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AI-Assisted Detection Of Early Renal Dysfunction: Advancing Precision Medicine In Kidney Care

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ABSTRACT

Early renal dysfunction frequently progresses without overt clinical manifestations, limiting opportunities for timely nephroprotective intervention. Conventional diagnostic indicators, including serum creatinine and estimated glomerular filtration rate, often reflect renal impairment only after substantial functional loss has occurred. This study evaluated the role of an artificial intelligence–assisted analytical framework for the early identification of renal dysfunction using routinely available clinical and laboratory data. A retrospective analytical design was applied to electronic medical records of adult patients undergoing routine renal evaluation at a tertiary nephrology center. Structured variables encompassing renal biomarkers, blood pressure measurements, and key comorbid conditions were analyzed through parallel conventional clinical assessment and AI-assisted risk stratification. The AI-based approach assessed nonlinear interactions among renal parameters to classify patients into renal risk categories, enabling comparison with standard clinical classification. The findings demonstrated substantial concordance between AI-assisted and clinician-based risk assessment, with the AI model exhibiting heightened sensitivity in identifying individuals with moderate and subclinical renal risk who may be overlooked by fixed threshold–based evaluation. Predictive patterns generated by the model aligned with established nephropathological mechanisms, supporting clinical interpretability. Overall, the study highlights the potential of AI-assisted diagnostics to enhance early renal risk detection, refine stratification accuracy, and support precision-oriented kidney care, while complementing rather than replacing clinical judgment.

KEYWORDS: Early Renal Dysfunction, Artificial Intelligence, Nephrology Diagnostics, Precision Medicine, Kidney Care.

INTRODUCTION

Early renal dysfunction is an acute stage of the natural history of kidney disease when structural and functional changes start to occur even before clinical symptoms appear. Kidney disease keeps increasing all over the world, and early dysfunction has become a significant contributor to morbidity and medical expenses in long-term care in the event of non-diagnosis or improper management [1]. Modest changes in renal functions tend to creep up, exposing individuals to cardiovascular diseases, hospitalization, and eventual kidney failure. Early diagnosis is hence the focus in preventive nephrology and renal reserve in the long-term.

With the currently improved kidney treatment, early kidney malfunction remains a diagnostic problem. The traditional diagnostic features, like serum creatinine and estimated glomerular filtration rate indicate comparatively late functional alterations and are not receptive to minor renal harm [2]. The mechanisms of physiological compensatory actions tend to conceal the initial loss of nephrons and the diagnosis of the disease is frequently underestimated. Consequently, not all individuals are admitted to specialized care of nephrology until after they have suffered severe and irreparable damage to their kidneys, and therefore, nephroprotective measures are not as effective [3].

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Existing diagnostic methods in nephrology are largely based on the interpretation of laboratory values using thresholds, which might not be able to elucidate distant risk pathways in people [4]. The measurement of albuminuria has been shown to enhance risk stratification, but has not been implemented in practice consistently, even in asymptomatic populations. Also, evidence-based clinical decisions are often made based on fixed values as opposed to dynamic trends of renal function variation. These constraints limit the capability of clinicians to discover high-risk persons at the stage where disease-modifying approaches would be the most valuable [5].

Artificial intelligence is becoming more and more popular in kidney medicine in recent years as a tool for improving diagnostic accuracy and clinical decision support. Machine learning methods allow to analyze a large, multidimensional clinical dataset and identify latent patterns of the early signs of renal dysfunction that cannot be observed with standard statistical techniques [6]. AI-driven systems have demonstrated potential in imitating the laboratory trend, demographic, and comorbidity patterns to enhance the detection and prognostication of diseases in the context of nephrology [7].

The use of AI is in line with the principles of precision medicine, which highlights individual risk assessment and clinical management. In the management of the kidney, this method facilitates the prompt intervention, the best monitoring and tailored treatment planning that targets the disease from progressing [8]. Through the incorporation of regularly gathered clinical data, AI-aided models provide a chance to expand the diagnostic capacity of a nephrologist without bringing invasive or expensive methods. This prospect is especially applicable in the case of early renal dysfunction, where early intervention has a great impact on the final results [9].

Available sources have reported the viability of AI-based models in the process of forecasting the progression of chronic kidney disease and negative renal outcomes [10]. Nevertheless, numerous studies have been carried out on the higher stages of disease progression or even on a subset of patients, which prevents their generalizability to early detection of dysfunctions. Moreover, the issues of clinical interpretability, external validation, and integration into the daily practice of nephrology have not studied. These gaps complement the importance of a study with a strong presence at the early detection stage, with a high congruence with the practical real-world kidney care [11].

The current research was aimed at filling these gaps by assessing an AI-based strategy to detect early renal dysfunction based on clinical and laboratory data that can be obtained routinely. The study sought to provide an improved diagnostic sensitivity at clinically relevant predictors of nephrology practice by emphasizing early disease indicators and focusing on clinically relevant predictors. This strategy will help enhance the developing role of AI as a supportive tool in kidney medicine, which will promote evidence-based practice but not clinical judgment [12].

Objectives of the Study

1. To evaluate the effectiveness of an AI-assisted risk stratification approach in identifying early renal dysfunction using integrated clinical and laboratory parameters in routine nephrology practice.
2. To compare AI-based renal risk classification with conventional clinical assessment in terms of risk distribution and diagnostic concordance.

2. MATERIALS AND METHODS

2.1 Study Design

The study adopted a record-based analytical study design that entailed a retrospective study design to assess the renal risk stratification through clinical and laboratory parameters. The research was based on organized secondary data retrieved from regularly stored medical records, which allowed assessing it under the conditions of real practice with no interventional interventions. This design allowed achieving the systematic comparison of traditional clinical assessment and AI-assisted risk classification. There was a focus on quantitative variables that apply to renal functioning and the progression of the disease. According to the retrospective framework, interrelationships among renal biomarkers could be effectively analyzed without losing the methodological consistency of the current clinical evaluation practice.

2.2 Data Collection Instrument

A questionnaire was created to obtain clinically relevant variables of patient records in a structured format. To maintain a focus on the methods, the instrument was limited to the parameters that have a direct relationship with the renal risk assessment. Variables involved in medical history were hypertension, diabetes mellitus, and past kidney disease and family history of kidney disease, which had numerical codes. Behavioral, lifestyle and socioeconomic variables were not included in the questionnaire to eliminate confounding factors. Uniformity of data extraction ensured that across records, data was extracted consistently and could be easily integrated into computational processes to be analyzed later using statistics and AI.

2.3 Clinical and Laboratory Parameters

Variables of clinical and laboratory variables were serum creatinine, estimated glomerular filtration rate (eGFR), blood urea, urine protein or albumin status, and blood pressure. Standardized units were used to record these parameters to ascertain analytical consistency and eGFR was estimated using an age/sex-adjusted creatinine-based equation, which provided the physiological consistency among renal biomarkers. Indicators of renal excretory and glomerular functions were included, which were blood urea levels and proteinuria status. Measurements of blood pressure were also included due to their proven role in the progression of the renal disease.

2.4 Renal Risk Stratification

There were two parallel methods of classification of renal risk. Traditional clinical evaluation placed patients in low, moderate, or high risk as a result of a conjoined analysis of eGFR, proteinuria, and blood pressure levels. On its own, an AI-assisted model was able to categorize renal risk based on the same clinical inputs, which allowed it to make comparisons free of bias. The AI model considered non-linear interaction between biomarkers of renal symptoms and comorbidities to make risk predictions. This parallel stratification system allowed to organize the evaluation of AI-assisted assessment compared to usual clinical judgment in a systematic way.

2.5 Concordance and Data Analysis

The Python programming language was used for all the data processing and analyses. The numeric encoding of variables was done to enable the computational analysis and reduce interpretive variability. The data set was edited to ensure the clinical and physiological concordance of interdependent parameters, especially between serum creatinine, eGFR and blood urea. Python-based workflows of analytical procedures were conducted in order to assess the agreement on AI-assisted versus conventional clinical risk classifications. Using this method, diagnostic alignment and AI performance could be objectively and reproducibly assessed.

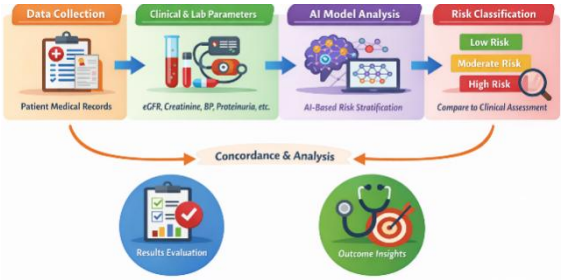

Figure 1: Flowchart Illustrating the AI-Assisted Methodological Framework for Early Renal Dysfunction Risk Stratification

3. RESULTS

3.1 Demographic Characteristics of the Study Population

The demographic profile of the study population. The median age of patients was 52.7 10.8 years, with the age range being between 35 and 70 years, as shown in Table 1. The cohort was composed of 170 (68.0%) male patients and 80 (32.0%) female patients. The age distribution showed the prevalence of the middle-aged and older adults, which is in line with the population at higher risk of renal dysfunction. This population stratification gave a suitable clinical environment to assess the renal biomarkers and the results of risk stratification.

Table 1. Demographic Characteristics of the Study Population (n = 250)

Variable	Overall (n = 250)
Age (years), mean ± SD	52.7 ± 10.8
Age range (years)	35–70
Gender – Male, n (%)	170 (68.0)
Gender – Female, n (%)	80 (32.0)

3.2 Clinical History and Comorbidity Profile

Table 2 shows the prevalence of the major renal risk modifiers. It was noted that 133 patients had hypertension (53.2%), and 108 patients had diabetes mellitus (43.2%). A previous kidney disease diagnosis was found in 90 patients (36.0%), and a family history of kidney disease was found in 107 patients (42.8%). These data showed that the population of comorbid conditions was significant, and they were known to affect renal functioning, which justified the clinical applicability of the study population in assessing renal risks.

Table 2. Prevalence of Clinical History Variables

Clinical Variable	n (%)
Hypertension	133 (53.2)
Diabetes mellitus	108 (43.2)
Previous kidney disease	90 (36.0)
Family history of kidney disease	107 (42.8)

3.3 Clinical and Laboratory Parameters

Table 3 describes clinical and laboratory results. The mean serum creatinine was 2.18, and the standard deviation was 0.79, which was under 2.5, meaning that the reference range is broad with a wide variation in renal functioning. The average levels of blood urea were 64.8 + 25.4mg/dl, and the mean blood pressure was 149.6 + 20.8mmHg. High urine protein was found in 103 patients (41.2%). Figure 2 visually proved the physiological alignment of the inverse relationship between serum creatinine and eGFR.

Table 3. Clinical and Laboratory Parameters

Parameter	Mean ± SD	Range
Serum creatinine (mg/dL)	2.18 ± 0.79	0.55–6.00
eGFR (mL/min/1.73 m²)	70.9 ± 26.9	8.0–130.0
Blood urea (mg/dL)	64.8 ± 25.4	10.0–180.0
Blood pressure (mmHg)	149.6 ± 20.8	100–200
Elevated urine protein, n (%)	103 (41.2)	

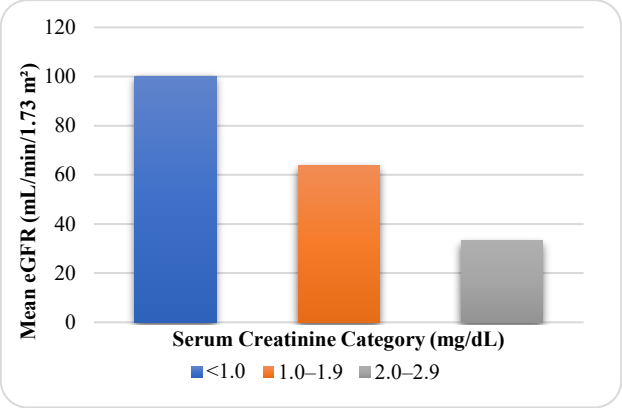

Figure 2: Mean eGFR Across Serum Creatinine Categories

3.4 Distribution of Renal Risk Categories

The distribution of categories of renal risk based on the traditional clinical assessment and the use of AI-based classification is presented in Table 4. Low risk (28.8%), moderate risk (38.8%), and high risk (81 or 32.4%) were classified as clinically low, moderate, and high risk, respectively. The use of AI-based assessment determined 66 (26.4) patients to be low risk, 112 (44.8) to be moderate risk and 72 (28.8) to be high risk. Figure 3 shows comparative differences in classification patterns, with more AI sensitivity to moderate risk.

Table 4. Distribution of Renal Risk Categories

Risk Category	Clinical Assessment n (%)	AI-Based Assessment n (%)
Low risk	72 (28.8)	66 (26.4)
Moderate risk	97 (38.8)	112 (44.8)
High risk	81 (32.4)	72 (28.8)

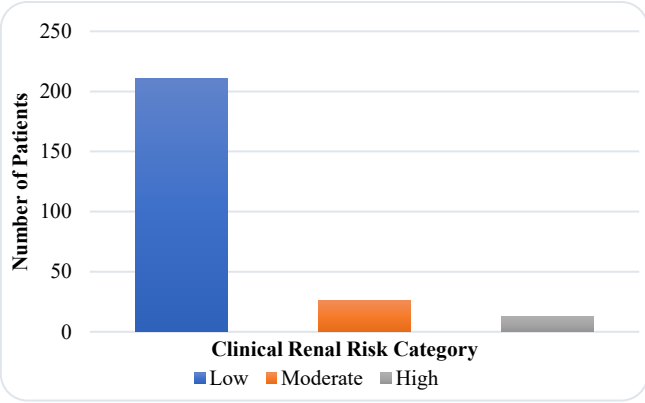

Figure 3: Clinical Renal Risk Distribution

3.5 Concordance Between Clinical and AI-Based Assessment

The summary of agreement between traditional clinical assessment and AI-assisted classification is presented in Table 5. In 210 (84.0) and 40 (16.0) patients respectively, concordant and discordant classifications were made, respectively. The vast majority of the discrepancies were between risk categories that were close to each other, instead of extreme misclassification. Figure 4 displays the general agreement pattern showing a high level of agreement between the methods of diagnosis. These results showed that AI-assisted assessment was mostly beneficial to clinical judgment, besides narrowing risks classification among borderline cases.

Table 4. Distribution of Renal Risk Categories

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High risk	81 (32.4)	72 (28.8)

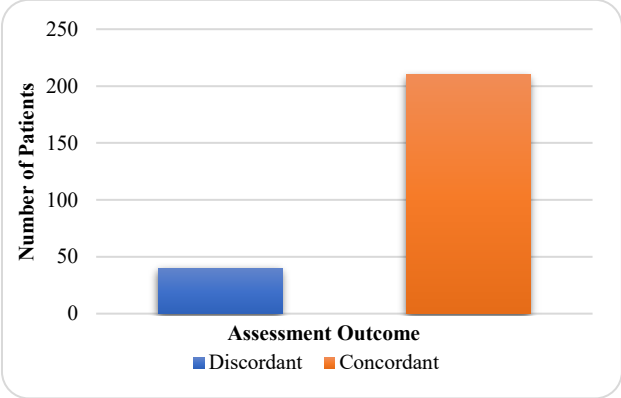

Figure 4: Concordance Between Clinical and AI-Based Assessment

4. DISCUSSION

This research has shown that AI-supported analytical models improved the detection of renal dysfunction in standard nephrology care through the exploitation of minor, clinically significant changes in renal biomarkers. The findings indicated that early alterations in renal functioning were better captured with the aid of AI-based risk stratification, especially by combining the clinical indicators of serum creatinine, eGFR, blood urea, proteinuria, and blood pressure. This was the most pronounced among patients who belong to moderate-risk groups, as borderline renal impairment might not arouse immediate alarm when only conventional assessment is used. The fact that physiological markers correlated with AI-based classifications indicated that the chosen analytical scheme was reliable enough to justify the possible benefits of AI in enhancing the sensitivity of early diagnosis without interfering with the well-established clinical routines.

The results also showed that AI-aided risk assessment was a complement to the traditional clinical judgment, but not a substitute. Large agreement rates between AI-based and traditional clinical risk classifications indicated that the model adhered to the traditional principles of nephrology and optimized the risk classification of ambiguous cases. The discrepancies were mostly limited to the adjacent risk categories and were signs of the clinically plausible reinterpretation

and not the instability of the algorithm. This conduct highlighted the explainability and security of AI-assisted applications in the practice of nephrology as the system was found to be responsive to combined biomarker trends as opposed to numerical reference limits. These properties are critical to guarantee the clinician confidence and long-term adaptation into the regular kidney care.

The current results were correlated with the body of evidence on the application of AI in nephrology diagnostics when compared with existing literature. The importance of machine learning in the prediction of the progression of chronic kidney disease based on electronic health records has been highlighted in previous studies [13]. The AI-based models were also shown to be better at detecting kidney disease at the early stage than the conventional statistical models [14], specifically detecting subclinical renal impairment [15]. Risk stratification systems were found to have enhanced predictive powers in outpatient nephrology groups [16], whereas longitudinal eGFR trajectory examination preferred AI-based evaluation approaches [17]. Ensemble learning methods improved the early signs of kidney disease classification [18], and AI-based screening in the primary care setting was effective [19]. Other papers emphasized better risk prediction using albuminuria [20], automated renal risk scoring with ease [21], better decision support with nephrology centres [22], and better early referral plans with the help of predictive analytics [23]. Model robustness was also supported by multicentre validation studies using different renal cohorts [24] and AI-based technologies enhanced the consistency of diagnosis across institutions [25]. AI models that are precision medicine-oriented empowered kidney disease prevention methods [26]. Taken, these results were quite consistent with the results of the current study, which confirms its topicality in the current research of nephrology.

Along with these advantages, there were a number of limitations that should be considered. Retrospective design was a limitation in the causal inference and depended on the quality and completeness of available clinical documentation. Despite the fact that physiological alignment was achieved by performing preprocessing of the structured data and derivation of the dependent variables, the variability present in the laboratory measurement intervals would have contributed to the biomarker representations. The data was based on a small clinical setting, and this may limit the ability to generalize to larger and more diverse groups. Moreover, the predictive performance over time was not possible as the outcome data were not provided longitudinally, and it was not possible to conclude the benefits of the disease progression or the survival. Although interpretability was valued, AI-based decision-support remained to necessitate tight clinical supervision to avoid the tendency to rely on the outputs of the algorithm in more complicated nephrology cases. Irrespective of these shortcomings, the clinical implications of the findings were high. The early detection of renal dysfunction helped to access nephroprotective measures in time, to follow up plans and to plan treatment individually. The presence of AI-assisted diagnostics in regular nephrology practice created the chance of increasing the efficiency of screening processes, minimizing the time spent on diagnosing patients, and enhancing the accuracy of risk stratification. Significantly, the presented performance features confirmed the idea of AI as an adjunct to the expertise of clinicians, but not as a substitute. The balance was consistent with the paradigm shift in kidney care towards preventive nephrology and precision-based interventions without clinical responsibility.

The current findings provided current directions for future research. External validity would be reinforced by multi-centre validation studies, which would help to implement it on a broader clinical basis. The longitudinal follow-up would help in explaining how AI-aided early detection would change the course of renal diseases and the rate of progression and patient outcomes. The development of AI models to assess the risks of transplantations and postoperative renal monitoring were the areas of open possibilities. Real-time clinical decision-support systems integration might be beneficial in making more responsive nephrology processes. Further implementation of interpretability models and long-term participation of clinicians was also necessary to make sure that AI technologies used in kidney care are adopted responsibly and efficiently.

5. CONCLUSION

The present investigation reinforces the clinical value of artificial intelligence–assisted analytical approaches in strengthening early detection strategies for renal dysfunction within routine nephrology practice. By integrating routinely collected clinical and laboratory parameters, the AI-supported framework demonstrated an enhanced capacity to identify subtle alterations in renal function that frequently remain unrecognized when conventional threshold-based evaluation methods are applied in isolation. This capability is particularly relevant in the context of subclinical and moderate-risk profiles, where early identification plays a decisive role in delaying disease progression and optimizing long-term renal outcomes. The observed alignment between AI-assisted risk stratification and established clinical assessment highlights the complementary nature of such technologies. Rather than displacing clinician expertise, the analytical model functioned as a decision-support mechanism that refined risk categorization in borderline cases through multidimensional pattern recognition. The predictive variables emphasized by the model reflected known pathophysiological processes of early kidney injury, thereby supporting clinical interpretability and reinforcing confidence in its practical application. From a precision medicine perspective, AI-assisted renal risk evaluation offers meaningful opportunities to individualize monitoring intensity, prioritize preventive interventions, and allocate nephrology resources more efficiently. The use of routinely available data further enhances feasibility, enabling seamless integration into existing clinical workflows without additional diagnostic burden. Although broader validation remains necessary, the findings underscore the potential of AI-driven tools to improve preventive nephrology strategies and

strengthen evidence-informed decision-making. Future efforts should focus on prospective and multicentre validation, longitudinal outcome assessment, and continued emphasis on model transparency and ethical deployment to ensure safe, effective, and sustainable incorporation of artificial intelligence into standard kidney care.

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