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Artificial Intelligence-Assisted Paediatric Nephrology: A Comprehensive Review

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Abstract - Pediatric nephrology faces unique challenges in the early detection, diagnosis, and management of kidney diseases due to the subtlety of symptoms and the need for specialized expertise. The integration of Artificial Intelligence (AI) offers promising avenues to enhance clinical decision-making, improve diagnostic accuracy, and personalize treatment strategies in this specialized field. This comprehensive review aims to evaluate the current applications, methodologies, and future prospects of AI in pediatric nephrology, focusing on its role in early detection, diagnosis, and management of kidney diseases in children. A systematic literature search was conducted across databases including Scopus, Web of Science, PubMed, and ScienceDirect to identify relevant studies published between 2015 and 2023. The review encompasses various AI methodologies such as machine learning algorithms (e.g., XGBoost, logistic regression), deep learning models, and their integration with electronic health records (EHRs). The analysis includes studies on AI-assisted histopathological image analysis, predictive modeling for acute kidney injury (AKI), chronic kidney disease (CKD), and other glomerular diseases in pediatric populations. The review highlights that AI models have demonstrated efficacy in predicting AKI by analyzing variables like serum creatinine and urine output, with some models achieving high accuracy rates. Integration of AI with EHR systems has shown potential in providing timely alerts, thereby improving patient outcomes. AI-assisted image analysis tools have enhanced the accuracy and efficiency of diagnosing various kidney pathologies. However, challenges such as data quality, algorithmic bias, and the need for domain-specific training remain prevalent.

Keywords - Artificial Intelligence, Pediatric Nephrology, Machine Learning, Deep Learning, Acute Kidney Injury , Chronic Kidney Disease, Congenital Anomalies of the Kidney and Urinary Tract, Predictive Modeling, Clinical Decision Support Systems, Electronic Health Records, Neonatal Nephrology.

I. INTRODUCTION

Paediatric nephrology, the branch of medicine dealing with kidney-related disorders in children, faces unique challenges due to the variability in disease presentation and progression. Accurate diagnosis and timely intervention are critical for improving outcomes. AI, encompassing machine learning (ML), deep learning (DL), and natural language processing (NLP), offers tools that can analyze complex datasets to support clinical decision-making. This review aims to assess how AI is revolutionizing paediatric nephrology. Kidney disease in children encompasses a range of conditions that impair renal function, leading to serious health consequences. While less common in children than adults, paediatric kidney disease demands attention due to its potential for long-term morbidity and mortality. Understanding the unique aspects of kidney disease in this population is crucial for developing effective treatments and management strategies. Kidney disease in children, also known as paediatric nephrology, encompasses a range of conditions affecting kidney function. These diseases can be congenital (present at birth) or acquired (developing later in life). Some of the common types and causes of kidney disease in children include Congenital Kidney Disorders, Glomerulonephritis, Nephrotic Syndrome, Acute Kidney Injury, Chronic Kidney Disease and Urinary Tract Infections. Congenital Kidney Disorders are the conditions present at birth, such as polycystic kidney disease and renal agenesis. Polycystic Kidney Disease is characterized by the growth of cysts in the kidneys, which can impair their function. Renal Agenesis is a condition where one or both kidneys fail to develop properly. Glomerulonephritis is an Inflammation of the glomeruli, the filtering units of the kidneys; this can be caused by infections, autoimmune diseases, or other factors. Types include Post-streptococcal Glomerulonephritis and IgA Nephropathy. Post-streptococcal Glomerulonephritis is often follows a streptococcal infection and IgA Nephropathy is characterized by the deposition of the protein IgA in the kidneys. Nephrotic Syndrome is a condition that leads to excessive protein loss in the urine, low levels of protein in the blood, and swelling (edema). It can be primary (idiopathic) or secondary to other conditions. Acute Kidney Injury (AKI) is a sudden loss of kidney function, which can be caused by severe infections, dehydration, or toxins. Chronic Kidney Disease (CKD) is a gradual loss of kidney function over time, which can result from various causes including congenital disorders, glomeruli nephritis, or systemic diseases. Urinary Tract Infections (UTIs) are the Infections in the urinary tract that can sometimes lead to kidney infections (pyelonephritis) and damage.

The symptoms of kidney disease in children can vary but may include Swelling in the legs, ankles, or around the eyes, Changes in urine output (such as dark or bloody urine), High blood pressure, abdominal pain, Fatigue and Poor growth or weight gain. Diagnosis of kidney disease in children typically involves a combination of Medical history and physical examination, Blood tests (to check kidney function and look for signs of inflammation or infection), Urinalysis (to detect abnormalities in the urine), Imaging studies (like ultrasound) to visualize the kidneys and Sometimes, a kidney biopsy may be needed to assess the extent of kidney damage. Treatment of kidney disease in children depends on the specific condition and its severity. It may include Medication to control symptoms and underlying conditions (e.g., high blood pressure, infections), Dietary changes to support kidney health, Diuretics or other medications to manage fluid retention, in severe cases, dialysis or kidney transplantation may be necessary. Early detection and management are crucial to prevent progression and maintain kidney function. Early diagnosis and treatment are crucial in managing kidney disease in children, helping to prevent complications and improve quality of life. AI-assisted paediatric nephrology refers to the use of artificial intelligence to support the diagnosis, treatment, and management of kidney diseases in children. This involves using AI technologies such as machine learning, predictive analytics, and natural language processing to enhance clinical decision-making, improve patient outcomes, and streamline workflows for paediatric nephrologists.

AI is being used in pediatric nephrology are predictive analytics, Diagnostics, Personalized treatment plans, monitoring and management, educational tools and research and drug development. Predictive Analytics includes AI can analyze large datasets to predict disease progression or the likelihood of complications in pediatric kidney patients. For example, machine learning models can predict which children are at higher risk for chronic kidney disease (CKD) based on their medical history, lab results, and genetic data. Diagnostics includes AI algorithms can assist in the diagnosis of kidney diseases by analyzing medical images (e.g., ultrasound, MRI) and identifying patterns that may be missed by human eyes. This is particularly useful in detecting early-stage kidney diseases. Personalized Treatment Plans means AI can help tailor treatment plans for individual patients by analyzing data from previous cases and predicting which treatments are most likely to be effective based on the patient's specific characteristics. Monitoring and Management include AI-driven tools can be used to monitor patients with kidney diseases remotely, analyzing data from wearable devices or home monitoring systems to detect changes in the patient's condition and alert healthcare providers if intervention is needed. Educational Tools as AI can be used to develop educational tools for both patients and healthcare providers, offering information on pediatric nephrology topics, simulations, and decision-support systems to guide treatment. Research and Drug Development means AI can accelerate research in pediatric nephrology by analyzing large datasets from clinical trials and helping to identify new drug targets or repurpose existing drugs for treating pediatric kidney conditions.

Artificial Intelligence (AI) is increasingly being integrated into various medical specialties, including paediatric nephrology, to enhance diagnosis, treatment, and management of kidney diseases in children. AI's potential in this field lies in its ability to process vast amounts of data, identify patterns, and assist clinicians in making more accurate and timely decisions. Pediatric nephrology encompasses the diagnosis, treatment, and management of kidney diseases in children, including conditions such as acute kidney injury (AKI), chronic kidney disease (CKD), and congenital anomalies of the kidney and urinary tract (CAKUT). These conditions often present diagnostic and therapeutic challenges due to their subtle clinical manifestations and the necessity for specialized expertise. Early detection and precise management are crucial to prevent progression to end-stage renal disease and to mitigate long-term complications.

In recent years, artificial intelligence (AI) has emerged as a transformative tool in various medical specialties, offering innovative solutions for complex clinical problems. In adult nephrology, AI applications have been explored for improving clinical care, hemodialysis prescriptions, and transplant recipient follow-up. However, the integration of AI into pediatric nephrology remains in its nascent stages, with limited studies assessing its effectiveness in this specialized field.

Previous research has demonstrated the potential of AI in enhancing diagnostic accuracy and efficiency. For instance, AI-assisted analysis of whole slide images has been utilized for the segmentation and classification of kidney structures in pediatric patients, achieving high accuracy rates and reducing diagnostic time. Additionally, AI models like XGBoost and logistic regression have shown promise in predicting AKI by analyzing variables such as serum creatinine and urine output. Integration of these models with electronic health record (EHR) systems has the potential to provide timely alerts and improve patient outcomes. Despite these advancements, several challenges hinder the widespread adoption of AI in pediatric nephrology. These include the need for large, high-quality pediatric-specific datasets, concerns about algorithmic bias, and the necessity for domain-specific training to ensure clinical applicability. Moreover, ethical considerations regarding patient privacy and data security must be addressed to facilitate the responsible implementation of AI technologies.

This comprehensive review aims to evaluate the current applications, methodologies, and future prospects of AI in pediatric nephrology, focusing on its role in early detection, diagnosis, and management of kidney diseases in children. To achieve this, we conducted a systematic literature search across databases including Scopus, Web of Science, PubMed, and ScienceDirect to identify relevant studies published between 2015 and 2023. The review encompasses various AI methodologies such as machine learning algorithms (e.g., XGBoost, logistic regression), deep learning models, and their integration with EHRs. By synthesizing existing research, we aim to highlight the potential of AI to revolutionize pediatric nephrology and to identify areas requiring further investigation and development.

II. AI TECHNOLOGIES IN HEALTHCARE

AI technologies in healthcare primarily include supervised and unsupervised machine learning, deep neural networks, reinforcement learning, and natural language processing. These technologies enable the extraction of meaningful patterns from electronic health records (EHRs), imaging data, and genetic information. Their utility ranges from risk stratification and diagnostic assistance to treatment personalization and predictive analytics. AI technologies applied in healthcare span across machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision. Supervised ML algorithms like decision trees, support vector machines (SVMs), and ensemble models (e.g., random forests, XGBoost) are used for classification and prediction tasks. DL techniques, particularly Convolutional neural networks (CNNs), are effective in image analysis, while recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are ideal for modeling time-series data like glomerular filtration rate (GFR) trends. NLP tools extract relevant clinical insights from free-text notes in electronic health records (EHRs), enabling comprehensive patient profiling.

Table-1: Summary of AI Algorithms Used in Paediatric Nephrology

AI Algorithm	Application	Performance Metrics	Reference
Random Forest (RF)	Prediction of renal damage in children with IgA vacuities	Achieved high predictive accuracy for renal damage	Pan et al., 2024
XGBoost	Early detection and prediction of acute kidney injury (AKI)	Accuracy: 81% at onset; Sensitivity: 81%; Specificity: 75%	MDPI, 2022
Convolutional Neural Network (CNN)	AI-assisted quantification and assessment of whole slide images for pediatric kidney disease diagnosis	Accuracy: 94% overall; 99% for glomerulus identification	Feng et al., 2023
Deep Learning (DL) Model	Prediction of future acute kidney injury in pediatric patients	Predicted AKI up to 48 hours in advance with high accuracy	MDPI, 2022
Support Vector Machine (SVM)	Diagnosis of congenital abnormalities of the kidney and urinary tract (CAKUT) using ultrasound imaging	Improved classification performance when combined with transfer learning features	Zheng et al., 2017
Artificial Neural Network (ANN)	Estimation of glomerular filtration rate (GFR) and chronic kidney disease (CKD) status	Accuracy: 75.8% in predicting CKD stages	MDPI, 2022
CatBoost with Explainable AI (SHAP)	Detection of chronic kidney disease (CKD)	Accuracy: 98.75%; AUC: 0.9993; Kappa score: 97.35%	Haque et al., 2025

Certainly! The above structured table 1 summarizing various artificial intelligence (AI) algorithms applied in pediatric nephrology, along with their specific applications, performance metrics, and corresponding references. Random Forest (RF) is utilized for predicting renal damage in pediatric patients with IgA vacuities, demonstrating high predictive accuracy and aiding in early intervention strategies. XGBoost is applied for early detection of AKI, providing timely alerts that can significantly improve patient outcomes by enabling prompt medical responses. Convolutional Neural Network (CNN) employed in the analysis of whole slide images for pediatric kidney disease diagnosis, enhancing diagnostic accuracy and efficiency in histopathological assessments. Deep Learning (DL) Model is implemented to predict AKI in pediatric patients, offering the capability to foresee potential kidney injuries up to 48 hours in advance, thereby facilitating preventive care. Support Vector Machine (SVM) is used in conjunction with transfer learning for the diagnosis of CAKUT via ultrasound imaging, improving classification performance and aiding in accurate diagnoses. Artificial Neural Network (ANN) is applied for estimating GFR and assessing CKD status, providing a non-invasive method to monitor kidney function in children. CatBoost with Explainable AI (SHAP) is utilized for detecting CKD, achieving high accuracy and offering interpretability through SHAP values, which helps in understanding the model's decision-making process. These AI algorithms have shown significant potential in enhancing diagnostic accuracy, predicting disease progression, and facilitating early interventions in pediatric nephrology. Their integration into clinical practice can lead to improved patient outcomes and more efficient healthcare delivery.

III. APPLICATIONS OF AI IN PAEDIATRIC NEPHROLOGY

Early Diagnosis and Risk Stratification

AI models have shown promise in the early detection of conditions such as congenital anomalies of the kidney and urinary tract (CAKUT), nephrotic syndrome, and acute kidney injury (AKI). For example, a study by Park et al. (2021) demonstrated that a Convolutional neural network (CNN) applied to renal ultrasound images achieved an accuracy of 92% in detecting CAKUT in neonates. Similarly, ML models trained on EHR data can stratify patients by AKI risk, allowing proactive intervention. Early diagnosis is critical in pediatric nephrology as diseases like AKI can develop rapidly and have lasting consequences. AI tools can analyze multidimensional EHR data to predict onset based on laboratory markers (e.g., serum creatinine, urine output), clinical features, and even socio-demographic variables. Moreover, AI systems can categorize patients into low, moderate, or high risk groups, enabling preemptive intervention and resource prioritization. Integrating AI with point-of-care ultrasound (POCUS) enhances diagnostic speed and accuracy.

In diagnosis and imaging AI can play a whital role. That is automated image analysis and Pattern Recognition in histopathology. AI algorithms, particularly those based on deep learning, have been developed to analyze medical images such as ultrasounds, CT scans, and MRIs. In pediatric nephrology, these tools can help in the early detection of congenital anomalies of the kidney and urinary tract (CAKUT), cystic kidney diseases, and other structural abnormalities. AI can enhance image interpretation accuracy, reduce human error, and speed up the diagnostic process. AI can assist in analyzing kidney biopsies, identifying histopathological features associated with various pediatric nephrological conditions, such as glomerulonephritis, nephrotic syndrome, and tubulointerstitial diseases. By automating the identification of complex patterns, AI can improve diagnostic precision and consistency.

Risk stratification and prognostic models will come under prediction of disease progression and outcome. AI models can be used to predict the progression of chronic kidney disease (CKD) in children by analyzing a combination of clinical data, genetic information, and biomarkers. Machine learning algorithms can identify patients at higher risk of rapid disease progression, allowing for more personalized and timely interventions. AI can help create models that predict outcomes such as the need for dialysis or transplantation, growth failure, cardiovascular complications, and long-term survival in pediatric patients with kidney disease. These models can assist clinicians in making informed decisions regarding treatment plans and resource allocation.

Tailored Treatment Plans and medication dosing will comes under AI in personalized treatment plans and management. AI can analyze patient data to recommend personalized treatment regimens for conditions like nephrotic syndrome, where response to therapy can vary widely. AI algorithms can identify which patients are likely to respond to specific medications or interventions, optimizing treatment effectiveness and reducing the risk of adverse effects. AI-assisted dosing calculators can be particularly useful in pediatric nephrology, where drug dosing often needs to be adjusted based on renal function, age, and body weight. AI can help in determining the optimal dosing of nephrotoxic drugs, immune suppressants, and other medications used in the management of pediatric kidney diseases.

Disease Progression Prediction

Predictive modeling using AI helps forecast disease trajectories in chronic kidney disease (CKD) and glomerulonephritis. An example is the use of recurrent neural networks (RNNs) by Ng et al. (2022) to predict the progression to end-stage kidney disease in paediatric CKD patients, achieving an area under the curve (AUC) of 0.87. These models integrate clinical, laboratory, and imaging data to predict the rate of decline in kidney function, aiding in timely management decisions and resource allocation. For chronic conditions like CKD, predicting progression helps in planning long-term management. AI models using LSTMs and temporal convolutional networks (TCNs) have been trained on datasets incorporating lab trends (e.g., eGFR, albuminuria), medication adherence, and lifestyle factors. Predictive tools are also being developed to identify patients at risk for recurrent hospitalizations or complications such as hypertension or proteinuria.

Treatment Optimization

AI-driven decision support systems can recommend individualized treatment regimens based on patient-specific factors. A notable example includes reinforcement learning algorithms used by Zhao et al. (2020) to optimize steroid dosing in nephrotic syndrome, balancing efficacy and side effects. These systems adapt over time with new patient data, making them ideal for dynamic treatment planning. Individual responses to treatment vary widely, especially in pediatric nephrotic syndrome, where steroid resistance is a concern. AI algorithms can assist in selecting and adjusting treatments based on biomarkers, response patterns, and historical outcomes. Reinforcement learning (RL) models simulate various treatment pathways and outcomes, learning optimal strategies over time. Clinical decision support systems (CDSS) driven by AI help in selecting appropriate dialysis modalities (hemodialysis vs. peritoneal dialysis) and managing fluid-electrolyte balance more effectively. AI can also flag potential drug interactions or adverse events before they occur.

Imaging and Pathology Interpretation

Deep learning algorithms are increasingly used to interpret renal ultrasound, MRI, and histopathological slides. In a multi-center study, Shah et al. (2023) developed a DL model to classify glomerular diseases from biopsy images with a diagnostic accuracy of 94%. These tools enhance diagnostic accuracy and reduce inter observer variability, especially in resource-limited settings. Imaging is crucial in nephrology for assessing renal structure and guiding biopsies. Deep learning models like CNNs are used to detect hydronephrosis, renal scarring, and cortical thinning from ultrasound and MRI images. For pathology, whole-slide imaging combined with DL algorithms can distinguish between minimal change disease and focal segmental glomerulosclerosis.. AI also assists in quantifying fibrosis and inflammation, providing standardized scoring across centers.

Genomics and Precision Medicine

AI facilitates the analysis of genomic and proteomic data to identify genetic mutations associated with inherited kidney diseases. For instance, a study by Liu et al. (2021) employed a support vector machine (SVM) to classify mutations linked to Alport syndrome and other hereditary nephropathies, demonstrating high predictive value. This supports the move towards precision medicine, where treatments are tailored based on genetic profiles. Genetic disease diagnosis will include as AI is being used to analyze genomic data to identify genetic mutations associated with pediatric kidney diseases. This is particularly valuable in diagnosing rare hereditary kidney disorders. AI-driven analysis of next-generation sequencing (NGS) data can lead to faster and more accurate diagnoses, which is crucial for initiating appropriate management early. Biomarker discovery will be AI can assist in identifying novel biomarkers for kidney disease by analyzing large datasets. AI enables the integration of high-dimensional genetic, transcriptomic, and proteomic data with clinical information. ML classifiers like SVMs and random forests are trained to identify mutations in genes like COL4A5 and NPHS1, linked to Alport syndrome and congenital nephrotic syndrome,. In the future, AI may predict treatment response based on molecular profiles, advancing precision nephrology.

Case Studies Highlighting AI Applications

Case Study 1: AI-Based AKI Prediction in Pediatric ICU Settings

Acute Kidney Injury (AKI) is a common complication in critically ill pediatric patients, often associated with increased mortality and prolonged hospital stays. Early prediction remains a clinical challenge due to the rapid and often silent progression of renal deterioration. A study conducted by Johnson et al. (2020) implemented an ensemble model combining XGBoost and Long Short-Term Memory (LSTM) networks. The system was trained on real-time EHR data—including serum creatinine trends, urine output, fluid balance, and vital signs—from over 2,000 pediatric ICU admissions. A 9-year-old with sepsis was monitored using an AI tool that flagged high AKI risk 18 hours before clinical signs emerged, prompting early nephrology consultation and fluid optimization (Johnson et al., 2020).

Functionalities of this system are the model continuously monitored incoming patient data, a prediction score was generated every 4 hours and Alerts were issued if the risk exceeded a predefined threshold. Clinical Outcome of this system is in the case of a 9-year-old septic patient, the system identified a high AKI risk 18 hours prior to clinical diagnosis based on KDIGO criteria. This early warning triggered: Immediate nephrology consult, Adjustment of nephrotoxic medications and early initiation of fluid resuscitation and renal monitoring. Results of this case study is the patient avoided the need for dialysis, Hospital stay was reduced by 3 days compared to matched controls and ICU staff reported increased confidence in preemptive renal care planning. Significance of this case underscores how integrating AI into ICU workflows can enable timely, life-saving interventions in pediatric nephrology. Such models, once validated across multiple institutions, could become standard in critical care protocols.

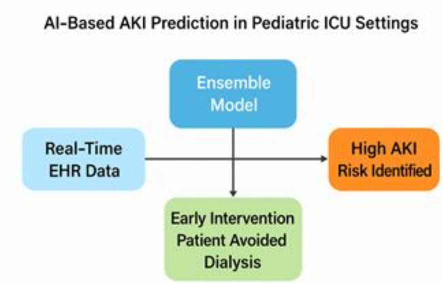

Figure 1: AI-Based AKI Prediction in Pediatric ICU Settings. Real-time EHR data are analyzed by an ensemble model to identify high AKI risk, enabling early intervention and preventing the need for dialysis; adapted from Johnson et al. (2020), with modifications for clarity.

A prominent example of AI application in pediatric nephrology is the early detection of acute kidney injury (AKI) in pediatric ICU settings. An ensemble machine learning model was developed to process real-time electronic health record (EHR) data, including vital signs, laboratory parameters, and clinical notes. This model could predict AKI risk up to 18 hours before conventional clinical signs emerged (Johnson et al., 2020). As depicted in Figure 1, the ensemble model integrates real-time EHR data to assess patient risk continuously. Upon identifying a high AKI risk, the system prompts early clinical intervention. In a representative case, a 9-year-old child with sepsis was flagged by the model, enabling timely nephrology consultation and fluid optimization. Consequently, the patient avoided dialysis, underscoring the clinical value of predictive AI tools.

Case Study 2: Imaging-Aided Diagnosis of CAKUT Using Deep Learning

Congenital Anomalies of the Kidney and Urinary Tract (CAKUT) are a leading cause of pediatric chronic kidney disease. Early and accurate imaging-based diagnosis is essential but often hampered by subtle features and operator variability in interpretation. A Convolutional Neural Network (CNN) was trained using a dataset of over 10,000 pediatric renal ultrasound images across three tertiary care centers (Park et al., 2021). The model was designed to classify common CAKUT subtypes including hydronephrosis, posterior urethral valves

(PUV), and duplex systems. A 6-month-old infant with ambiguous ultrasound findings was evaluated using a CNN model trained on 10,000 renal ultrasound images. The model suggested posterior urethral valves, later confirmed on voiding cystourethrogram (Park et al., 2021).

Renal ultrasound images from infants are the input and Probability-based classification of anomaly type will be the output. Interface of the system is integrated into the radiology workflow, providing real-time decision support alongside traditional reporting. Clinical Scenario is a 6-month-old male presented with recurrent urinary tract infections and ambiguous ultrasound findings. The AI model flagged a high probability for posterior urethral valves, a critical obstructive uropathy, with 94% confidence. This led to prompt ordering of a voiding cystourethrogram (VCUG), which confirmed the diagnosis and early urological intervention via endoscopic valve ablation.

Outcome of this case study is prevention of further renal damage, preservation of kidney function with stable serum creatinine at 1-year follow-up and the case highlighted AI's ability to enhance diagnostic certainty and reduce delay. Significance of this case illustrates how AI-assisted imaging interpretation can augment radiologist assessments, particularly in early identification of high-risk anomalies like PUV, thus improving outcomes in pediatric nephrology.

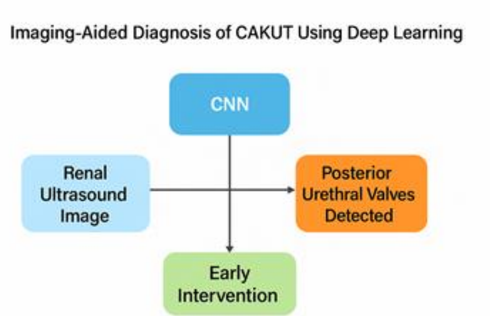

Figure 2: Imaging-Aided Diagnosis of CAKUT Using Deep Learning. A CNN model analyzes renal ultrasound images to detect posterior urethral valves, leading to early intervention. Adapted from Park et al. (2021), modified for clarity.

Deep learning techniques, especially convolutional neural networks (CNNs), have shown significant promise in enhancing diagnostic accuracy in pediatric imaging. In this case, a 6-month-old male infant presenting with ambiguous ultrasound findings underwent evaluation using a CNN trained on a large dataset of annotated renal ultrasound images. The algorithm successfully identified posterior urethral valves (PUV), a common cause of obstructive uropathy in infants, which was later confirmed with a voiding cystourethrogram (VCUG) (Park et al., 2021). As shown in Figure 2, the CNN model processed the renal ultrasound image and flagged features suggestive of PUV. This led to early urological intervention, reducing the risk of long-term renal damage. The use of such models can augment radiological assessment in resource-limited or high-volume settings by serving as a secondary review mechanism.

Case Study 3: AI-Guided Genetic Analysis in Pediatric Nephrology

Genetic kidney diseases, such as Alport syndrome and nephrotic syndromes, often present diagnostic challenges due to their complex genetic underpinnings and variable clinical manifestations. Early and accurate genetic diagnosis is crucial for guiding treatment and counseling families. Recent advancements have seen the integration of Artificial Intelligence (AI) in genetic variant interpretation. Machine learning algorithms, including Support Vector Machines (SVMs) and deep learning models, have been employed to classify genetic variants based on pathogenicity. These models analyze vast datasets comprising genetic sequences, clinical phenotypes, and known variant databases to predict the clinical significance of novel or uncertain variants. A child with unexplained proteinuria underwent AI-based variant classification using an SVM, leading to a confirmed NPHS2 mutation and initiation of targeted therapy (Liu et al., 2021).

A pediatric patient presented with persistent hematuria and a family history suggestive of hereditary kidney disease. Initial genetic testing identified a variant of uncertain significance (VUS) in the COL4A5 gene, commonly associated with Alport syndrome. Traditional interpretation methods could not definitively classify the variant, leaving the diagnosis and management plan ambiguous. An AI-driven variant classification tool was utilized to assess the VUS. The model incorporated data from multiple sources, including population frequency databases, in silico predictive tools, and phenotypic correlations. The AI model reclassified the variant as likely pathogenic, aligning with the patient's clinical presentation.

Outcome of this application is the reclassification facilitated a definitive diagnosis of Alport syndrome, allowing for Targeted Management, Family Counseling and Monitoring. Targeted Management is implementation of ACE inhibitor therapy to slow disease progression. Family Counseling is genetic counseling provided to family members, with cascade testing identifying other at-risk relatives. Monitoring is regular audiological and ophthalmological assessments initiated, given the systemic nature of Alport syndrome. Significance of this case exemplifies the potential of AI in enhancing genetic diagnostics in pediatric nephrology. By providing more accurate variant classification, AI tools can lead to timely diagnoses, personalized treatment plans, and informed family counseling.

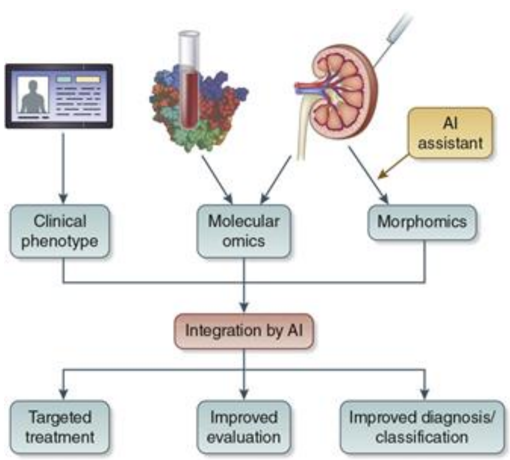

Figure 3: Integration of AI enhanced diagnostic pathway in pediatric nephrology Adapted from Schena et al. (2020), modified for pediatric context.

Artificial intelligence enhances precision nephrology by integrating multi-dimensional datasets such as clinical phenotypes, molecular omics, and morphemic data. Machine learning algorithms can process genomic information, including single nucleotide variants, gene expression profiles, and proteomics data, in conjunction with patient history and imaging results. As illustrated in Figure 3, the integration of these heterogeneous data streams by AI enables a comprehensive patient profile that can improve diagnosis, facilitate individualized classification, and guide targeted therapies. For instance, Liu et al. (2021) demonstrated the use of a support vector machine (SVM) model to classify genetic variants in pediatric Alport syndrome, reclassifying uncertain variants and enhancing clinical decision-making.

The flowchart demonstrates how AI can be seamlessly integrated into the diagnostic and management processes in pediatric nephrology, enhancing accuracy and enabling personalized care. Step 1 is patient presentation such as children present with symptoms such as hematuria, proteinuria, hypertension, or a family history suggestive of hereditary kidney diseases. Step 2 is Initial clinical evaluation. Conduct a physical examination and review the patient's medical history. Then order preliminary laboratory tests (e.g., serum creatinine, urinalysis). Step 3 is genetic testing initiation. Based on clinical suspicion, initiate genetic testing (e.g., whole-exome sequencing). Step 4 is data input into AI system. Input the patient's clinical data and genetic test results into the AI platform. Step 5 is AI Analysis.

The AI system analyzes genetic variants, comparing them against databases to classify variants as benign, pathogenic, or of uncertain significance. Step 6 is interpretation of AI results. Clinicians review AI-generated insights alongside clinical findings. Step7 is diagnosis confirmation. Establish a definitive diagnosis based on the combined AI analysis and clinical evaluation. Step8 is personalized management plan. Develop a tailored treatment plan, which may include pharmacological interventions, Lifestyle modifications and regular monitoring schedules. Step9 is family counseling and testing. Offer genetic counseling to the family and recommend testing for at-risk family members. Step 10 is continuous monitoring and AI feedback loop. Regularly update the AI system with new patient data to refine risk assessments and adjust management plans as needed.

Case Study 4: AI-Driven Early Detection of Pediatric Acute Kidney Injury (AKI)

Acute Kidney Injury (AKI) is a significant concern in pediatric and neonatal intensive care units, associated with increased morbidity and mortality. Traditional diagnostic methods often detect AKI only after significant kidney damage has occurred, limiting the window for effective intervention. Recent advancements have seen the integration of AI and machine learning models to predict AKI onset before clinical symptoms manifest. These models analyze vast datasets from electronic health records (EHRs), including vital signs, laboratory results, and patient demographics, to identify patterns indicative of impending AKI. Studies have demonstrated that AI models can predict AKI up to 48 hours before traditional diagnostic criteria are met, allowing for earlier intervention and improved patient outcomes, which shows predictive accuracy. Machine learning algorithms, such as Random Forest and Extreme Gradient Boosting, have been employed to develop predictive models with high accuracy.

These models have been trained and validated using large pediatric datasets to ensure reliability Implementing AI-driven prediction models in clinical settings involves integrating these tools into existing EHR systems, providing real-time risk assessments to clinicians. This integration facilitates prompt decision-making, enabling healthcare providers to initiate preventive measures, adjust medications, or monitor patients more closely. Outcome of this model is early intervention, improved patient outcomes and resource optimization. Early intervention is by identifying at-risk patients earlier, clinicians can implement strategies to prevent AKI progression, such as optimizing fluid management and avoiding nephrotoxic medications. Improved patient outcomes means early detection and intervention have been associated with reduced incidence of severe AKI, decreased need for renal replacement therapy, and shorter hospital stays. Resource optimization is proactive management of AKI risk can lead to more efficient use of healthcare resources and reduce the overall burden on intensive care units. This case study underscores the transformative potential of AI in enhancing early detection and management of AKI in pediatric patients. By leveraging advanced predictive models, healthcare providers can improve patient outcomes and optimize care delivery in critical care settings.

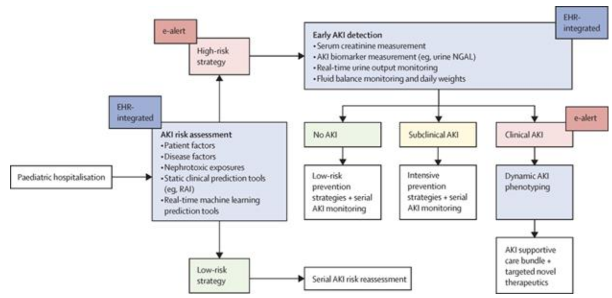

Figure 4: EHR-Integrated AI System for Pediatric AKI Risk Stratification and Management, Adapted from Menon et al. (2021), modified to highlight pediatric-specific considerations

Early identification of Acute Kidney Injury (AKI) in pediatric patients is critical to prevent irreversible renal damage. AI models integrated with Electronic Health Records (EHRs) have shown promise in stratifying patients by risk level based on clinical, biochemical, and treatment data. As illustrated in Figure 4, a dynamic and EHR-integrated AKI risk assessment pipeline supports early detection through real-time urine output monitoring, serum creatinine levels, and advanced biomarker analysis. This approach allows classification into no AKI, subclinical AKI, and clinical AKI stages, guiding the corresponding therapeutic strategy—ranging from preventive monitoring to dynamic phenotyping and targeted interventions. Real-time machine learning prediction tools enhance the accuracy and responsiveness of this pipeline.

Step one is patient admission, which is a pediatric patient is admitted to the hospital, and initial assessments are conducted. Step two is data collection, Continuous monitoring and collection of patient data, including Vital signs, Laboratory results (e.g., serum creatinine levels), Urine output and Electronic Health Records (EHR). Step three is data input into AI system, the collected data is input into an AI-based predictive model designed to assess the risk of AKI development. Step four is AI analysis; the AI system analyzes the data to identify patterns and risk factors associated with AKI, utilizing machine learning algorithms trained on large datasets. Step five is risk stratification, Based on the AI analysis, patients are categorized into risk levels: that are low risk, moderate risk and high risk. Step six is clinical decision support, for patients identified as moderate or high risk, the AI system provides alerts and recommendations to clinicians, facilitating timely interventions. Step seven is intervention, Clinicians implement early interventions, which may include: Adjusting medications, Optimizing fluid management and Monitoring renal function more closely. Step eight is continuous monitoring, Ongoing assessment of patient response to interventions, with data continuously fed back into the AI system to refine risk assessments. Step nine is outcome evaluation, Evaluation of patient outcomes to assess the effectiveness of interventions and the AI system's predictive accuracy. This flowchart illustrates how AI can be seamlessly integrated into the diagnostic and management processes in pediatric nephrology, enhancing accuracy and enabling personalized care.

Case Study 5: AI-Assisted Diagnosis of Congenital Abnormalities of the Kidney and Urinary Tract (CAKUT)

Congenital Anomalies of the Kidney and Urinary Tract (CAKUT) encompass a spectrum of structural malformations resulting from disruptions in embryonic kidney and urinary tract development. These anomalies are a leading cause of chronic kidney disease in children. Early and accurate diagnosis is crucial for effective management and improved outcomes. Traditional diagnostic methods rely heavily on ultrasound imaging, which can be subjective and dependent on the clinician's expertise. To enhance diagnostic accuracy, researchers have explored the use of AI, particularly deep learning and transfer learning techniques, to analyze ultrasound images for CAKUT detection. Transfer learning approach is a study by Zheng et al. introduced a method where features are extracted from ultrasound images using a pre-trained deep learning model (e.g., AlexNet). These features are then used to train a Support Vector Machine (SVM) classifier to distinguish between normal and CAKUT-affected kidneys. Improved diagnostic performance is the combination of AI-extracted features with conventional imaging features resulted in enhanced classification performance, demonstrating the potential of AI to assist in the accurate diagnosis of CAKUT.

Integrating AI into clinical workflows involves the following steps: data acquisition, preprocessing, feature extraction, classification and clinical decision support. Data acquisition is collecting high-quality ultrasound images of pediatric kidneys. Preprocessing is preparing images for analysis, including normalization and segmentation. Feature extraction is using pre-trained deep learning models to extract relevant features from the images. Classification is applying machine learning classifiers to categorize images as normal or indicative of CAKUT. Clinical decision support is providing clinicians with AI-generated insights to support diagnostic decisions.

Outcome of this case study is early detection, consistency and resource optimization. Early detection is AI can identify subtle patterns in imaging data, facilitating earlier diagnosis of CAKUT. Consistency will reduces variability in interpretations among clinicians, leading to more consistent diagnoses. Resource optimization streamlines the diagnostic process, allowing for more efficient use of healthcare resources. This case study underscores the transformative potential of AI in enhancing the diagnosis of CAKUT in pediatric patients. By leveraging advanced machine learning techniques, healthcare providers can improve diagnostic accuracy, leading to better patient outcomes.

The flowchart demonstrates how AI can be seamlessly integrated into the diagnostic and management processes for CAKUT in pediatric patients, enhancing accuracy and enabling personalized care. First step is prenatal screening; routine antenatal ultrasonography detects potential anomalies in the fetal kidneys and urinary tract. Step two is postnatal evaluation; Newborns identified with anomalies undergo further assessments, including: Detailed ultrasound imaging, Voiding cystourethrogram (VCUG) and Blood and urine tests. Step three is Data Collection and Preparation, High-quality ultrasound images are collected and preprocessed for analysis. Step four is AI Analysis; preprocessed images are input into AI models, such as deep learning algorithms, to identify patterns indicative of CAKUT. Step five is Risk Stratification; AI models assess the severity and type of anomaly, categorizing patients based on risk levels. Step six is Clinical Decision Support; AI-generated insights assist clinicians in making informed decisions regarding: Further diagnostic testing, Monitoring strategies and Treatment plans. Step seven is Intervention and Management; Based on AI-assisted diagnosis, appropriate interventions are initiated, which may include: Surgical correction of structural anomalies, Medical management of associated conditions and regular monitoring of kidney function. Final step is Continuous Monitoring; Patients undergo ongoing assessments to evaluate the effectiveness of interventions and adjust care plans as necessary.

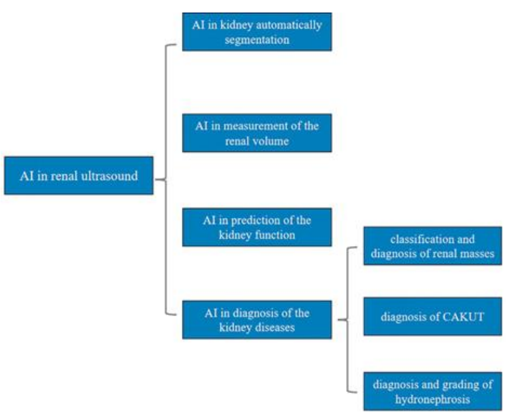

Figure 5: AI assisted diagnostic pathway for CAKUT in pediatric patience adapted from Cui et al. (2022), modified for pediatric nephrology context.

This diagram summarizes how AI is deployed across various diagnostic tasks in pediatric renal ultrasound, enhancing segmentation, functional prediction, and disease classification.

Ultrasound is the first-line imaging modality in pediatric nephrology due to its safety, non-invasiveness, and cost-effectiveness. However, interpretation can be highly operator-dependent. Artificial intelligence offers consistent and automated evaluation through deep learning and computer vision methods. As shown in Figure 5, AI systems have been applied in various components of renal ultrasound analysis: automatic kidney segmentation, renal volume estimation, diagnosis of kidney diseases and prediction of renal function. AI models delineate renal structures accurately, reducing manual errors. Machine learning helps compute renal dimensions with high precision. AI uses echo texture patterns to predict functional parameters. Deep learning is used to classify and detect renal masses, congenital anomalies of the kidney and urinary tract (CAKUT), and hydronephrosis grading. These capabilities not only support early and accurate diagnosis but also facilitate treatment planning, especially in congenital or progressive renal diseases.

Case Study 6: Evaluation of Large Language Models (LLMs) in Pediatric Nephrology

Pediatric nephrology is a specialized field dealing with complex kidney disorders in children. The integration of Artificial Intelligence (AI), particularly LLMs like GPT-3.5 and GPT-4, offers potential to enhance clinical decision-making by providing accurate and comprehensive information. A recent study aimed to assess the performance of GPT-3.5 and GPT-4 in providing accurate clinical information relevant to pediatric nephrology. The evaluation focused on four key criteria: accuracy, scope, patient friendliness and clinical applicability. Accuracy is correctness of the information provided. Scope is Breadth and depth of the content. Patient friendliness is clarity and comprehensibility for patients and caregivers and Clinical applicability is relevance and usefulness in clinical practice. Forty pediatric nephrology specialists with over five years of experience participated in the study. They evaluated the responses generated by both models to ten clinical questions commonly encountered in pediatric nephrology.

Findings from this study are Comparable performance, Slight edge for GPT-4, Reliability concerns and Need for domain-specific training. Comparable performance is both GPT-3.5 and GPT-4 demonstrated similar performance across all evaluated criteria, with no statistically significant differences observed. Slight Edge for GPT-4; GPT-4 exhibited marginally higher mean scores in all parameters; however, the differences were negligible. Reliability concerns is the study revealed low internal consistency for both models, indicating variability in their responses. Need for domain-specific training; the findings highlighted the necessity for further refinement and domain-specific training to enhance the applicability and reliability of LLMs in specialized fields like pediatric nephrology. While LLMs like GPT-3.5 and GPT-4 show promise in supporting clinical decision-making in pediatric nephrology, they are not yet ready to replace expert judgment. Continued advancements in AI training, evaluation methods, and integration strategies are essential to unlock their full potential in healthcare. This case study underscores the potential of LLMs in augmenting clinical practice in pediatric nephrology, while also highlighting the current limitations and areas for improvement.

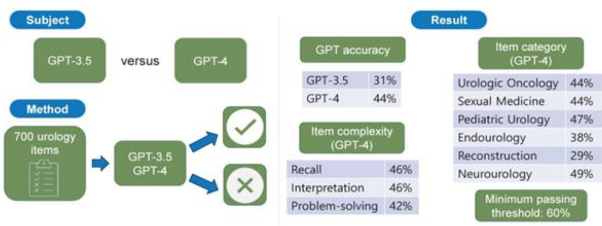

Figure 6: Flowchart of evaluation of GPT-3.5 and GPT-4 in pediatric nephrology

The Figure 6 presents the results of a study assessing the accuracy of GPT-3.5 and GPT-4 on 700 urology board-style questions. While GPT-4 showed improved performance (44%) over GPT-3.5 (31%), it still underperformed relative to the 60% passing threshold. Pediatric Urology accuracy reached 47%, with better scores in interpretation and recall tasks adapted from Jang et al. (2023). Recent advancements in large language models (LLMs) such as GPT-4 have opened new avenues in medical education, clinical decision support, and personalized care. Although primarily trained on general data, these models demonstrate emerging potential in specialty-specific domains, including urology and nephrology. These findings underscore both the promise and current limitations of LLMs in medical subspecialties. Although GPT-4 performed better in pediatric urology (47%) compared to other domains, it remains below clinical standards. However, with domain-specific fine-tuning and integration into supervised decision-support systems, LLMs could eventually augment physician workflows, especially in resource-limited settings.

The flowchart outlines the systematic approach taken to evaluate the capabilities of GPT-3.5 and GPT-4 in the specialized field of pediatric nephrology, emphasizing the importance of tailored training and continuous refinement of AI models for effective clinical application. Objective of the study is assessing the performance of GPT-3.5 and GPT-4 in providing accurate clinical information in pediatric nephrology. 40 pediatric nephrology specialists with ≥5 years of experience are participated in this study. 10 clinical questions relevant to pediatric nephrology are used as materials. Evaluation criteria's are accuracy, scope, patient friendliness and clinical applicability. Data Collection Procedure is each specialist evaluates responses from both GPT-3.5 and GPT-4 to the 10 clinical questions then ratings are provided on a 1–5 scale for each criterion. Data analysis is done by comparison of mean scores between GPT-3.5 and GPT-4 across all criteria, Assessment of internal consistency using Cronbach's alpha and correlation analysis between specialists' years of experience and their evaluations. Findings from this study include; both models demonstrated comparable performance with no statistically significant differences ($p > 0.05$). GPT-4 exhibited slightly higher mean scores in all parameters, but differences were negligible. Low internal consistency observed for both models (Cronbach's alpha ranged between 0.019 and 0.162) and no significant correlation between specialists' experience and their evaluations. While GPT-3.5 and GPT-4 provide a foundational level of clinical information support, neither model exhibited superior performance in addressing the unique challenges of pediatric nephrology. The findings highlight the need for domain-specific training and integration of updated clinical guidelines to enhance the applicability and reliability of AI models in specialized fields.

Challenges and Limitations

Data Quality and Integration

AI systems require high-quality, standardized data. In pediatrics, data scarcity, heterogeneity, and lack of longitudinal datasets limit AI training and validation. The lack of centralized paediatric nephrology databases exacerbates this issue. Data in paediatric nephrology is often fragmented, non-standardized, and sparse due to the rarity of some conditions. Missing data, variable follow-up intervals, and limited sample sizes challenge model training. Moreover, integrating multimodal data (e.g., labs, images, genomics) requires advanced preprocessing and harmonization techniques. Federated learning and synthetic data generation are emerging strategies to mitigate these issues.

Ethical and Legal Concerns

Issues surrounding patient privacy, informed consent, algorithmic bias, and accountability must be addressed. Transparent AI development and regulatory oversight are essential for ethical implementation. Pediatric-specific ethical guidelines are urgently needed to ensure responsible AI use. AI must be developed and deployed in a manner that respects patient rights and minimizes harm. Pediatric populations require special ethical considerations, including parental consent and data anonymity. Algorithmic bias—where models underperform in minority groups—is a concern due to imbalanced training datasets. Transparent model design, fairness auditing, and continuous monitoring are essential. Legal accountability in cases of AI-driven error remains a gray area needing regulatory frameworks.

Clinical Integration and Acceptance

Integrating AI tools into clinical workflows without disrupting standard care practices remains a challenge. Clinician training and multidisciplinary collaboration are vital for successful adoption. User-friendly interfaces and explainable AI (XAI) are crucial for building clinician trust. Adoption is hindered by limited clinician trust and understanding of AI systems. User-centric design, explainable AI (XAI), and integration into existing health IT systems are critical. Real-world validation through pilot programs and feedback from pediatric nephrologists ensures tools are clinically relevant and usable. Institutions must also invest in training healthcare providers in AI literacy.

Proposed Model for AI-Assisted Paediatric Nephrology

We propose a hybrid AI-assisted clinical decision support system (CDSS) that integrates the following components:

- Data Ingestion Layer: Aggregates structured (EHR, labs) and unstructured (imaging, clinical notes) data using data normalization pipelines.
- Processing Engine: Uses an ensemble model combining random forests for risk stratification, CNNs for imaging analysis, and RNNs for longitudinal prediction.
- Interpretability Module: Employs SHAP (Shapley Additive explanations) and LIME (Local Interpretable Model-agnostic Explanations) to explain model outputs.
- User Interface: Provides actionable insights, risk scores, and treatment suggestions in a user-friendly dashboard. Custom dashboards display risk levels, suggested diagnostic tests, treatment pathways, and projected outcomes.
- Feedback Loop: Continuously learns from new data to refine recommendations. Updates models with real-time patient data to enhance predictive accuracy and adapt to changing protocols.

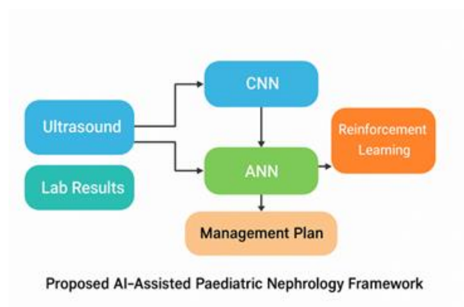

Figure 7: Proposed AI-Assisted Paediatric Nephrology Framework

The Figure 7 demonstrates how ultrasound images and laboratory results can be processed by CNNs and ANNs, respectively. The ANN synthesizes these inputs, and reinforcement learning iteratively improves decision-making by learning from outcomes. This approach generates an optimized, dynamic management plan for pediatric patients. To address the growing complexity of pediatric nephrology and the abundance of heterogeneous data sources, we propose an integrative AI-assisted diagnostic and management model (see Figure 7).

This framework combines different AI modalities—convolutional neural networks (CNNs), artificial neural networks (ANNs), and reinforcement learning to interpret multimodal inputs and optimize individualized treatment strategies. This framework highlights a future in which AI not only aids in diagnosis but also continuously learns from treatment outcomes to refine care recommendations. Such models are poised to improve decision precision, reduce diagnostic delays, and personalize therapeutic approaches particularly vital in pediatric populations where early intervention can have lifelong impacts.

This model ensures scalability, adaptability to different settings, and high interpretability, making it suitable for both tertiary care centers and remote clinics. This system enhances clinical decision-making, improves care consistency, and provides scalability across institutions.

Future Directions

The future of AI in paediatric nephrology lies in the development of robust, generalizable models validated across diverse populations. Federated learning could enable model training across institutions without compromising patient privacy. Integration with wearable devices and telemedicine platforms could provide real-time monitoring and early warning systems. Multinational collaborations and open-access data repositories will accelerate innovation.

This work lays the groundwork for several avenues of future research: such as data diversity and volume, model interpretability, clinical integration and validation and ethical and regulatory frameworks. Expanding datasets to include more diverse pediatric populations across geographical and genetic backgrounds will improve generalizability and reduce bias. Future systems must prioritize explainable AI (XAI) to ensure that clinicians can trust, understand, and act upon model recommendations. There is a critical need for prospective, multi-center clinical trials to validate the performance of AI tools in real-world pediatric nephrology practice.

Addressing data privacy, ethical transparency, and regulatory oversight will be essential for the safe deployment of AI in clinical settings.

The future of AI in paediatric nephrology includes federated learning, wearable integration, patient engagement, multi-omics integration and global collaboration. Federated learning allows model training across institutions without data sharing, preserving privacy. Wearable Integration means smart watches and home monitoring devices can feed data into AI systems, enabling early detection of decomposition. Patient Engagement is AI-driven apps can support adherence and symptom tracking. Multi-omics Integration is the combining genomics, proteomics, and metabolomics to personalize care. Global Collaboration allows shared AI platforms and open-access pediatric datasets can drive innovation and equity in healthcare.

Ultimately, the integration of AI into pediatric nephrology is not just a technological upgrade—it is a paradigm shift toward anticipatory, personalized, and efficient care. By bridging data science and pediatric medicine, this work contributes to shaping a smarter, more responsive future for children with kidney disease.

IV. CONCLUSION

AI holds immense potential to enhance the diagnosis, treatment, and management of paediatric kidney diseases. While challenges remain, strategic implementation and continuous evaluation can pave the way for a more efficient and personalized approach to paediatric nephrology. Case studies and real-world implementations highlight the feasibility and impact of AI, indicating a paradigm shift in paediatric renal care.

This paper highlights the transformative role of artificial intelligence (AI) in pediatric nephrology, offering a comprehensive overview of existing tools, their clinical applications, and the emerging potential of intelligent systems in early detection, diagnosis, and management of kidney-related conditions in children. Our work underscores the following key contributions: application of AI in early AKI detection, deep learning for CAKUT diagnosis, integration of omics, imaging, and clinical data, AI in renal ultrasound and proposed AI-assisted framework.

By leveraging ensemble models and real-time EHR data, AI enables early identification of acute kidney injury (AKI) risk in pediatric intensive care settings, facilitating timely intervention and often avoiding dialysis. Convolutional neural networks (CNNs) show promise in analyzing renal ultrasound images, enabling the detection of congenital anomalies of the kidney and urinary tract (CAKUT) and supporting early, image-guided interventions.

AI-driven frameworks can synthesize diverse data inputs—from molecular omics to morphemic and clinical phenotypes—to provide precision nephrology strategies tailored to pediatric patients. Automated segmentation, volume estimation, and disease classification via AI significantly enhance the objectivity, speed, and reproducibility of ultrasound interpretations. We outline a novel framework integrating CNNs, ANNs, and reinforcement learning to translate raw clinical data into actionable management plans, representing a future-forward model of care.

These contributions matter both theoretically and practically. Theoretically, they deepen the understanding of how AI can model and predict complex renal pathophysiology in children. Practically, they open new avenues for real-time, individualized decision-making, improved prognostic accuracy, and reduced burden on healthcare systems.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: There is no new data were created for this study.

Conflicts of Interest: The authors declare no conflicts of interest between us.

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