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Acute kidney injury: Diagnosis, causes, and latest treatments- An updated review article

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***Abstract*---Background:** Acute kidney injury (AKI) is a critical clinical syndrome characterized by a rapid decline in renal function, with various precipitating factors including heart failure, sepsis, and nephrotoxic drugs. The prevalence in hospitalized patients is concerning, particularly among those with COVID-19, where AKI incidence has reached approximately 36.6%. The current diagnostic criteria primarily rely on serum creatinine (SCR) levels and urine output (UO), which often fail to identify AKI early enough for effective intervention. **Aim:** This review aims to consolidate current knowledge on AKI, highlighting its diagnosis, causes, and the latest treatment approaches, with a focus on emerging technologies that improve early

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detection. **Methods:** The article reviews literature on AKI diagnostic criteria, imaging techniques, biomarkers, and the application of machine learning algorithms in predicting AKI. Emphasis is placed on novel biomarkers and biosensors that enhance early detection, as well as machine learning models that synthesize data from electronic health records. **Results:** Advances in biomarkers like NGAL and KIM-1, alongside biosensors, offer improved sensitivity for early AKI detection. Additionally, machine learning models have demonstrated high predictive accuracy, achieving area under the receiver operating characteristic curve (AUC) values exceeding 0.9 across various clinical contexts. **Conclusion:** The integration of novel biomarkers, biosensors, and machine learning approaches can revolutionize AKI diagnosis and management, significantly improving patient outcomes.

***Keywords*---**Acute kidney injury, biomarkers, machine learning, diagnosis, treatment, nephrology.

Introduction

Acute kidney injury (AKI) represents a prevalent clinical syndrome marked by an abrupt impairment of renal function. The kidneys serve as critical metabolic organs within the human body. Various factors can precipitate AKI, including heart failure, sepsis, hemorrhage, nephrotoxic medications, and COVID-19, among others [1-8]. For instance, Hirsh et al. documented a significant prevalence of AKI among hospitalized COVID-19 patients, reported at 36.6% [9]. It is estimated that 20% of individuals admitted to hospitals progress to AKI, with 10% of those requiring renal replacement therapy (RRT). The mortality rate for patients undergoing RRT can reach 50%. Moreover, individuals who recover from AKI face an increased risk of chronic kidney disease and potentially end-stage renal disease [10-13]. Treatment alternatives for AKI are notably limited. Early identification of AKI, coupled with appropriate preventive interventions, can substantially enhance recovery outcomes. Presently, the diagnostic criteria for AKI rely on serum creatinine (SCR) levels and urine output (UO), as outlined in the 2012 guidelines from Kidney Disease: Improving Global Outcomes [14]. However, both SCR and UO exhibit non-specificity and may be delayed in the early identification of AKI. For example, SCR levels can be influenced by various non-renal factors, such as elevated muscle mass or the consumption of certain medications, including trimethoprim and cimetidine [15]. Additionally, only consistent oliguria serves as a reliable indicator of acute kidney injury, which complicates timely AKI diagnosis based on UO alone [16]. Furthermore, alterations in SCR and UO occur with a significant delay relative to critical structural changes in the kidneys associated with AKI. By the time SCR and UO exhibit substantial changes, renal function is often severely compromised, leading to missed opportunities for timely intervention in AKI treatment [17, 18].

Imaging modalities, including ultrasound and computed tomography, can evaluate renal morphology and offer insights into kidney function, perfusion, and potential AKI etiology [19, 20]. Nevertheless, these imaging techniques are accompanied by drawbacks, such as low resolution, the risk of radiation exposure, and potential nephrotoxic effects from contrast agents, rendering them less suitable for early AKI diagnosis.

In recent years, advancements in information technology, nanotechnology, and biomedicine have significantly enhanced early AKI diagnosis [21, 22]. On one hand, novel functions of artificial intelligence in biomedicine are being continuously explored [23-25]. Specifically, machine learning, a subset of artificial intelligence, has proven effective in predicting AKI by constructing predictive models through the analysis of extensive datasets related to medical treatments and patient outcomes [26]. On the other hand, the comprehensive investigation of AKI pathology has led to the discovery of increasingly effective early biomarkers, such as neutrophil gelatinase-associated lipoprotein (NGAL), γ-glutamyl transpeptidase (GGT), kidney injury molecule-1 (KIM-1), microRNA (miRNA), and reactive oxygen and nitrogen species (RONS) [27-30]. The concentrations of these biomarkers in renal tissues or body fluids (such as blood or urine) significantly rise prior to the manifestation of renal organic and functional diseases. Consequently, these biomarkers provide greater sensitivity for early AKI detection compared to SCR and UO. However, as clinical demands evolve, traditional detection techniques (such as ELISA and PCR) for these novel biomarkers are becoming increasingly impractical. In response, a variety of biosensors, including optical probes, electrochemical probes, and surface plasmon resonance (SPR) probes, have been developed using advanced nanotechnology, DNA technology, and synthesis techniques, enabling high-sensitivity and selective detection of these markers. This review elucidates the pivotal roles of RONS and other biomarkers in the early progression of AKI and systematically summarizes the applications of emerging detection technologies for RONS, NGAL, GGT, KIM-1, and miRNA in early AKI detection. Furthermore, we comprehensively summarize the application of machine learning in AKI prediction algorithms and specific contexts. Ultimately, we propose valuable strategies for advancing these technologies in clinical settings.

Machine Learning

Currently, the early diagnosis of acute kidney injury (AKI) poses significant challenges. Even seasoned clinicians cannot assure the accuracy of AKI diagnoses due to the complex and varied changes associated with the condition across different patients. Machine learning, which centers on algorithms that emulate human learning behaviors, holds great potential for enhancing diagnostic accuracy in disease detection [31-33]. Theoretically, with an adequate supply of biomedical and patient datasets, machine learning can reliably diagnose early AKI by leveraging "ground truth" data, where the relationships between data points and outcomes are established. However, data collection remains a critical bottleneck for machine learning applications [34].

On one hand, the effectiveness of machine learning training is constrained by dataset size. Small datasets or simplistic features may lead to overfitting, while overly large datasets with excessive features can significantly increase the training burden and computational complexity due to potential linear correlations among certain features. On the other hand, the data collection approach is contingent upon specific circumstances. A careful decision must be made regarding whether to utilize manual extraction of data features, weighing the labeling costs against the algorithm's accuracy. Fortunately, the widespread implementation of electronic health records (EHR) has alleviated some data collection issues, leading to a substantial impact of machine learning on AKI prediction and patient monitoring.

Numerous machine learning techniques have been developed for AKI prediction, with the Area Under the Receiver Operating Characteristic Curve (AUC) serving as a crucial metric. AUC quantifies the likelihood that a machine learning algorithm can prioritize positive samples (AKI patients) over negative samples (non-AKI patients) [35]. AUC is statistically consistent and offers greater discrimination than other performance metrics when evaluating classification problems. While it is challenging to definitively categorize an algorithm as good or bad due to variability in datasets and processing methods, AUC provides a reasonable benchmark for assessing predictive performance. Over the past five years, machine learning has advanced significantly in predicting AKI, with some models achieving exceptional accuracy, reflected in AUC values exceeding 0.9. Depending on the model's application scope, these machine learning methods can be classified into categories such as preoperative AKI risk prediction, AKI prediction during surgery, real-time postoperative AKI prediction, intensive care unit AKI prediction, and AKI prediction across all hospital wards.

Preoperative AKI Risk Prediction

Preoperative data encompasses various factors associated with the onset of acute kidney injury (AKI), including demographic characteristics (such as age, race, and sex), medical history and acuity (e.g., Charlson comorbidity index, smoking habits, and heart failure), physiological measurements (e.g., blood pressure, pulse, and heart rate), and the type of anesthesia used. Machine learning can effectively synthesize the relationships between preoperative data and AKI, enabling precise predictions through appropriate algorithms. For instance, Bihorac et al. developed an automated analytical framework employing generalized additive models and random forest techniques for the preoperative risk algorithm (MySurgeryRisk) within a single-center cohort of patients undergoing major surgeries [47]. Utilizing the University of Florida Health Integrated Data Repository as an Honest Broker, they established a perioperative longitudinal cohort that integrated electronic health records (EHR) with public datasets. The dataset consisted of 285 basic features, a sample size of 51,457 patients, and a maximum of 10,000 feature classifications. MySurgeryRisk assessed the risks of morbidity and mortality across eight postoperative complications, including AKI, and autonomously determined the optimal threshold to categorize patients into low-risk and high-risk AKI groups, achieving an AUC of 0.88 for AKI prediction. The MySurgeryRisk prediction interface was user-friendly; patients with risk scores exceeding the threshold were labeled as high risk, with the associated disease area highlighted in red, while lower-risk patients were marked in green. MySurgeryRisk has also been integrated as a key component of the intelligent perioperative platform, facilitating real-time clinical workflows for automated surgical risk prediction and AKI forecasting.

Incorporating preoperative variables closely associated with AKI can further enhance the accuracy of machine learning models. For example, preoperative compound hemodynamic parameters, such as pulmonary artery pulsatility index (PAPI) and right atrial pressure (RAP), are significantly correlated with the incidence of AKI following heart transplantation [48]. Recently, Guven et al. developed a logistic regression model within a cohort of 595 patients to assess the impact of preoperative PAPI and RAP on AKI prediction within 30 days post-heart transplantation [49]. Patient data were gathered from the hospital database, electronic records, chart reviews, and catheterization reports at the Erasmus Medical Center. The findings indicated that the AUC of the model improved from 0.76 to 0.79 with the inclusion of preoperative PAPI and RAP variables.

AKI Prediction During Surgery

The predictive accuracy for acute kidney injury (AKI) can be significantly enhanced by incorporating intraoperative data into machine learning algorithms. Recently, Xue et al. developed a model that utilized preoperative, intraoperative, and composite data from 111,888 operations performed at a single center to forecast the occurrence of postoperative AKI. They employed various methods, including logistic regression (LR), support vector machine (SVM), random forest (RF), gradient boosting decision tree (GBDT), and deep neural network (DNN) techniques [50]. For the RF model, the optimal hyperparameters were determined to be 300 base learners, a maximum depth of 200, and a minimum of 4 samples required for splits. For the DNN, a learning rate of 0.001 and a batch size of 2048 were selected. Data elements were extracted from preoperative assessments and anesthesia records, while target outcomes related to AKI were sourced from electronic health records (EHR). Missing preoperative data were imputed using a dummy indication technique, substituting missing values with zeros, while intraoperative variables underwent data-level or feature-level imputation.

Among the various models assessed, the GBDT model utilizing composite data demonstrated the highest predictive accuracy, achieving an AUC of 0.848. Interestingly, the model relying solely on preoperative data outperformed the model that utilized only intraoperative data, with the combined data model yielding the best results. However, the intraoperative datasets for these models lacked certain critical features, such as detailed descriptions of the operation, timing, blood transfusion data, urine output, and medication administered.

In a complementary study, Tseng et al. explored the impact of these intraoperative data on predictive performance for AKI in the first week following heart surgery. They established models using both preoperative and intraoperative data, employing five individual methods: logistic regression, decision tree, SVM, RF, and extreme gradient boosting (XGBoost), as well as an integrated approach combining RF and XGBoost within a single-center cohort of 671 patients. The intraoperative time series data were collected within 240 minutes after the commencement of surgery, deliberately excluding the first 10 minutes (to avoid noise interference) and the 50-100 minute window (during cardiopulmonary bypass). Principal component analysis was then utilized to reduce the dimensionality of the dataset.

Among the individual models, the RF approach achieved the highest AUC of 0.839, while the decision tree model exhibited the lowest performance with an AUC of 0.781. Notably, the integrated model (RF + XGBoost) demonstrated improved predictive performance over the individual models with an AUC of 0.843. Additionally, key intraoperative factors—including urine volume, intravenous fluid administration, blood transfusion products, and hemodynamic parameters—were identified as significant contributors to AKI risk, which had previously been overlooked by traditional risk scoring models, as indicated by SHAP (SHapley Additive exPlanations) diagrams.

Postoperative AKI Real-Time Prediction

Patients are typically surrounded by monitoring instruments for 24 hours post-surgery, generating a significant volume of data that presents opportunities for machine learning to monitor patient dynamics and issue timely AKI warnings based on this data. For instance, Rank et al. developed a recurrent neural network (RNN) model using data from a single-center cohort of 15,564 cases to predict AKI in real time within the first seven days following cardiothoracic surgery. Their study involved a retrospective analysis of EHR time series data collected at a tertiary care center specializing in cardiovascular diseases. The researchers selected 96 routinely collected clinical parameters, which included both static and dynamic features as well as medication data.

In normal ward settings, AKI was defined solely by the creatinine criterion. However, in the recovery room or intensive care unit (ICU), both AKI criteria—creatinine levels and urine output—were utilized to enhance prediction accuracy. The RNN model provided predictions every 15 minutes, enabling continuous monitoring of patient conditions and facilitating timely interventions in the event of potential AKI development. The ability to leverage real-time data through machine learning not only improves the accuracy of AKI predictions but also enhances clinical decision-making by allowing healthcare providers to respond swiftly to changes in patient status. This approach exemplifies the growing role of artificial intelligence in improving postoperative care and patient outcomes, ultimately leading to more effective management of complications such as AKI.

Intensive Care Unit AKI Prediction

Acute Kidney Injury (AKI) is a prevalent concern in Intensive Care Units (ICUs), where patients undergo constant monitoring, generating substantial data streams that are ideal for machine learning applications. Recently, Chiofolo et al. developed an AKI prediction model using the random forest method based on data from a single-center cohort to monitor AKI development in the ICU . Their data were sourced from the Multidisciplinary Epidemiology and Translational Research in Intensive Care Data Mart, employing a validated AKI detection tool known as the AKI "sniffer," which automatically identifies AKI based on the AKIN definition. The random forest model comprised 200 trees and utilized 19 distinct elements, reaching a sample size of 6,530. The model achieved an impressive AUC of 0.88, enabling AKI detection more than six hours earlier than serum creatinine (SCR) levels in 30% of patients, and in 53% of those with stages 2-3 AKI. Moreover, this model facilitated dynamic monitoring, providing near real-time information on AKI status in the ICU.

Flechet et al. further evaluated AKI diagnosis accuracy by comparing the random forest analysis model with Neutrophil Gelatinase-Associated Lipocalin (NGAL) measurements from arterial blood samples taken upon ICU admission. Using logistic regression, they assessed NGAL's predictive performance alongside the admission model. The combination of NGAL and admission information significantly enhanced the AUC of the prediction model; however, the decision curve revealed that this improvement was only applicable to high-risk AKI patients. The additional costs associated with measuring NGAL rendered the predictive benefit clinically insignificant in these cases, particularly in the absence of effective treatment options.

In a similar vein, Dong et al. reported on an interpretable AKI prediction model designed for pediatric ICUs. This model was based on an age-dependent ensemble machine learning approach that utilizes multiple simpler "weak classifiers." The model incorporated four types of data elements—vital signs, laboratory values, medication history, and ventilation parameters—culminating in 250 candidate predictors. It accurately predicted moderate to severe AKI (AUC = 0.89) up to 48 hours before its onset, using EHR data from 16,863 pediatric ICU patients aged 1 month to 21 years. Notably, the model also provided actionable insights regarding potential interventions, such as recommended examination levels and dosages for aminoglycoside medications, enabling timely clinical responses to mitigate AKI risk.

AKI Prediction in All Hospital Wards

The application of machine learning has expanded beyond ICUs to emergency departments and general hospital wards for AKI prediction. For example, Tomasev et al. developed a machine learning method utilizing the U.S. Department of Veterans Affairs clinical database, encompassing data from 1,239 medical institutions with over 700,000 patients. The data, deidentified and transferred to DeepMind, were not subjected to missing numerical value imputation. The best-performing recurrent neural network (RNN) architecture featured a cell size of 200 units per layer across three layers, achieving an AUC of 0.92. Remarkably, this model predicted 55.8% of AKI cases accurately 48 hours in advance at critical points, with less than 3% of inpatients being alerted daily, making it suitable for low-cost but high-yield interventions.

Koyner et al. developed another AKI prediction model based on Gradient Boosting Decision Trees (GBDT) for adult patients throughout the hospital. By accessing demographic, location, vital sign, laboratory value, intervention, medication, nursing documentation, and diagnostic order data through the Clinical Research Data Warehouse at the University of Chicago, the GBDT model effectively identified patients at risk of severe AKI or renal replacement therapy (RRT) 1-2 days prior to SCR detection, with an AUC exceeding 0.9. Notably, GBDT models incorporating SCR parameters did not demonstrate superior accuracy for predicting severe AKI compared to those without SCR, indicating that SCR may not always serve as a reliable biomarker.

Furthermore, Sandokji et al. conducted a review of 8,473 EHRs for pediatric AKI diagnosis in patients under 18 years. Their logistic regression model, which employed a penalty level for selecting only ten variables, predicted the risk of AKI in pediatric patients 48 hours in advance, achieving high AUC values (0.76-0.81). While these machine learning models show promising results, they often function as black-box predictions, making it challenging for clinicians to interpret the outcomes. To address the need for transparency and interpretability in clinical applications of artificial intelligence, Lauritsen et al. developed the AKI Early Warning Score (XAI-EWS). This model consists of a temporal convolutional network (TCN) prediction component coupled with a deep Taylor decomposition (DTD) interpretation module. The TCN sequentially processes individual EHRs, providing predictions within a range of 0-100%. Meanwhile, the DTD module breaks down the TCN output concerning input variables, enhancing the understanding of predictions. The model was optimized to minimize cross-entropy loss using the Adam optimizer with a mini-batch size of 200, a learning rate of 0.001, and a dropout rate of 10%. The AUC and precision-recall curve (PRC) of XAI-EWS outperformed traditional assessment scores, with AUC values ranging from 0.79 to 0.88 in the 24 hours leading up to AKI onset. XAI-EWS effectively communicated to clinicians the relevant EHR data that informed the prediction results from both a global and individual patient perspective [66].

How XAI-EWS Works

The AKI Early Warning Score (XAI-EWS) is designed to enhance the interpretability and usability of machine learning models in predicting Acute Kidney Injury (AKI). Here’s a breakdown of its components and functionality:

1. **Model Architecture:**
   - **Temporal Convolutional Network (TCN):**
     - The TCN component of XAI-EWS processes the electronic health records (EHRs) in a sequential manner. This allows the model to capture time-dependent patterns and trends in patient data, which is crucial for predicting AKI, as the condition often develops over time due to various physiological changes.
     - The TCN outputs a prediction score, representing the likelihood of an AKI event occurring within a specified timeframe.
2. **Input Data:**
   - XAI-EWS utilizes a wide range of patient data collected from EHRs, which may include demographic information, vital signs, laboratory values, medication history, and other relevant clinical parameters.
   - The model can process both static (unchanging) and dynamic (changing over time) features, enabling it to make predictions based on the patient's clinical trajectory.
3. **Deep Taylor Decomposition (DTD):**
   - **Interpretation Module:**
     - After the TCN generates a prediction, the DTD module interprets the prediction by breaking down the TCN output concerning the input features. This is achieved by decomposing the output into contributions from each input

variable, providing insight into which factors most influenced the prediction.

- The DTD method helps identify and visualize the impact of specific clinical variables on the prediction score. This makes the model's decision-making process more transparent and understandable for clinicians.

4. **Training and Optimization:**
   - The XAI-EWS model is trained to optimize a loss function, typically cross-entropy loss, using the Adam optimizer. This involves adjusting the model parameters to minimize prediction errors based on the training dataset.
   - The model is trained with a mini-batch size of 200, a learning rate of 0.001, and a dropout rate of 10% to prevent overfitting, ensuring that it generalizes well to unseen patient data.
5. **Performance Evaluation:**
   - The performance of XAI-EWS is evaluated using metrics like the Area Under the Receiver Operating Characteristic Curve (AUC) and Precision-Recall Curve (PRC). High AUC values indicate that the model is effective in distinguishing between patients who will develop AKI and those who will not.
   - During evaluation, the AUC ranged from 0.79 to 0.88, demonstrating the model's predictive capability in the 24 hours leading up to AKI onset.
6. **Clinical Utility:**
   - The primary goal of XAI-EWS is to provide clinicians with actionable insights. By delivering understandable predictions along with explanations of the influencing factors, it empowers healthcare providers to make informed decisions and timely interventions to mitigate AKI risk.
   - The model outputs predictions within a range of 0-100%, indicating the probability of an AKI event occurring, which helps clinicians prioritize monitoring and management for at-risk patients. XAI-EWS combines advanced machine learning techniques with interpretability tools to enhance AKI prediction in clinical settings. By providing not only predictions but also clear explanations of how those predictions are derived, it aims to bridge the gap between complex AI models and clinical practice, thereby facilitating better patient management and outcomes.

Conclusion

Acute kidney injury (AKI) poses significant challenges for clinicians, particularly due to its insidious onset and the non-specificity of traditional diagnostic criteria. As the healthcare landscape evolves, the need for timely and accurate detection of AKI becomes paramount, particularly given the condition's association with high morbidity and mortality rates. Early diagnosis is crucial as it facilitates timely interventions that can prevent the progression to chronic kidney disease and potentially end-stage renal failure. The current reliance on serum creatinine (SCR) levels and urine output (UO) for AKI diagnosis is inadequate, as these metrics often fail to detect renal dysfunction in its earliest stages. The review emphasizes the critical role of emerging biomarkers such as neutrophil gelatinase-associated lipoprotein (NGAL), kidney injury molecule-1 (KIM-1), and reactive oxygen and nitrogen species (RONS) in enhancing early detection. These biomarkers, detected through advanced biosensors, exhibit higher sensitivity and specificity compared to conventional methods, allowing for earlier intervention strategies. Furthermore, the integration of machine learning technologies into clinical practice presents a transformative approach to AKI prediction and management. Machine learning algorithms trained on extensive datasets derived from electronic health records (EHR) can identify risk factors and predict the likelihood of AKI with remarkable accuracy. As demonstrated in various studies, models that synthesize preoperative, intraoperative, and postoperative data have achieved AUC values exceeding 0.9, indicating their efficacy in clinical settings. Looking ahead, the incorporation of machine learning into clinical workflows can streamline AKI detection and risk stratification, leading to improved patient management. The ongoing evolution of biosensor technology, combined with machine learning advancements, holds promise for reshaping AKI diagnostics. However, addressing challenges related to data collection, model validation, and clinical implementation will be vital to fully realize the potential of these innovations in enhancing patient outcomes. As research continues to unfold, the integration of these technologies into routine clinical practice may ultimately transform AKI management and significantly reduce the associated healthcare burden.

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إصابة الكلى الحادة: التشخيص، الأسباب، وأحدث العلاجات - مراجعة محدثة

الملخص:

خلفية :الإصابة الحادة في الكلى (AKI) هي متلازمة سريرية حرجة تتميز بانخفاض سريع في وظيفة الكلى، مع وجود عوامل مسببة متعددة بما في ذلك قصور القلب، الإنتان، والأدوية السامة للكلى. إن انتشار هذه الحالة بين المرضى في المستشفيات مقلق، خاصة بين أولئك المصابين بفيروس COVID-19، حيث بلغت نسبة حدوث الإصابة الحادة في الكلى حوالي 36.6%. تعتمد معايير التشخيص الحالية بشكل أساسي على مستويات الكرياتينين في المصل (SCR) وإنتاج البول(UO) ، والتي غالباً ما تفشل في التعرف على الإصابة الحادة في الكلى مبكراً بما يكفي للتدخل الفعال.

الهدف :تهدف هذه المراجعة إلى توحيد المعرفة الحالية حول الإصابة الحادة في الكلى، مع تسليط الضوء على تشخيصها، وأسبابها، وأحدث طرق العلاج، مع التركيز على التقنيات الناشئة التي تحسن من الكشف المبكر.

الطرق :يستعرض المقال الأدبيات حول معايير التشخيص للإصابة الحادة في الكلى، وتقنيات التصوير، وعوامل المؤشرات الحيوية، وتطبيق خوارزميات التعلم الآلي في التنبؤ بالإصابة الحادة في الكلى. يتم التركيز على مؤشرات حيوية جديدة وأجهزة استشعار حيوية تعزز الكشف المبكر، بالإضافة إلى نماذج التعلم الآلي التي تدمج البيانات من السجلات الصحية الإلكترونية.

النتائج :تقدم التطورات في مؤشرات حيوية مثل NGAL وKIM-1، جنباً إلى جنب مع أجهزة الاستشعار الحيوية، حساسية محسّنة للكشف المبكر عن الإصابة الحادة في الكلى. بالإضافة إلى ذلك، أثبتت نماذج التعلم الآلي دقة تنبؤية عالية، حيث حققت قيم منطقة تحت منحنى التشغيل الاستقبالي (AUC) تتجاوز 0.9 عبر سياقات سريرية مختلفة.

الخلاصة :يمكن أن يؤدي دمج مؤشرات حيوية جديدة، وأجهزة استشعار حيوية، ونهج التعلم الآلي إلى ثورة في تشخيص الإصابة الحادة في الكلى وإدارتها، مما يحسن بشكل كبير من نتائج المرضى.

الكلمات الرئيسية :الإصابة الحادة في الكلى، مؤشرات حيوية، التعلم الآلي، التشخيص، العلاج، طب الكلى.