
[112]	Data Analysis	Chronic Kidney Disease Prediction and Comparison
[113]	Data Analysis	Prediction of Chronic Kidney Disease
[114]	Data Analysis	Prediction of Chronic Kidney Disease
[115]	Data Analysis	Prediction of Chronic Kidney Disease

transformative impact of artificial intelligence, particularly in the areas of machine learning and deep learning, is evident in the progress made towards early disease detection and personalized treatment plans. AI applications not only improve the diagnostic process, but also provide healthcare professionals with predictive information, potentially improving patient outcomes and resource utilization.

Furthermore, the synergy between computer tools and an expert-based approach is of great importance. While automation increases the efficiency of routine tasks and data analysis, the knowledge of nephrologists remains irreplaceable. The common nature of these approaches increases the precision and reliability of diagnoses, emphasizing the importance of a balanced integration strategy. However, integrating automation in nephrology is not without challenges. Ethical considerations, data privacy and the need for continuous validation of algorithms pose significant obstacles. Addressing these concerns is essential to ensure responsible and ethical implementation and to strengthen trust in the healthcare community and among patients.

The completeness of biomedical knowledge bases poses a significant challenge for the effective automation of decision-making processes in nephrology. There are biomedical terms and concepts that are not currently included in computer-interpretable terminologies, leading to issues with data mapping and result interpretation. To address this, systematic supplementation and updating of biomedical knowledge bases are necessary to enable the full utilization of the potential of automatic decision support systems in clinical practice.

Additionally, initiatives such as SMART on FHIR for API standards and Clinical Decision Support (CDS) for assisting clinician decision-making processes play a pivotal role in improving care efficiency and clinical outcomes. The importance of consistency in coding standards, such as Logical Observation Identifiers Names and Codes (LOINC), and terminological standards cannot be overstated, as they ensure a uniform representation of data and facilitate result interpretation.

In the face of growing healthcare data volumes and the dynamic advancement of artificial intelligence-based applications, there is an urgent need for unified standards that enable efficient data exchange and interpretation. By embracing a coherent approach to interoperability standards, we will not only streamline data flow in healthcare but also open doors to innovative solutions that contribute to enhancing patient care, not only in nephrology.

Two key limitations in the integration of numerical algorithms, artificial intelligence, and expert approaches in nephrology include the challenge of incomplete biomedical knowledge bases hindering effective automation of decision-making processes, and the necessity for unified standards to facilitate efficient data exchange and interpretation, especially in the face of growing healthcare data volumes and dynamic advancements in AI-based applications.

In terms of policy implications, our findings advocate for the development of regulatory frameworks to govern the ethical use of AI in nephrology. Policymakers can leverage our insights to allocate resources effectively, investing in training programs to enhance healthcare professionals' proficiency in AI-driven technologies. Moreover, comparative effectiveness research is crucial to evaluate the performance of AI-driven interventions against standard care practices, guiding future healthcare policies. It is also necessary to take into account the fact that the mere study of modern algorithms without their clinical implementation means that there is no interference with the human being as an individual. It is crucial that the data being analyzed is anonymized.

This article also lays the foundations for further research by both the authors and other scientists. As part of open problems and further work, the authors aim to create an automated expert system to support nephrologists' decisions. These studies will result in further publications and detailed descriptions of the results, which will include, among others, the prediction of laboratory test results. In addition, the software is intended to help diagnose and treat diseases such as membranous and diabetic nephropathy, chronic kidney disease, and acute kidney disease. These and other studies, after appropriate tests, may have clinical applications and thus change current approaches.

Essentially, the analysis presented in this article demonstrates the potential of numerical algorithms, artificial intelligence, and expert approaches to change the landscape of nephrology. By leveraging these innovative tools, the field can make strides toward more accurate diagnoses, personalized treatment strategies, and ultimately better patient outcomes. As these considerations continue, it is critical to remain vigilant, consider ethical issues, and refine methodologies to unlock the full potential of automation and decision support in nephrology.

APPENDIX

See Table 3.

REFERENCES

[1] O. Niel and P. Bastard, "Artificial intelligence in nephrology: Core concepts, clinical applications, and perspectives," *Amer. J. Kidney Diseases*, vol. 74, no. 6, pp. 803–810, Dec. 2019.

[2] S. Copur, C. Tanriover, F. Yavuz, M. J. Soler, A. Ortiz, A. Covic, and M. Kanbay, "Novel strategies in nephrology: What to expect from the future?" *Clin. Kidney J.*, vol. 16, no. 2, pp. 230–244, Feb. 2023.

[3] M. H. Rosner and J. S. Berns, "Transforming nephrology," *Clin. J. Amer. Soc. Nephrol.*, vol. 13, no. 2, pp. 331–334, 2018.

[4] J. Himmelfarb, R. Vanholder, R. Mehrotra, and M. Tonelli, "The current and future landscape of dialysis," *Nature Rev. Nephrol.*, vol. 16, no. 10, pp. 573–585, Oct. 2020.

[5] C.-C. Wu, M. M. Islam, T. N. Poly, and Y.-C. Weng, "Artificial intelligence in kidney disease: A comprehensive study and directions for future research," *Diagnostics*, vol. 14, no. 4, p. 397, Feb. 2024.

[6] A. Ali, "Insights into futuristic renal medicine," *Saudi J. Kidney Diseases Transplantation*, vol. 32, no. 4, pp. 901–916, 2021.

[7] P. P. Galuzio and A. Cherif, "Recent advances and future perspectives in the use of machine learning and mathematical models in nephrology," *Adv. Chronic Kidney Disease*, vol. 29, no. 5, pp. 472–479, Sep. 2022.

[8] C. Delrue, S. De Bruyne, and M. M. Speeckaert, "Application of machine learning in chronic kidney disease: Current status and future prospects," *Biomedicines*, vol. 12, no. 3, p. 568, Mar. 2024.

[9] R. Magherini, E. Mussi, Y. Volpe, R. Furferi, F. Buonamici, and M. Servi, "Machine learning for renal pathologies: An updated survey," *Sensors*, vol. 22, no. 13, p. 4989, Jul. 2022.

[10] E. R. Gottlieb, M. Samuel, J. V. Bonventre, L. A. Celi, and H. Mattie, "Machine learning for acute kidney injury prediction in the intensive care unit," *Adv. Chronic Kidney Disease*, vol. 29, no. 5, pp. 431–438, Sep. 2022.

[11] T. Bajaj and J. L. Koyner, "Artificial intelligence in acute kidney injury prediction," *Adv. Chronic Kidney Disease*, vol. 29, no. 5, pp. 450–460, Sep. 2022.

[12] T. Arora, M. Martin, A. Grimshaw, S. Mansour, and F. P. Wilson, "Prediction of outcomes after acute kidney injury in hospitalised patients: Protocol for a systematic review," *BMJ Open*, vol. 10, no. 12, Dec. 2020, Art. no. e042035.

[13] B. M. Eskofier and J. Klucken, "Predictive models for health deterioration: Understanding disease pathways for personalized medicine," *Annu. Rev. Biomed. Eng.*, vol. 25, no. 1, pp. 131–156, Jun. 2023.

[14] Ş. Busnatu, A.-G. Niculescu, A. Bolocan, G. E. D. Petrescu, D. N. Păduraru, I. Năstasă, M. Lupusoru, M. Geantă, O. Andronic, A. M. Grumezescu, and H. Martins, "Clinical applications of artificial intelligence—An updated overview," *J. Clin. Med.*, vol. 11, no. 8, p. 2265, 2022.

[15] L. Chan, A. Vaid, and G. N. Nadkarni, "Applications of machine learning methods in kidney disease: Hope or hype?" *Current Opinion Nephrol. Hypertension*, vol. 29, no. 3, pp. 319–326, 2020.

[16] C. W.-L. Ho and K. Caals, "A call for an ethics and governance action plan to harness the power of artificial intelligence and digitalization in nephrology," *Seminars Nephrol.*, vol. 41, no. 3, pp. 282–293, 2021.

[17] J. Miao, C. Thongprayoon, S. Suppadungsuk, O. A. G. Valencia, F. Qureshi, and W. Cheungpasitporn, "Ethical dilemmas in using AI for academic writing and an example framework for peer review in nephrology academia: A narrative review," *Clinics Pract.*, vol. 14, no. 1, pp. 89–105, Dec. 2023.

[18] C. P. Kovesdy, "Epidemiology of chronic kidney disease: An update 2022," *Kidney Int. Supplements*, vol. 12, no. 1, pp. 7–11, 2022.

[19] L. Rees, D. Bockenhauer, N. J. A. Webb, and M. G. Punaro, *Paediatric Nephrology*. London, U.K.: Oxford Univ. Press, 2019.

[20] C. Zoccali, P. J. Blankestijn, A. Bruchfeld, G. Capasso, D. Fliser, D. Fouque, D. Goumenos, Z. Massy, I. Rychlık, M. J. Soler, K. Stevens, G. Spasovski, and C. Wanner, ''The nephrology crystal ball: The medium-term future,'' *Nephrol. Dialysis Transplantation*, vol. 35, no. 2, pp. 222–226, Oct. 2019.

[21] F. Persson and P. Rossing, ''Diagnosis of diabetic kidney disease: State of the art and future perspective,'' *Kidney Int. Supplements*, vol. 8, no. 1, pp. 2–7, Jan. 2018.

[22] J. Floege, R. J. Johnson, and J. Feehally, *Comprehensive Clinical Nephrology E-Book*. Amsterdam, The Netherlands: Elsevier Health Sciences, 2010.

[23] M. W. Taal, G. M. Chertow, P. A. Marsden, K. Skorecki, and S. L. Alan, *Brenner & Rector's Kidney*. Philadelphia, PA, USA: Saunders, 2012.

[24] KDIGO Group, ''KDIGO clinical practice guideline for acute kidney injury,'' *Kidney Int. Suppl.*, vol. 2, pp. 1–141, Mar. 2012.

[25] A. S. Levey, K.-U. Eckardt, Y. Tsukamoto, A. Levin, J. Coresh, J. Rossert, D. D. E. Zeeuw, T. H. Hostetter, N. Lameire, and G. Eknoyan, ''Definition and classification of chronic kidney disease: A position statement from kidney disease: Improving global outcomes (KDIGO),'' *Kidney Int.*, vol. 67, no. 6, pp. 2089–2100, Jun. 2005.

[26] R. W. Schrier, *Schrier's Diseases of the Kidney*. Wolters Kluwer Health, 2012. [Online]. Available: https://books.google.pl/books?id=6NjvvQAACAAJ

[27] N. N. Turner, N. Lameire, D. J. Goldsmith, C. G. Winearls, J. Himmelfarb, and G. Remuzzi, *Oxford Textbook of Clinical Nephrology*. London, U.K.: Oxford Univ. Press, 2015.

[28] B. M. Koeppen and B. A. Stanton, *Renal Physiology E-Book: Mosby Physiology Monograph Series*. Amsterdam, The Netherlands: Elsevier Health Sciences, 2012.

[29] J. Chow, ''Nephrology secrets third edition,'' *Renal Soc. Australasia J.*, vol. 8, no. 1, pp. 38–39, 2012.

[30] T. K. Chen, D. H. Knicely, and M. E. Grams, ''Chronic kidney disease diagnosis and management: A review,'' *J. Amer. Med. Assoc.*, vol. 322, no. 13, pp. 1294–1304, 2019.

[31] O. J. Wouters, D. J. O'Donoghue, J. Ritchie, P. G. Kanavos, and A. S. Narva, ''Early chronic kidney disease: Diagnosis, management and models of care,'' *Nature Rev. Nephrol.*, vol. 11, no. 8, pp. 491–502, Aug. 2015.

[32] J. A. Neyra, M. C. Hu, and O. W. Moe, ''Klotho in clinical nephrology: Diagnostic and therapeutic implications,'' *Clin. J. Amer. Soc. Nephrol.*, vol. 16, no. 1, pp. 162–176, 2021.

[33] L. F. De Arizón, E. R. Viera, M. Pilco, A. Perera, G. De Maeztu, A. Nicolau, M. Furlano, and R. Torra, ''Artificial intelligence: A new field of knowledge for nephrologists?'' *Clin. Kidney J.*, vol. 16, no. 12, pp. 2314–2326, 2023.

[34] R. T. Calumby, A. A. Duarte, M. F. Angelo, E. Santos, P. Sarder, W. L. C. dos-Santos, and L. R. Oliveira, ''Toward real-world computational nephropathology,'' *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 6, pp. 809–812, 2023.

[35] G. N. Nadkarni, ''Introduction to artificial intelligence and machine learning in nephrology,'' *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 3, pp. 392–393, 2023.

[36] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. van den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, S. Dieleman, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever, T. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis, ''Mastering the game of go with deep neural networks and tree search,'' *Nature*, vol. 529, no. 7587, pp. 484–489, Jan. 2016.

[37] O. Vinyals et al., ''Grandmaster level in StarCraft II using multi-agent reinforcement learning,'' *Nature*, vol. 575, no. 7782, pp. 350–354, Nov. 2019.

[38] M. Hutson, ''AI learns the art of diplomacy,'' *Science*, vol. 378, no. 6622, p. 818, Nov. 2022.

[39] A. A. H. de Hond, A. M. Leeuwenberg, L. Hooft, I. M. J. Kant, S. W. J. Nijman, H. J. A. van Os, J. J. Aardoom, T. P. A. Debray, E. Schuit, M. van Smeden, J. B. Reitsma, E. W. Steyerberg, N. H. Chavannes, and K. G. M. Moons, ''Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: A scoping review,'' *NPJ Digit. Med.*, vol. 5, no. 1, p. 2, Jan. 2022.

[40] B. Shickel, T. J. Loftus, Y. Ren, P. Rashidi, A. Bihorac, and T. Ozrazgat-Baslanti, ''Digital health transformers and opportunities for artificial intelligence-enabled nephrology,'' *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 4, pp. 527–529, 2023.

[41] A. Verma, V. C. Chitalia, S. S. Waikar, and V. B. Kolachalama, ''Machine learning applications in nephrology: A bibliometric analysis comparing kidney studies to other medicine subspecialities,'' *Kidney Med.*, vol. 3, no. 5, pp. 762–767, Sep. 2021.

[42] Q. Li, Q.-L. Fan, Q.-X. Han, W.-J. Geng, H.-H. Zhao, X.-N. Ding, J.-Y. Yan, and H.-Y. Zhu, ''Machine learning in nephrology: Scratching the surface,'' *Chin. Med. J.*, no. 6, pp. 687–698, Mar. 2020.

[43] C. Cassol and S. Sharma, ''Nephrology lagging behind in machine learning utilization,'' *Kidney Med.*, vol. 3, no. 5, pp. 693–695, Sep. 2021.

[44] A. Scala, I. Loperto, R. Carrano, S. Federico, M. Triassi, and G. Improta, ''Assessment of proteinuria level in nephrology patients using a machine learning approach,'' in *Proc. 5th Int. Conf. Med. Health Informat.*, May 2021, pp. 13–16.

[45] K. V. Lemley, ''Machine learning comes to nephrology,'' *J. Amer. Soc. Nephrol.*, vol. 30, no. 10, pp. 1780–1781, 2019.

[46] C. Yang, G. Kong, L. Wang, L. Zhang, and M. Zhao, ''Big data in nephrology: Are we ready for the change?'' *Nephrology*, vol. 24, no. 11, pp. 1097–1102, Nov. 2019.

[47] S. Anand and A. Verma, ''Artificial intelligence in nephrology,'' in *Artificial Intelligence in Clinical Practice*, C. Krittanawong, Ed. New York, NY, USA: Academic, 2024, ch. 23, pp. 201–209.

[48] G. Xie, T. Chen, Y. Li, T. Chen, X. Li, and Z. Liu, ''Artificial intelligence in nephrology: How can artificial intelligence augment nephrologists' intelligence?'' *Kidney Diseases*, vol. 6, no. 1, pp. 1–6, 2020.

[49] D. Farrell and L. Chan, ''Application of natural language processing in nephrology research,'' *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 6, pp. 806–808, 2023.

[50] N. Arivazhagan and T. T. Van Vleck, ''Natural language processing basics,'' *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 3, pp. 400–401, 2023.

[51] Q. Li, H. Peng, J. Li, C. Xia, R. Yang, L. Sun, P. S. Yu, and L. He, ''A survey on text classification: From shallow to deep learning,'' 2020, *arXiv:2008.00364*.

[52] E. Hossain, R. Rana, N. Higgins, J. Soar, P. D. Barua, A. R. Pisani, and K. Turner, ''Natural language processing in electronic health records in relation to healthcare decision-making: A systematic review,'' 2023, *arXiv:2306.12834*.

[53] L. Xu, L. Sanders, K. Li, and J. C. L. Chow, ''Chatbot for health care and oncology applications using artificial intelligence and machine learning: Systematic review,'' *JMIR Cancer*, vol. 7, no. 4, Nov. 2021, Art. no. e27850.

[54] Y. Luo, W. K. Thompson, T. M. Herr, Z. Zeng, M. A. Berendsen, S. R. Jonnalagadda, M. B. Carson, and J. Starren, ''Natural language processing for EHR-based pharmacovigilance: A structured review,'' *Drug Saf.*, vol. 40, no. 11, pp. 1075–1089, Nov. 2017.

[55] R. Collobert, J. Weston, L. Bottou, M. Karlen, K. Kavukcuoglu, and P. Kuksa, ''Natural language processing (almost) from scratch,'' *J. Mach. Learn. Res.*, vol. 12, pp. 2493–2537, Aug. 2493.

[56] J. Miao, C. Thongprayoon, S. Suppadungsuk, O. A. G. Valencia, F. Qureshi, and W. Cheungpasitporn, ''Innovating personalized nephrology care: Exploring the potential utilization of ChatGPT,'' *J. Personalized Med.*, vol. 13, no. 12, p. 1681, Dec. 2023.

[57] K. Khezeli, S. Siegel, B. Shickel, T. Ozrazgat-Baslanti, A. Bihorac, and P. Rashidi, ''Reinforcement learning for clinical applications,'' *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 4, pp. 521–523, Apr. 2023.

[58] T. Jaiswal and S. Jaiswal, ''Deep learning in medicine,'' *Int. J. Trend Sci. Res. Develop.*, vol. 3, no. 4, pp. 212–217, Jun. 2019.

[59] K. Shankar, Y. Zhang, Y. Liu, L. Wu, and C.-H. Chen, ''Hyperparameter tuning deep learning for diabetic retinopathy fundus image classification,'' *IEEE Access*, vol. 8, pp. 118164–118173, 2020.

[60] T. Chen, X. Li, Y. Li, E. Xia, Y. Qin, S. Liang, F. Xu, D. Liang, C. Zeng, and Z. Liu, ''Prediction and risk stratification of kidney outcomes in IgA nephropathy,'' *Amer. J. Kidney Diseases*, vol. 74, no. 3, pp. 300–309, Sep. 2019.

[61] A. Loupy et al., ''Prediction system for risk of allograft loss in patients receiving kidney transplants: International derivation and validation study,'' *BMJ*, vol. 366, p. l4923, Sep. 2019.

[62] P. Hu, Z. Mo, Y. Chen, Y. Wu, L. Song, L. Zhang, Z. Li, L. Fu, H. Liang, Y. Tao, S. Liu, Z. Ye, and X. Liang, ''Derivation and validation of a model to predict acute kidney injury following cardiac surgery in patients with normal renal function,'' *Renal Failure*, vol. 43, no. 1, pp. 1205–1213, Jan. 2021.

[63] L. Z. Zhou, X. B. Yang, Y. Guan, X. Xu, M. T. Tan, F. F. Hou, and P. Y. Chen, "Development and validation of a risk score for prediction of acute kidney injury in patients with acute decompensated heart failure: A prospective cohort study in China," *J. Amer. Heart Assoc.*, vol. 5, no. 11, Oct. 2016.

[64] K. Thishya, K. K. Vattam, S. M. Naushad, S. B. Raju, and V. K. Kutala, "Artificial neural network model for predicting the bioavailability of tacrolimus in patients with renal transplantation," *PLoS ONE*, vol. 13, no. 4, Apr. 2018, Art. no. e0191921.

[65] N. Tomašev et al., "A clinically applicable approach to continuous prediction of future acute kidney injury," *Nature*, vol. 572, no. 7767, pp. 116–119, Aug. 2019.

[66] F. P. Schena, V. W. Anelli, J. Trotta, T. Di Noia, C. Manno, G. Tripepi, G. D'Arrigo, N. C. Chesnaye, M. L. Russo, M. Stangou, A. Papagianni, C. Zoccali, V. Tesar, and R. Coppo, "Development and testing of an artificial intelligence tool for predicting end-stage kidney disease in patients with immunoglobulin a nephropathy," *Kidney Int.*, vol. 99, no. 5, pp. 1179–1188, 2021.

[67] M. Hermsen, T. de Bel, M. den Boer, E. J. Steenbergen, J. Kers, S. Florquin, J. J. T. H. Roelofs, M. D. Stegall, M. P. Alexander, B. H. Smith, B. Smeets, L. B. Hilbrands, and J. A. W. M. van der Laak, "Deep learning-based histopathologic assessment of kidney tissue," *J. Amer. Soc. Nephrol.*, vol. 30, no. 10, pp. 1968–1979, 2019.

[68] H. Zhang, D. Preddie, W. Krackov, M. Sor, P. Waguespack, Z. Kuang, X. Ye, and P. Kotanko, "Deep learning to classify arteriovenous access aneurysms in hemodialysis patients," *Clin. Kidney J.*, vol. 15, no. 4, pp. 829–830, Mar. 2022.

[69] H. Lee, D. Yun, J. Yoo, K. Yoo, Y. C. Kim, D. K. Kim, K.-H. Oh, K. W. Joo, Y. S. Kim, N. Kwak, and S. S. Han, "Deep learning model for real-time prediction of intradialytic hypotension," *Clin. J. Amer. Soc. Nephrol.*, vol. 16, no. 3, pp. 396–406, 2021.

[70] M. van Smeden, J. B. Reitsma, R. D. Riley, G. S. Collins, and K. G. Moons, "Clinical prediction models: Diagnosis versus prognosis," *J. Clin. Epidemiol.*, vol. 132, pp. 142–145, Apr. 2021.

[71] G. S. Collins, J. B. Reitsma, D. G. Altman, and K. G. Moons, "Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) the TRIPOD statement," *Circulations*, vol. 131, no. 2, pp. 211–219, 2015.

[72] R. D. Riley, J. Ensor, K. I. E. Snell, F. E. Harrell, G. P. Martin, J. B. Reitsma, K. G. M. Moons, G. Collins, and M. van Smeden, "Calculating the sample size required for developing a clinical prediction model," *BMJ*, vol. 368, p. m441, Mar. 2020.

[73] E. Christodoulou, M. van Smeden, M. Edlinger, D. Timmerman, M. Wanitschek, E. W. Steyerberg, and B. Van Calster, "Adaptive sample size determination for the development of clinical prediction models," *Diagnostic Prognostic Res.*, vol. 5, no. 1, pp. 1–12, Dec. 2021.

[74] R. D. Riley, T. P. A. Debray, G. S. Collins, L. Archer, J. Ensor, M. van Smeden, and K. I. E. Snell, "Minimum sample size for external validation of a clinical prediction model with a binary outcome," *Statist. Med.*, vol. 40, no. 19, pp. 4230–4251, Aug. 2021.

[75] L. Archer, K. I. E. Snell, J. Ensor, M. T. Hudda, G. S. Collins, and R. D. Riley, "Minimum sample size for external validation of a clinical prediction model with a continuous outcome," *Statist. Med.*, vol. 40, no. 1, pp. 133–146, Jan. 2021.

[76] P. Xia et al., "Development of a multiple convolutional neural network–facilitated diagnostic screening program for immunofluorescence images of IgA nephropathy and idiopathic membranous nephropathy," *Clin. Kidney J.*, vol. 16, no. 12, pp. 2503–2513, Nov. 2023.

[77] X. Zhang, X. Song, W. Li, C. Chen, M. Wusiman, L. Zhang, J. Zhang, J. Lu, C. Lu, and X. Lv, "Rapid diagnosis of membranous nephropathy based on serum and urine Raman spectroscopy combined with deep learning methods," *Sci. Rep.*, vol. 13, no. 1, p. 3418, Feb. 2023.

[78] F. Hao, M. Li, X. Liu, X. Li, J. Yue, and W. Han, "Classification of glomeruli with membranous nephropathy on renal digital pathological images with deep learning," in *Proc. Conf. Artif. Intell. Healthcare*, Oct. 2020, pp. 239–243.

[79] X. Hou, C. Tian, W. Liu, Y. Li, W. Li, and Z. Wang, "Construction of artificial intelligence non-invasive diagnosis model for common glomerular diseases based on hyperspectral and urine analysis," *Photodiagnosis Photodynamic Therapy*, vol. 44, Dec. 2023, Art. no. 103736.

[80] L. Dongmei, L. Qunjuan, and L. Xumeng, "Application of artificial intelligence-based analytic renal pathology system in patients with membranous nephropathy," *Chin. J. Nephrol., Dialysis Transplantation*, vol. 32, no. 3, p. 201, 2023.

[81] L. Duo, L. Chen, Y. Zuo, J. Guo, M. He, H. Zhao, Y. Kang, and W. Tang, "Machine learning model to estimate probability of remission in patients with idiopathic membranous nephropathy," *Int. Immunopharmacol.*, vol. 125, Dec. 2023, Art. no. 111126.

[82] A. Destere, M. Teisseyre, D. Merino, M. Cremoni, A. O. Gérard, T. Crepin, N. Jourde-Chiche, D. Graça, K. Zorzi, C. Fernandez, V. Brglez, S. Benzaken, V. L. M. Esnault, S. Benito, M.-D. Drici, and B. Seitz-Polski, "Optimization of rituximab therapy in adult patients with PLA2R1-associated membranous nephropathy with artificial intelligence," *Kidney Int. Rep.*, vol. 9, no. 1, pp. 134–144, Jan. 2024.

[83] F. Hao, X. Liu, M. Li, and W. Han, "Accurate kidney pathological image classification method based on deep learning and multi-modal fusion method with application to membranous nephropathy," *Life*, vol. 13, no. 2, p. 399, Jan. 2023.

[84] J. Gao, S. Wang, L. Xu, J. Wang, J. Guo, H. Wang, and J. Sun, "Computer-aided diagnosis of primary membranous nephropathy using expert system," *Biomed. Eng. OnLine*, vol. 22, no. 1, pp. 1–24, Feb. 2023.

[85] A. Uleri, M. Baboudjian, A. Gallioli, A. Territo, J. M. Gaya, I. Sanz, J. Robalino, M. Casadevall, P. Diana, P. Verri, G. Basile, O. Rodriguez-Faba, A. Rosales, J. Palou, and A. Breda, "A new machine-learning model to predict long-term renal function impairment after minimally invasive partial nephrectomy: The fundació puigvert predictive model," *World J. Urol.*, vol. 41, no. 11, pp. 2985–2990, Sep. 2023.

[86] P. Kotanko, H. Zhang, and Y. Wang, "Artificial intelligence and machine learning in dialysis: Ready for prime time?" *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 6, pp. 803–805, 2023.

[87] W. Luo, D. Phung, T. Tran, S. Gupta, S. Rana, C. Karmakar, A. Shilton, J. Yearwood, N. Dimitrova, T. B. Ho, S. Venkatesh, and M. Berk, "Guidelines for developing and reporting machine learning predictive models in biomedical research: A multidisciplinary view," *J. Med. Internet Res.*, vol. 18, no. 12, p. e323, Dec. 2016.

[88] L. J. Liu, T. Takeuchi, J. Chen, and J. A. Neyra, "Artificial intelligence in continuous kidney replacement therapy," *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 5, pp. 671–674, 2023.

[89] T. Bajaj and J. L. Koyner, "Cautious optimism: Artificial intelligence and acute kidney injury," *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 5, pp. 668–670, 2023.

[90] E. A. Balczewski, J. Cao, and K. Singh, "Risk prediction and machine learning: A case-based overview," *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 4, pp. 524–526, 2023.

[91] Y. Park and J. Hu, "Bias in artificial intelligence: Basic primer," *Clin. J. Amer. Soc. Nephrol.*, vol. 18, no. 3, pp. 394–396, 2023.

[92] A. M. Lee, J. Hu, Y. Xu, A. G. Abraham, R. Xiao, J. Coresh, C. Rebholz, J. Chen, E. P. Rhee, H. I. Feldman, V. S. Ramachandran, P. L. Kimmel, B. A. Warady, S. L. Furth, and M. R. Denburg, "Using machine learning to identify metabolomic signatures of pediatric chronic kidney disease etiology," *J. Amer. Soc. Nephrol.*, vol. 33, no. 2, pp. 375–386, 2022.

[93] J. U. Becker, D. Mayerich, M. Padmanabhan, J. Barratt, A. Ernst, P. Boor, P. A. Cicalese, C. Mohan, H. V. Nguyen, and B. Roysam, "Artificial intelligence and machine learning in nephropathology," *Kidney Int.*, vol. 98, no. 1, pp. 65–75, 2020.

[94] T. A. Potretzke et al., "Clinical implementation of an artificial intelligence algorithm for magnetic resonance-derived measurement of total kidney volume," *Mayo Clinic Proc.*, vol. 98, no. 5, pp. 689–700, May 2023.

[95] F. P. Schena, R. Magistroni, F. Narducci, D. I. Abbrescia, V. W. Anelli, and T. Di Noia, "Artificial intelligence in glomerular diseases," *Pediatric Nephrol.*, vol. 37, no. 11, pp. 2533–2545, Nov. 2022.

[96] A. Rajkomar, J. Dean, and I. Kohane, "Machine learning in medicine," *New England J. Med.*, vol. 380, no. 14, pp. 1347–1358, 2019.

[97] H. W. Kim, S.-J. Heo, J. Y. Kim, A. Kim, C.-M. Nam, and B. S. Kim, "Dialysis adequacy predictions using a machine learning method," *Sci. Rep.*, vol. 11, no. 1, p. 15417, Jul. 2021.

[98] Z. Zhang, K. M. Ho, and Y. Hong, "Machine learning for the prediction of volume responsiveness in patients with oliguric acute kidney injury in critical care," *Crit. Care*, vol. 23, no. 1, pp. 1–10, Dec. 2019.

[99] K. Sridharan and S. Shah, "Developing supervised machine learning algorithms to evaluate the therapeutic effect and laboratory-related adverse events of cyclosporine and tacrolimus in renal transplants," *Int. J. Clin. Pharmacy*, vol. 45, no. 3, pp. 659–668, Jun. 2023.
[100] W. Yuan, L. Sui, H. Xin, M. Liu, and H. Shi, "Discussion on machine learning technology to predict tacrolimus blood concentration in patients with nephrotic syndrome and membranous nephropathy in real-world settings," *BMC Med. Informat. Decis. Making*, vol. 22, no. 1, p. 336, Dec. 2022.
[101] F. Hamedan, A. Orooji, H. Sanadgol, and A. Sheikhtaheri, "Clinical decision support system to predict chronic kidney disease: A fuzzy expert system approach," *Int. J. Med. Informat.*, vol. 138, Jun. 2020, Art. no. 104134.
[102] H. Bolt, A. Suffel, J. Matthewman, F. Sandmann, L. Tomlinson, and R. Eggo, "Seasonality of acute kidney injury phenotypes in england: An unsupervised machine learning classification study of electronic health records," *BMC Nephrol.*, vol. 24, no. 1, p. 234, Aug. 2023.
[103] M. A. Islam, M. Z. H. Majumder, and M. A. Hussein, "Chronic kidney disease prediction based on machine learning algorithms," *J. Pathol. Informat.*, vol. 14, Jan. 2023, Art. no. 100189.
[104] M. M. El Sherbiny, E. Abdelhalim, H. E.-D. Mostafa, and M. M. El-Seddik, "Classification of chronic kidney disease based on machine learning techniques," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 32, no. 2, p. 945, Nov. 2023.
[105] L. Chan, G. N. Nadkarni, F. Fleming, J. R. McCullough, P. Connolly, G. Mosoyan, F. El Salem, M. W. Kattan, J. A. Vassalotti, B. Murphy, M. J. Donovan, S. G. Coca, and S. M. Damrauer, "Derivation and validation of a machine learning risk score using biomarker and electronic patient data to predict progression of diabetic kidney disease," *Diabetologia*, vol. 64, no. 7, pp. 1504–1515, Jul. 2021.
[106] Md. M. S. Raihan, E. Ahmed, A. Karim, S. Azam, M. Raihan, L. Akter, and M. M. Hassan, "Chronic renal disease prediction using clinical data and different machine learning techniques," in *Proc. 2nd Int. Informat. Softw. Eng. Conf. (IISEC)*, Dec. 2021, pp. 1–5.
[107] C. Hu, Q. Tan, Q. Zhang, Y. Li, F. Wang, X. Zou, and Z. Peng, "Application of interpretable machine learning for early prediction of prognosis in acute kidney injury," *Comput. Structural Biotechnol. J.*, vol. 20, pp. 2861–2870, Jan. 2022.
[108] C. Li, Z. Yao, M. Zhu, B. Lu, and H. Xu, "Biopsy-free prediction of pathologic type of primary nephrotic syndrome using a machine learning algorithm," *Kidney Blood Pressure Res.*, vol. 42, no. 6, pp. 1045–1052, 2017.
[109] M. Han, Y. Wang, X. Huang, P. Li, X. Liang, R. Wang, and K. Bao, "Identification of hub genes and their correlation with immune infiltrating cells in membranous nephropathy: An integrated bioinformatics analysis," *Eur. J. Med. Res.*, vol. 28, no. 1, p. 525. Springer, 2023.
[110] Y. Chen, Y. He, and G. Xing, "Using machine learning to identify risk factors and establishing a clinical prediction model to predict atherosclerosis complications in idiopathic membranous nephropathy," *Discovery Med.*, vol. 35, no. 177, p. 517, 2023.
[111] P. Ghosh, F. M. J. M. Shamrat, S. Shultana, S. Afrin, A. A. Anjum, and A. A. Khan, "Optimization of prediction method of chronic kidney disease using machine learning algorithm," in *Proc. 15th Int. Joint Symp. Artif. Intell. Natural Lang. Process. (iSAI-NLP)*, Nov. 2020, pp. 1–6.
[112] V. Chaurasia, M. K. Pandey, and S. Pal, "Chronic kidney disease: A prediction and comparison of ensemble and basic classifiers performance," *Human-Intell. Syst. Integr.*, vol. 4, nos. 1–2, pp. 1–10, Jun. 2022.
[113] K. M. Zubair Hasan and M. Zahid Hasan, "Performance evaluation of ensemble-based machine learning techniques for prediction of chronic kidney disease" in *Emerging Research in Computing, Information, Communication and Applications*, N. R. Shetty, L. M. Patnaik, H. C. Nagaraj, P. N. Hamsavath, and N. Nalini, Eds. Singapore: Springer, 2019, pp. 415–426.
[114] M. S. Azam, U. Kulsom, S. M. H. S. Iqbal, and M. T. Ahmed, "An empirical study of various machine learning approaches in prediction of chronic kidney disease," *Int. J. Sci. Bus.*, vol. 4, no. 11, pp. 101–110, 2020.
[115] D. Baidya, U. Umaima, M. N. Islam, F. M. J. M. Shamrat, A. Pramanik, and M. S. Rahman, "A deep prediction of chronic kidney disease by employing machine learning method," in *Proc. 6th Int. Conf. Trends Electron. Informat. (ICOEI)*, Apr. 2022, pp. 1305–1310.
[116] L. M. Stevens, B. J. Mortazavi, R. C. Deo, L. Curtis, and D. P. Kao, "Recommendations for reporting machine learning analyses in clinical research," *Circulation, Cardiovascular Quality Outcomes*, vol. 13, no. 10, Oct. 2020, Art. no. e006556.
[117] S. T. Segun, "From machine ethics to computational ethics," *AI Soc.*, vol. 36, no. 1, pp. 263–276, Mar. 2021.
[118] X. Liu, S. C. Rivera, D. Moher, M. J. Calvert, and A. K. Denniston, "Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: The CONSORT-AI extension," *Lancet Digital Health*, vol. 2, no. 10, pp. e537–e548, Sep. 2020.
[119] J. Mongan, L. Moy, and C. E. Kahn Jr., "Checklist for artificial intelligence in medical imaging (CLAIM): A guide for authors and reviewers," *Radiol., Artif. Intell.*, vol. 2, no. 2, 2020, Art. no. e200029.
[120] T. J. Loftus, B. Shickel, T. Ozrazgat-Baslanti, Y. Ren, B. S. Glicksberg, J. Cao, K. Singh, L. Chan, G. N. Nadkarni, and A. Bihorac, "Artificial intelligence-enabled decision support in nephrology," *Nature Rev. Nephrol.*, vol. 18, no. 7, pp. 452–465, Jul. 2022.
[121] K. Alhasan, R. Raina, A. Jamal, and M. Temsah, "Combining human and AI could predict nephrologies future, but should be handled with care," *Acta Paediatrica*, vol. 112, no. 9, pp. 1844–1848, Sep. 2023.
[122] O. A. G. Valencia, S. Suppadungsuk, C. Thongprayoon, J. Miao, S. Tangpanithandee, I. M. Craici, and W. Cheungpasitporn, "Ethical implications of chatbot utilization in nephrology," *J. Personalized Med.*, vol. 13, no. 9, p. 1363, Sep. 2023.
[123] D. Pawuś and S. Paszkiel, "Application of EEG signals integration to proprietary classification algorithms in the implementation of mobile robot control with the use of motor imagery supported by EMG measurements," *Appl. Sci.*, vol. 12, no. 11, p. 5762, Jun. 2022.
[124] D. Pawuś and S. Paszkiel, "The application of integration of EEG signals for authorial classification algorithms in implementation for a mobile robot control using movement imagery—Pilot study," *Appl. Sci.*, vol. 12, no. 4, p. 2161, Feb. 2022.
[125] D. Pawuś and S. Paszkiel, "BCI wheelchair control using expert system classifying EEG signals based on power spectrum estimation and nervous tics detection," *Appl. Sci.*, vol. 12, no. 20, p. 10385, Oct. 2022.
[126] S. Sokół, D. Pawuś, P. Majewski, and M. Krok, "The study of the effectiveness of advanced algorithms for learning neural networks based on FPGA in the musical notation classification task," *Appl. Sci.*, vol. 12, no. 19, p. 9829, Sep. 2022.
[127] J. Adamy, "Nonlinear control of linear and nonlinear systems," in *Nonlinear Systems and Controls*. Berlin, Germany: Springer, 2022, pp. 503–599, doi: 10.1007/978-3-662-65633-4_6.
[128] Y. Ren, Z. Zhao, C. Zhang, Q. Yang, and K.-S. Hong, "Adaptive neural-network boundary control for a flexible manipulator with input constraints and model uncertainties," *IEEE Trans. Cybern.*, vol. 51, no. 10, pp. 4796–4807, Oct. 2021.
[129] N. Kriegeskorte and T. Golan, "Neural network models and deep learning," *Current Biol.*, vol. 29, no. 7, pp. R231–R236, Apr. 2019.
[130] K. Suzuki, *Artificial Neural Networks: Architectures and Applications*. IntechOpen, Jan. 2013, 10.5772/3409.
[131] D. Chicco, "Siamese neural networks: An overview," in *Artificial Neural Networks*, H. Cartwright, Ed. New York, NY, USA: Springer, 2021, pp. 73–94, doi: 10.1007/978-1-0716-0826-5_3.
[132] D. Pawuś and S. Paszkiel, "Identification and expert approach to controlling the cement grinding process using artificial neural networks and other non-linear models," *IEEE Access*, vol. 12, pp. 26364–26383, 2024.
[133] Y. Zhang, P. Tino, A. Leonardis, and K. Tang, "A survey on neural network interpretability," *IEEE Trans. Emerg. Topics Comput. Intell.*, vol. 5, no. 5, pp. 726–742, Oct. 2021.
[134] S. Ruder, "An overview of multi-task learning in deep neural networks," 2017, *arXiv:1706.05098*.
[135] A. Morán-Durán, A. Martínez-Sibaja, J. P. Rodríguez-Jarquin, R. Posada-Gómez, and O. S. González, "PEM fuel cell voltage neural control based on hydrogen pressure regulation," *Processes*, vol. 7, no. 7, p. 434, Jul. 2019.
[136] Q. Shi, H.-K. Lam, C. Xuan, and M. Chen, "Adaptive neuro-fuzzy PID controller based on twin delayed deep deterministic policy gradient algorithm," *Neurocomputing*, vol. 402, pp. 183–194, Aug. 2020.
[137] R. Shanthi, S. Kalyani, and P. M. Devie, "Design and performance analysis of adaptive neuro-fuzzy controller for speed control of permanent magnet synchronous motor drive," *Soft Comput.*, vol. 25, no. 2, pp. 1519–1533, Jan. 2021.
[138] R. Vignesh, B. Ashok, M. S. Kumar, D. Szpica, A. Harikrishnan, and H. Josh, "Adaptive neuro fuzzy inference system-based energy management controller for optimal battery charge sustaining in biofuel powered non-plugin hybrid electric vehicle," *Sustain. Energy Technol. Assessments*, vol. 59, Oct. 2023, Art. no. 103379.

DAWID PAWUŚ received the B.Sc. and M.Sc. degrees in automation and robotics from Opole University of Technology, in 2022 and 2023, respectively, where he is currently pursuing the Ph.D. degree. In his doctoral thesis, he examines the impact of artificial intelligence as part of an expert system on improving the diagnosis of kidney diseases.

He cooperates with the medical sector by conducting various types of research on large data sets. He is the author of several publications that concern research on artificial intelligence, BCI systems, EEG signals, and control systems. He is also the coauthor of several projects for industry and state institutions. His research focuses primarily on the practical aspects of application use, especially those based on expert approaches, neural networks, and advanced control using classic approaches and those based on artificial intelligence. He also conducts research on image recognition and classification systems.

Mr. Pawuś was a winner of many awards and distinctions, such as the scholarship from the Minister of Education of the Republic of Poland, the scholarship from the President of Opole, the Marshal of the Opole Voivodeship, and the Rector of Opole University of Technology. His diploma theses, closely related to research for industry, allowed him to win several national competitions. He is also the author of reviews for the Springer publishing house.

TOMASZ PORAŻKO received the M.D. and Ph.D. degrees. He is an University Professor, a Specialist in internal medicine and nephrology, and the Clinical Director with the Department of Internal Medicine and Nephrology, Institute of Medical Sciences, Opole University Hospital. He is the author of several publications and congress presentations. He is a member of editorial boards and the scientific working groups of European and international nephrological societies. He was awarded for his works by ERA EDTA, Ministry of Health, Republic of Poland; and a Rectors of Wroclaw Medical University and Opole University.

SZCZEPAN PASZKIEL received the Ph.D. degree in technical sciences (automatics and robotics), in 2011, and the Habilitation degree, in 2021.

He is an University Professor with the Faculty of Electrical Engineering, Automatic Control and Informatics, Opole University of Technology. He is the author of more than 100 publications, including those from ISI primary journal list and a lecturer on several dozen scientific conferences, festivals, and panel discussions. He was a recipient of grants for young scientists. He holds leadership roles as the Chairperson of the Program Commission for Biomedical Engineering, Opole University of Technology; and the Head Organizer of the International Scientific Conference on Brain–Computer Interfaces in Opole. He is a researcher and an editor, having authored and edited several significant monographs in the field of brain–computer interfaces (BCI). Noteworthy among these are *Applications of Brain–Computer Interfaces in Intelligent Technologies* (Springer International Publishing, 2022) and *Analysis and Classification of EEG Signals for Brain–Computer Interfaces* (Springer International Publishing, 2020). He is also a co-editor of the monograph *Control, Computer Engineering and Neuroscience*, which encompasses the proceedings of IC Brain–Computer Interface 2021 (Springer, 2021). His impact on the field is further evidenced by his authorship of the first handbook in Poland titled *Brain–Computer Interfaces: Neuroinformatics*, in 2014. His research interests focus on modern methods of control systems, brain–computer technology, and modeling of neuronal cell fractions.

Prof. Paszkiel was a winner of many prizes and competitions, including those organized by the Ministry of Science and Higher Education, Republic of Poland. As an active member of various scientific bodies, he has contributed to the field through his involvement in conferences, such as the Fourth International Scientific Conference on Brain–Computer Interfaces (BCI 2022) and the third International Scientific Conference on Brain–Computer Interfaces (BCI 2018). His dedication extends to serving on the Metrology Commission of the Polish Academy of Sciences, Katowice Branch, and the Faculty Engineering, Automatic Control, and Informatics Council at Opole University of Technology. He is recognized as an expert and a representative of esteemed institutions, including the National Centre for Research and Development, the Centre of OPI Processing Information in the National Research Centre (PIB), the European Commission, and Wroclaw Research Centre EIT. In addition to his editorial and organizational roles, he has made significant contributions as a reviewer for reputable journals and a member of expertise panels in the National Centre for Research and Development.