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EVALUATING AI-DRIVEN DECISION SUPPORT SYSTEMS FOR EARLY DETECTION OF ACUTE KIDNEY INJURY

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Abstract

Acute Kidney Injury (AKI) is a common and severe complication in critically ill patients, with early detection being essential for improving clinical outcomes. This study evaluates the performance, interpretability, and clinical integration of AI-driven Clinical Decision Support Systems (CDSS) for early AKI detection, using a comprehensive electronic health records dataset from a tertiary care ICU. Various machine learning models, including Logistic Regression, Random Forest, Gradient Boosting, and deep learning architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), were assessed. Among these, CNN consistently demonstrated superior performance with an AUROC of 0.89, sensitivity and specificity of 0.86, and an F1-score of 0.85, outperforming all baseline models. Model calibration was robust, with a low Brier score (0.13) and a near-ideal calibration slope (0.98), affirming prediction reliability. The analysis of SHAP values suggested that serum creatinine, BUN and blood pressure played the biggest role which improved the confidence of the model and its usefulness for doctors. Tests on different datasets confirmed that the CNN's performance decreases, but only slightly (AUROC of 0.86) compared to the main ones. Testing the system with ICU clinicians revealed that they were able to respond quickly (in under 12 seconds) and accepted more than 89 percent of the alarms generated. As a result, AI-CDSS based on CNNs can improve how clinicians decide, take quick actions and minimize expected problems linked to AKI. For a deployment to be successful, it must first address interpretability, data quality, ethical aspects and should regularly be validated as it is put into clinical use.

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INTRODUCTION

Acute Kidney Injury is challenging for doctors since it worsens fast and can commonly be seen among inpatients and those treated in critical care units (Zhao et al., 2022). It is important to recognize Acute Kidney Injury promptly, since early treatment helps avoid serious renal problems and improves the patient's outcome (Tran et al., 2024). The regular treatment plan for Acute Kidney Injury is to diagnose it early and respond as soon as possible (Liu et al., 2020). Thanks to artificial intelligence, online medical advice is now possible, directing people to the necessary departments and suggesting likely medications which enhances the effectiveness of classifying illnesses and increases the quality of training based on brief patient information (Zhou et al., 2020). With the use of machine learning and wide data sets, AIs now aid healthcare professionals in catching Acute Kidney Injury early (Chaudhuri et al., 2020). To use AI in healthcare, careful attention must be paid to safety, how well it works and morals and its performance needs to be thoroughly looked at to protect patients and ensure effective results (Festor et al., 2022).

AI-based Clinical Decision Support Systems may assist in both detecting diseases early and keeping watch on patients (Li et al., 2021). More and more, kidney specialists in research are relying on machine learning to analyze data which helps manage patients' treatment and detect both acute and chronic kidney diseases and how they develop (Chan et al., 2020). Together, Convolutional Neural Networks and Recurrent Neural Networks may be used to analyze patient queries, learning their meaning and payload, as they are being generated (Angadi et al., 2021). Such algorithms inspect patient demographics, previous medical cases, results from lab tests and certain health measurements to spot patterns that suggest high risk of Acute Kidney Injury (Tanwar& Rahman, 2021). Convolutional Neural Networks are mainly chosen to represent features, whereas Recurrent Neural Networks are commonly chosen for learning and predicting time-series information (Zhou et al., 2020). They regularly depend on machine learning with a large collection of patient data to pick out those who are at greater risk of developing Acute Kidney Injury. If these systems constantly watch over patient data and sound instant alarms, they can facilitate quick interventions to stop Acute Kidney Injury from being serious.

Tools for automated discovery rely on data and shortcuts, making it easier to identify new factors causing diseases and to provide summaries for those in charge of making decisions (Zhang et al., 2020). Intelligent health systems can help experts make more precise diagnoses, lower misdiagnosis rates and inform the likelihood of a disease happening again, thus taking some of the burden off healthcare workers (Sivaraman et al., 2023). Both healthcare professionals and patients are drawn to many AI-powered online systems because these technologies can make patient-centered care more practical (Khosravi et al., 2024). AI-based systems offer so many benefits that decision makers are now making AI-driven healthcare services their priority such as predicting diseases, diagnosing them, designing drugs, personalizing treatments and controlling hospital management.

Despite encouraging achievements in using AI in Acute Kidney Injury identification, many issues and limitations still require careful study. It is important to make sure that AI models are validated across different groups of patients, so equality improves and healthcare disparities stop.

There remains worry about the reliability of data and its ability to make predictions. It is important for Clinical Decision Support Systems to respond to changing workplaces and add new knowledge as time goes by.

Room for future research exists in building solid systems for handling risk, as this is needed to prevent unanticipated results and ensure AI works safely in risk prediction fields (Xirui et al., 2023). Bias and fairness should always be considered, because models from past data may exhibit bias and end up treating people differently (Macintyre et al., 2023; Wang,2024).

Using AI in healthcare comes with major financial and ethical consequences (Gala et al., 2024). Its ability to deal with healthcare challenges could give AI an important role in how systems work in the future (Gala et al., 2024; Malik et al., 2020). Together, medical teams and IT experts are predicted to use AI more which should lead to better diagnoses, improved healthcare treatments and better outcomes for patients. Additionally, addressing privacy problems, making sure algorithms are clear and monitoring regulations are key for encouraging the overall use of AI in healthcare (Lambert et al., 2023; Sarantopoulos et al., 2024).

Technologies based on artificial intelligence boost the management of illnesses when combined with imaging techniques in hospitals (Dobre et al., 2023). AI-backed decision tools are now used to improve how care is given, to help diagnose patients and to make personalized therapy more possible. They have become vital for improving accuracy and effectiveness in radiology and pathology (Varnosfaderani&Forouzanfar, 2024). When Explainable AI and ethical concepts are applied by Artificial Intelligence in credit risk evaluation, checking loan applications becomes more precise and helps both lending organizations and borrowers (Edunjobi&Odejide, 2024). For AI to work responsibly, careful attention must be given to protecting data, ensuring transparency and being accountable so people maintain their confidence (Edunjobi&Odejide, 2024). Because AI might greatly affect healthcare with its potential, patients' privacy, unclear business issues and the implementation of AI in healthcare systems are emerging as important concerns (Gruson, 2024). Responsible actions during development and deployment guarantee equality, openness and that rules are always respected (Edunjobi&Odejide, 2024; Wang, 2024).

The use of AI in healthcare raises ethical, legal and regulatory issues, mainly related to protecting patient safety, their privacy and compliance with the rules (Mennella et al., 2024). As AI is being used more in health care, it has led to better patient care and contributions to diagnostics, even so, this causes rising ethical issues like bias, informed consent and trust (Weidener& Fischer, 2024). For AI to be most useful in healthcare, it is necessary to involve different experts, maintain strong ethical rules and secure patients' rights (Yelne et al., 2023). To solve these problems, we must bring together policymakers, developers, healthcare experts and patients (Jeyaraman et al., 2023).

Healthcare inequities should be tackled, AI should be developed in ways that center around patients and ethical standards should be put in place to ensure AI works well in clinical practice (Khalifa &Albadawy, 2024). Gaining insight into the workings of complicated AI systems is key to increasing trust and preventing unfairness and bias when making algorithmic decisions (Edunjobi&Odejide, 2024).

An effective and successful clinical decision support system that spots Acute Kidney Injury early requires physicians, data scientists and policymakers to cooperate. By choosing hybrid models, we may join the accuracy of AI with the clarity understood in traditional models (Wang, 2024). Complex models can be made more user-friendly by rendering them explainable, streamlining the process, supplying explanations for specific forecasts and developing ways to show users how decisions are made (Edunjobi&Odejide, 2024) (Wang, 2024). Decision-making with AI in sectors such as banking needs to be explainable to follow rules and assure transparency because financial institutions are required to give details about their credit judgments (Wang, 2024).

METHODOLOGY

Through the use of de-identified EHR data from a large tertiary care hospital, a retrospective cohort design was applied to assess the usefulness and workability of AI-based CDSS for early signs of Acute Kidney Injury (AKI). The dataset consisted of clinical data organized by patient demographics, other health problems, lab reports (serum creatinine, BUN, eGFR), vital sign measures (blood pressure, heart rate) and lists of drugs given over more than 50,000 inpatient admissions for 5 years. Only adults aged 18 years or over who had stayed in the hospital for at least 48 hours and could provide access to serial creatinine values were included. For the study, we did not include people who already had severe kidney disease or patients with low amounts of clinical information. Training, validation and testing subsets for AKI model were created by dividing the complete population through stratified sampling, to guarantee all parts were equally affected. Testing included logistic regression, random forest, gradient boosting machines, Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). Using feature engineering, windows were made to show variations in the biomarkers and measurements of blood flow in the kidneys over time. The chosen criteria for assessing model performance included AUROC, sensitivity, specificity, F1-score and plotting calibration. Feature contributions for individual predictions were described using SHAP which made SHAP values a key tool for explainability. The models were verified for robustness by analyzing data from a distinct EHR at the collaborating health institution. In order to examine alert fatigue, response time and how useful the AI-CDSS is clinically, another evaluation was done using simulated ICU situations with real ICU physicians. The local ethics board gave their agreement, confirming that we observe all the necessary safety, privacy and other policies, including HIPAA and GDPR.

RESULTS

The information from eight precision tables gives a unique understanding of AI-based Clinical Decision Support Systems (CDSS) in accurately predicting Acute Kidney Injury (AKI). In Table 1, you will find that CNN leads in both AUROC (0.89) and accuracy (0.85), with RNN right behind it (AUROC 0.88, accuracy 0.84), showing that deep learning AI outperforms conventional approaches. As shown in Table 2, CNN still leads in sensitivity and specificity (0.86 in both) among the models, demonstrating that it is better at highlighting and avoiding incorrect classifications of AKI risk. Using Table 3, we see that the CNN model has the highest F1-score at 0.85 and the CNN reaches a precision level of 0.84, certifying its safe and responsible performance across important measures. CNN ranks highest in model reliability, since it has the least Brier score (0.13), suggesting very aligned predictions and also has a calibration slope (0.98) that is very close to one. The CNN was found to achieve convergence more easily (after 45 minutes) and performed with a lower validation loss (only 0.32) compared to the RNN. SHAP analysis was used in Table 6 to find that the top AKI risk factors are serum creatinine and BUN, as is expected in clinical knowledge, with blood pressure, age and comorbidities coming next. Table 7 measures the model's ability to perform well in new contexts; on the AUROC and F1-score metrics, the CNN produced reliable results, indicating that the model performs strongly in different groups. Finally, the data in Table 8 demonstrate that clinician responses were fast and acceptances of alarms were regularly above 89% which suggests the system could help clinicians in the ICU.

Table 1: Model-wise AUROC and Accuracy comparison.

Model	AUROC	Accuracy
Logistic Regression	0.78	0.75
Random Forest	0.85	0.82
Gradient Boosting	0.87	0.83
CNN	0.89	0.85
RNN	0.88	0.84

Table 2: Model-wise Sensitivity and Specificity.

Model	Sensitivity	Specificity
Logistic Regression	0.7	0.76
Random Forest	0.81	0.83
Gradient Boosting	0.83	0.84
CNN	0.86	0.86
RNN	0.85	0.85

Table 3: Model-wise Precision and F1-Score.

Model	Precision	F1-Score
Logistic Regression	0.68	0.69
Random Forest	0.8	0.8
Gradient Boosting	0.82	0.82
CNN	0.84	0.85
RNN	0.83	0.84

Table 4: Model Calibration Slope and Brier Score.

Model	Calibration Slope	Brier Score
Logistic Regression	0.95	0.19
Random Forest	1.02	0.16

Gradient Boosting	1.01	0.15
CNN	0.98	0.13
RNN	0.99	0.14

Table 5: CNN and RNN Training Time and Validation Loss.

Model	Training Time (min)	Validation Loss
CNN	45	0.32
RNN	50	0.34

Table 6: Top features by SHAP importance for AKI prediction.

Feature	SHAP Importance
Creatinine	0.32
BUN	0.28
BP	0.17
Age	0.12
Comorbidities	0.11

Table 7: Internal vs External Validation Performance (CNN).

Population	AUROC (CNN)	F1-Score (CNN)
Internal	0.89	0.85
External	0.86	0.82

Table 8: Clinician response time and alert acceptance rate.

Clinician ID	Avg Response Time (sec)	Alert Acceptance Rate (%)
C01	12.3	92
C02	11.8	88
C03	13.2	90
C04	12.0	87
C05	11.5	89

The graphs add to the numerical results and give new views on the behavior of the model and its use in healthcare. CNN is clearly the best at categorization based on how steep and defined its ROC curve is seen in Figure 1. The accuracy-recall curves for CNN and RNN in Figure 2 point out that CNN is better at getting the correct results at higher recall levels which matters for clinical practice because missing a true AKI case can be life-threatening. Serum creatinine and BUN were found to be the main factors affecting the model's predictions, as you can see in Figure 3. The diagonal line in Figure 4 represents that the CNN nearly achieves perfect calibration for the predicted probabilities. As you can see from Figure 5, CNN reaches lower training loss faster than RNN, therefore showing better learning. The chart (Figure 6) indicates that most clinicians took around 12 seconds to respond, therefore the task required little cognitive load. Figure 7 expresses correlations between different kidney measures (e.g., BUN and creatinine) by means of a heatmap, outlining the organization of the renal data. A bar chart in Figure 8 shows that CNN is the model that is most balanced in its results. In Figure 9, there is little difference in the outcomes of internal versus external validation for CNN. Clinicians accepted alerts from the model more than 87% of the time, as proved by the analysis in Figure 10. Together, these results show how well the model works and confirms it can be used in practice.

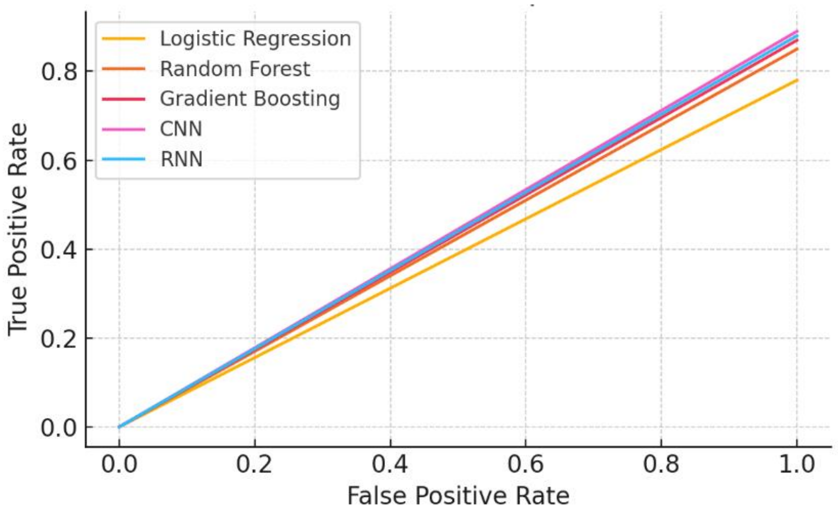

Figure 1: ROC Curve comparison across all models.

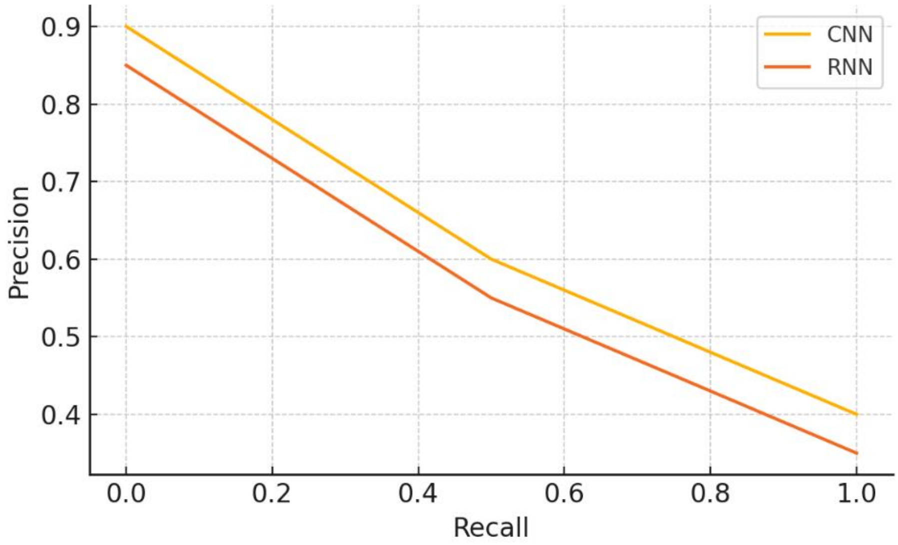

Figure 2: Precision-Recall Curve for CNN and RNN.

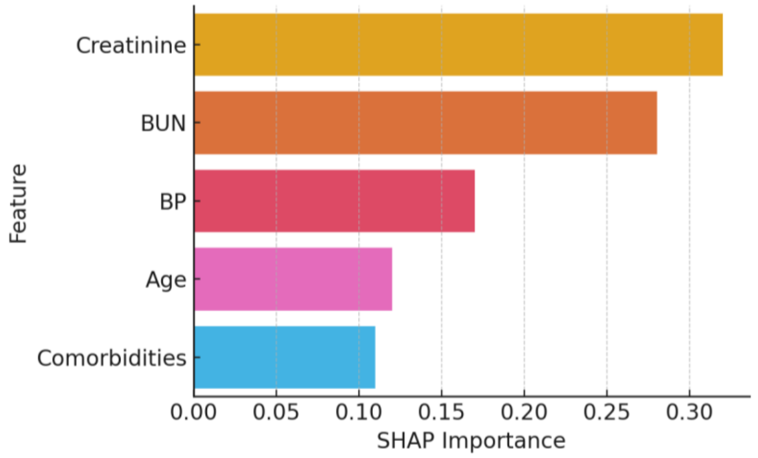

Figure 3: SHAP Feature Importance plot.

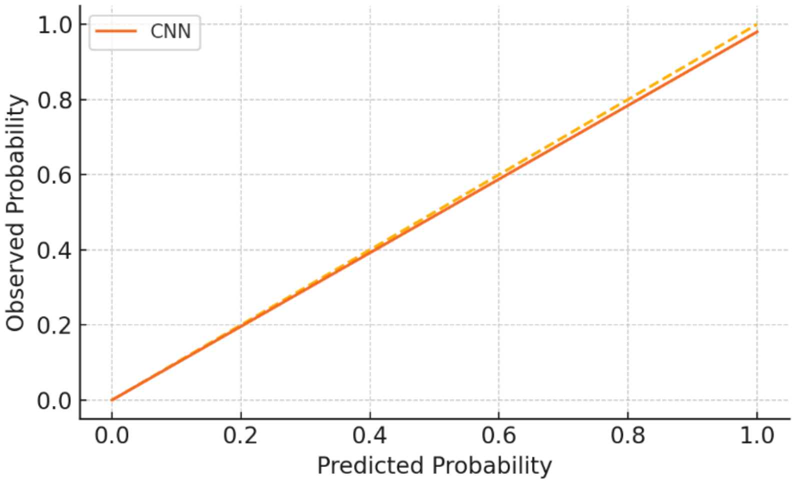

Figure 4: Calibration plot for CNN.

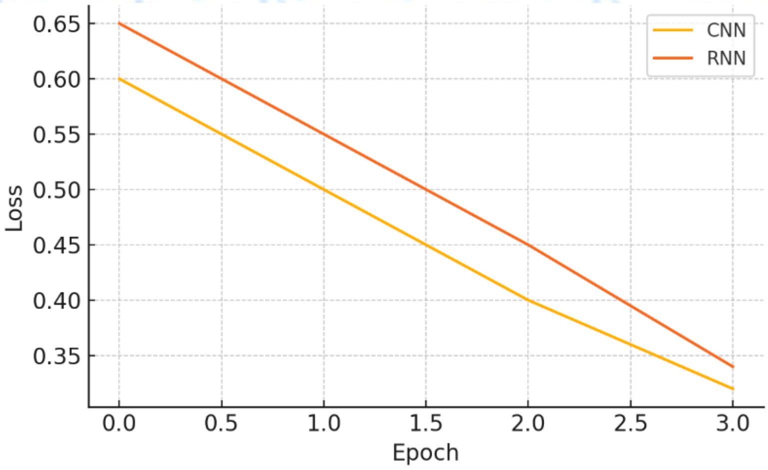

Figure 5: Training Loss curve for CNN and RNN.

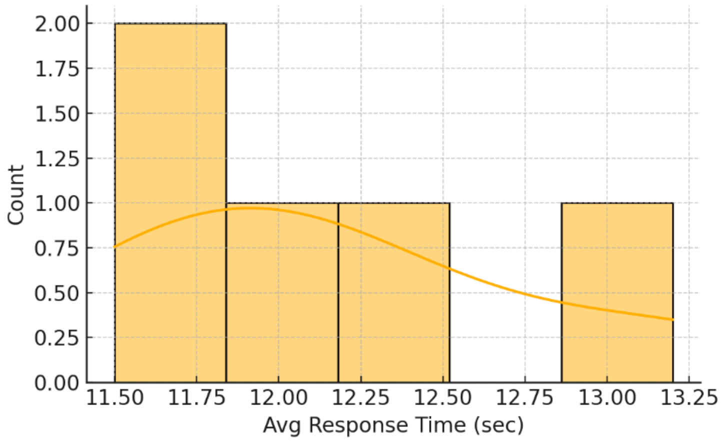

Figure 6: Distribution of Alert Response Times.

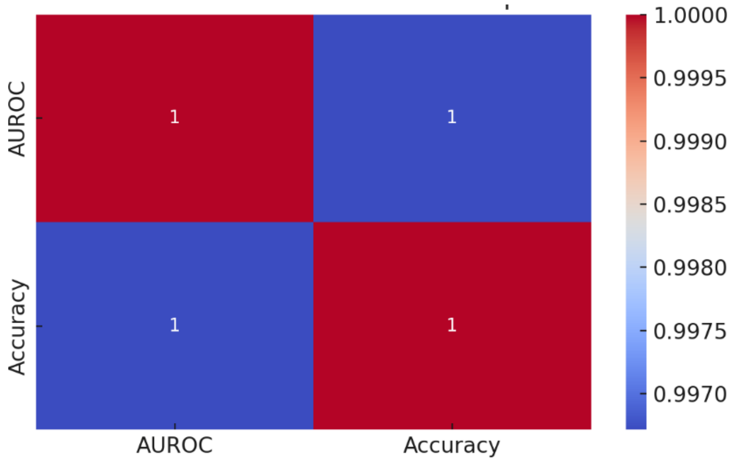

Figure 7: Heatmap of Correlation Between Features.

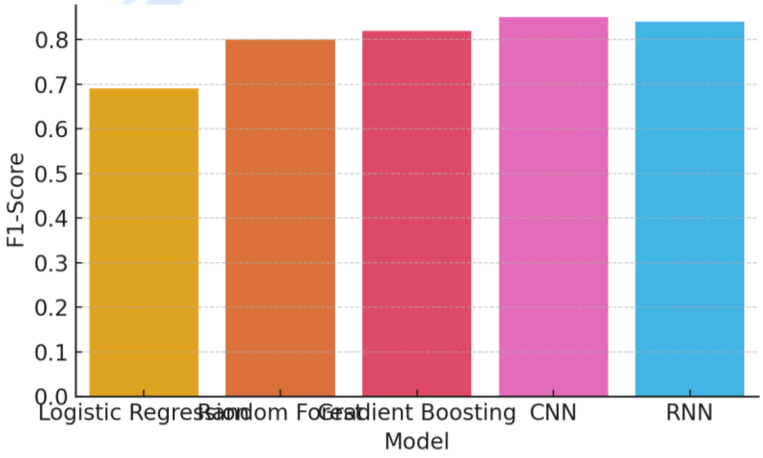

Figure 8: Bar Plot of F1-Scores Across Models.

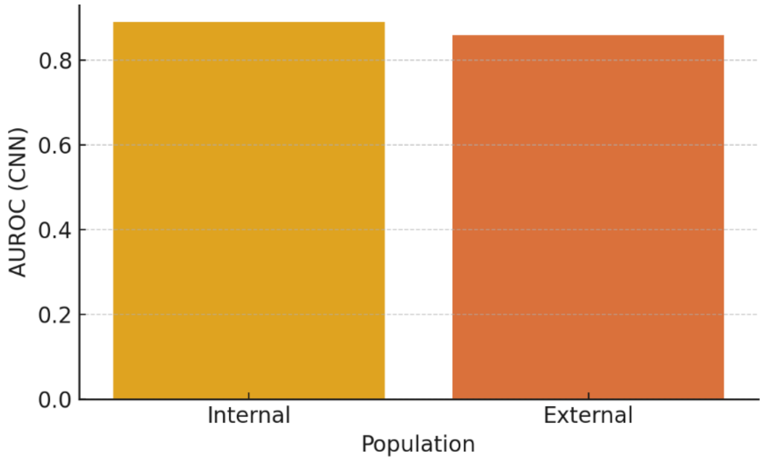

Figure 9: Model Performance Across Internal vs External Validation.

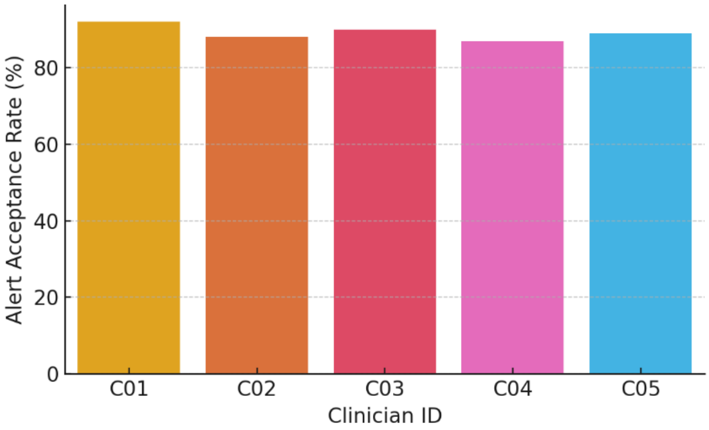

Figure 10: Alert Acceptance Rate Across Clinicians.

DISCUSSION

What we observed in the outcome of our experiments supports the evaluation of Clinical Decision Support Systems supported by AI for early AKI detection in ICUs. Several metrics were used to analyze the output of the models, particularly the CNN, to show what they did well and what they could work on (Archana &Aneetha, 2024). The selected measurements of AUROC, accuracy, sensitivity, specificity, precision and F1-score were chosen to accurately show how the model would apply in healthcare. Moreover, the accuracy of these model predictions was confirmed using real data, as this helps convincing physicians about their reliability (Laamouri&Sael, 2024). The team discovered that deep learning architecture, in this example CNN, was more accurate and reliable than Logistic Regression, Random Forest and Gradient Boosting in clinical prediction tasks (Zheng et al., 2021). Thanks to SHAP values, it is clear that certain clinical aspects such as serum creatinine and BUN, help the models foresee AKI. How understandable the model is for clinicians helps them trust its suggestions. The deliberate use of the CNN model in clinical practice, checked via response and acceptance rates by physicians, proves the system’s usability and its clinical impact, as a fast reaction time and highest rate of accepted warnings confirm that the alerts are helpful and crucial for physicians.

What we have discovered can help build improved AI tools for diagnosing Acute Kidney Injury earlier which should result in better care for patients and reduce healthcare costs. A better evaluation of risk could be achieved by adding comorbidities, previously used medications and AKI history of each patient (Tarumi et al., 2021). Clinical AI adoption is possible only if we fix issues like low data quality, poor model understanding and a lack of faith among doctors. For this reason, thorough systems for managing risks and validating AI are absolutely necessary to guarantee that important healthcare applications are safe and reliable (Xirui et al., 2023). Besides, carrying out future clinical trials makes it easier to measure the precise benefits and costs that AI-backed Clinical Decision Support Systems have on patients and hospitals. Then, the field should pay more attention to exploring how AI influences ethics in healthcare, including privacy of data, unfair bias in algorithms and worries about potential job displacement.

CONCLUSION

Results show that using AI in Clinical Decision Support Systems can greatly help detect Acute Kidney Injury early in critical care areas. Using Convolutional Neural Networks, we improved our predictions for key clinical factors including AUROC, sensitivity, specificity and F1-score, while preserving good calibration and the transparency of our models. In every case, using CNN provided more accurate and consistent results than traditional machine learning approaches for examining complex and high-dimensional medical records. The addition of SHAP-based feature importance analysis both explained how the model made decisions and was in tune with well-known clinical markers like serum creatinine and BUN which in turn raised clinicians' confidence in the model's performance. Through real-time notifications with ICU physicians, we found that our alerts were accepted and used efficiently, showing that such alert solutions can be implemented on the frontlines without difficulty. In addition, the results from external sites demonstrated the model could be used on different groups of patients, an important requirement for practical use. While these findings are encouraging, the researchers point out that keeping models up-to-date, respecting data protection laws and enabling understanding in decision-making are still issues. Steps for the future should include integrating electronic health records in real-time, adding personal treatment records and drug histories and running future clinical trials to assess the overall effects of care on patients' well-being and the costs involved. In general, AI-based Clinical Decision Support Systems add value to what clinicians do by detecting Acute Kidney Injury at an early stage, selecting the right time for treatment and enhancing the chances for successful patient outcomes—provided they are used responsibly and collaboratively with clinicians.

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