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#### Review article



# Comparison of machine learning and logistic regression models in predicting acute kidney injury: A systematic review and meta-analysis

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#### ARTICLE INFO

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#### ABSTRACT

*Introduction:* We aimed to assess whether machine learning models are superior at predicting acute kidney injury (AKI) compared to logistic regression (LR), a conventional prediction model.

*Methods*: Eligible studies were identified using PubMed and Embase. A total of 24 studies consisting of 84 prediction models met inclusion criteria. Independent samples *t*-test was performed to detect mean differences in area under the curve (AUC) between ML and LR models. One-way ANOVA and post-hoc *t*-tests were performed to assess mean differences in AUC between ML methods.

Results: AUC data were similar between ML (0.736  $\pm$  0.116) and LR (0.748  $\pm$  0.057) models (p = 0.538). However, specific ML models, such as gradient boosting (0.838  $\pm$  0.077), exhibited superior performance at predicting AKI as compared to other ML models in the literature (p < 0.05). Creatinine and urine output, standard variables assessed for AKI staging, were classified as significant predictors across multiple ML models, although the majority of significant predictors were unique and study specific.

*Conclusions*: These data suggest that ML models perform equally to that of LR, however ML models exhibit variable performance with some ML models displaying exceptional performance. The variability in ML prediction of AKI can be attributed, in part, to the specific ML model utilized, variable selection and processing, study and subject characteristics, and the steps associated with model training, validation, testing, and calibration.

#### 1. Introduction

The success of patient care in a clinical setting is dependent on the assessment and treatment of primary conditions as well as timely identification of sequelae that occur as a result of, or accompany, the original condition. Acute kidney injury (AKI) is associated with a loss in glomerular filtration rate (GFR) and can be a primary cause for hospitalization as well as secondary to other conditions, such as sepsis, surgeries, burns, and heart conditions [1,2]. AKI has a rapid onset with classification systems (Risk, Injury, Failure, Loss of kidney function, and End-stage kidney disease [RIFLE], Acute Kidney Injury Network [AKIN], Kidney Disease: Improving Global Outcomes [KDIGO]) utilizing changes in serum creatinine and urine output as indicators for GFR dysfunction

and AKI progression (stage). Importantly, the development of AKI increases the risk of morbidity (e.g., chronic kidney disease [CKD]) as well as mortality, the latter including associations between AKI-induced inflammatory responses and distal organ dysfunction [3]. AKI treatment places significant demands on hospital resources, in part, due to a prolonged length of stay [4]. Similarly, average healthcare costs increase with the development of AKI; thus, it is of great interest to predict those patients who have the highest probability of developing AKI to improve patient health and resource management while lowering healthcare costs.

Machine learning (ML, artificial intelligence) has seen a rise in popularity in healthcare environments. For example, artificial neural networks have been utilized to learn from, and eventually identify,

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Abbreviations: AKI, acute kidney injury; GFR, glomerular filtration rate; RIFLE, risk, injury, failure, loss of kidney function, and end-stage kidney disease; AKIN, acute kidney injury network; KDIGO, kidney disease: improving global outcomes; CKD, chronic kidney disease; ML, machine learning; LR, logistic regression; HER, electronic health records; AUC, area under the curve; SD, standard deviation; BUN, blood urea nitrogen.

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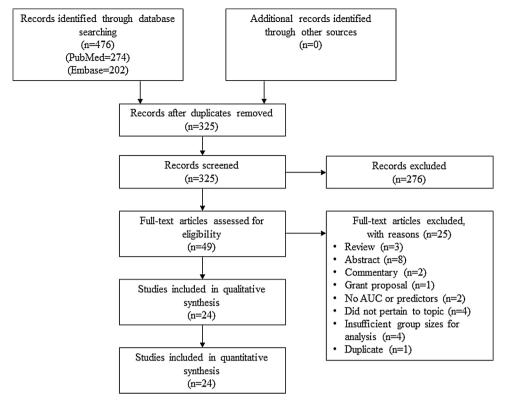


Fig. 1. PRISMA flow diagram of study selection.

patterns in digital images to enhance clinical diagnostic accuracy [5]. ML algorithms, such as extreme gradient boosting, have been implemented to improve prediction models for disease [6,7]. An important advantage of ML over conventional statistical methods (e.g., logistic regression [LR]) is that the various ML algorithms do not require data to conform to statistical assumptions, such as independence of observations and the avoidance of multicollinearity of independent variables. A second advantage lies in the abundance of data in the form of electronic health records (EHR) along with the computing power of modern-day computer systems. Collectively, these factors have made ML algorithms attractive options for predicting disease under real-time conditions. Similar to statistical methods, there are a large number of ML algorithms (random forest, Bayesian network, support vector machine, etc.) to choose from to develop a prediction model. However, it is unclear if one or more ML algorithms are superior to others in predicting disease.

Here, we performed a meta-analysis on the efficacy of ML algorithms to predict AKI. Moreover, we contrasted the performance of ML algorithms against conventional statistical methods such as LR to better characterize the overall performance of the models.

#### 2. Methods

A systematic literature search was performed to identify studies investigating artificial intelligence used in predicting, diagnosing, or assessing acute kidney injury (AKI). A set of search terms including "acute kidney injury machine algorithm, ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("acute kidney injury" OR AKI), ("Acute Kidney Injury/diagnosis"[MAJR]) AND "Machine Learning"[MAJR], ("Acute Kidney Injury/diagnosis"[MAJR]) AND "Artificial intelligence"[MAJR], acute kidney artificial intelligence, acute kidney injury machine algorithm, acute kidney machine learning" were performed in PubMed. A single search term was searched in Embase: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("acute kidney injury" OR AKI). Studies were included if they presented

information and/or data related to AKI and artificial intelligence together. The following article types were excluded: review, editorial, correspondence, and abstract.

# 2.1. Data analysis

Data are expressed as mean  $\pm$  standard deviation (SD). Due to the diversity of models under study, models were categorized by type (random forest, neural network, etc.) irrespective of variable selection procedures, number of predictor variables in the model, and number or characteristics (including treatments) of subjects in the study. Similarly, predictor variables were grouped for analysis; for example, measures (preoperative values, change over time, min/max) related to creatinine were grouped as creatinine. The majority of models (68/84, 82.9 %) were tested to predict AKI occurrence, while the remaining 17.1 % (14/ 82) were tested to predict specific AKI stages according to AKIN or KDIGO classification [8,9]. In the event of multiple AUC data from a single model and study (multiple tests of the same model from the same study), we prioritized the selection of predicting AKI occurrence data followed by predicting AKI stage 3, stage 2, or stage 1, respectively, in order to express optimal model performance. We did not select all AUC data from a single model and study as this could skew group data due to a high or low performing model that was run with great frequency. An independent samples t-test was performed to detect mean differences in AUC between ML and LR models. A one-way ANOVA was performed to assess mean differences in AUC between ML methods. Post-hoc t-tests were performed to identify ML models with superior performance. Statistical analyses were performed using IBM SPSS Statistics for Windows, v24 (IBM Corp., Armonk, NY). Significance was set at p < 0.05.

# 3. Results

A total of 476 studies were identified, and after auto-exclusion of duplicates, non-human studies, and non-English studies, a total of 325 studies remained. Of the screened studies, 276 were excluded and 49

(continued on next page)

Table 1 St

Table 1 Study Character	ristics				Table 1 (continu	ued)			
Author, year	N	Subject characteristics	Model type	Outcomes (top models/	Author, year	N	Subject characteristics	Model type	Outcomes (top models/ predictors)
Cronin et al., 2015 [10]	1,620,898	Patient hospitalizations	LR, RF	model performance was similar.  BP meds NSAIDs Antibiotics				DT, GB, RF, SVM	GB exhibited superior performance.  • Packed RBCs (intraop)  • Hematocrit (preop)
Kate et al., 2016 [11]	25,521	Hospital stays (>60 y.o.)	LR, BN, ENS, RF, SVM	IV fluids (48 h) ENS best at AKI prediction.     Comorbidities     History of AKI     Heart/lung     pathologies     Diabetes     Combination	Lee et al., 2018 [19]	1,211	Liver transplant	LR, ANN, BN, DT, GB, RF, SVM	Creatinine (preop) GB exhibited superior performance. Cold ischemic time Mean SvO2 (intraop) Mean cardiac
Thottakkara et al., 2016 [12]	50,318	Any major surgery	LR, BN, SVM	drugs LR and SVM performed better than BN.					<ul><li>index</li><li>Urine output</li><li>Glucose</li></ul>
Davis et al., 2017 [13]	170,675	Any admission	LR, ANN, BN, RF	RF and ANN were superior.  • Antiemetics (@ adm)	Mohamadlou et al., 2018 [20]	19,737	Inpatient encounters	GB	(preop) Extreme GB outperformed SOFA for AKI
				Vancomycin (@ adm) Age (@ adm) Mean GFR History of cancer and diabetes	Park et al., 2018 [21]	21,022	Cancer	LR, RF	prediction. RF possessed greater F1, precision, and sensitivity for AKI prediction. • Serum
Chen et al., 2018 [14]	358	Tertiary care (≥2 days)	ANN, ENS, DT, KNN, RF	ENS, DT, KNN, and RF performed similarly.	Adhikari	2,911	Inpatient operative	RF	creatinine • Inverse of serum creatinine RF models with
				<ul><li>1,2,6- hexanetriol</li><li>Famotidine</li><li>Benzimidazole</li></ul>	et al., 2019 [22]		procedure		intraop data performed better than RF models with preop data
Cheng et al., 2018 [15]	48,955	Inpatient encounters	LR, AB, RF	RF performed best. Increase in prediction time to AKI onset reduces model					only. • Hypotension (intraop) • Elevated HR (intraop)
				performance.  • Medications  • Admission diagnosis  • Comorbidity	Chiofolo et al., 2019 [23]	6,530	ICU - medical, surgical	RF	RF model performs well for continuous prediction of AKI in ICU
Huang et al., 2018 [16]	947,091	Percutaneous coronary intervention	LR, GB	Extreme GB performed better.	Flechet et al., 2019 [24]	252	ICU - critically ill	RF	population. RF performed similarly to
Koyner et al., 2018 [17]	121,158	Adult inpatients	GB	Extreme GB performance decreases with lower AKI stage (e.g., S1) prediction. • Serum					physician in AKI prediction, less overestimation of AKI risk.  Serum creatinine  Urine output
				creatinine (change in) • Length of hospital stay	He et al., 2019 [25]	76,957	Inpatient encounters	LR, BN, ENS, RF	ENS exhibited best performance.
				Serum creatinine (current) BUN (change in) Saturation (pO2/FiO2)	Ibrahim et al., 2019 [26]	889	Coronary angiography	LR	ML identified markers contributed to good LR performance.  • History of diabetes
Lee et al., 2018 [18]	2,010	Heart surgery	LR, ANN,						BUN/ creatinine ratio

#### Table 1 (continued)

Author, year	N	Subject characteristics	Model type	Outcomes (top models/ predictors)
				C-reactive protein Osteopontin CD5 antigenlike Factor VII
Parreco et al., 2019 [27]	151,098	ICU stays	LR, ANN, GB	GB possessed superior performance. • Slope of minimum creatinine • Creatinine (max, day 1)
Sun et al., 2019 [28]	16,558	ICU - critical care	LR, ANN, BN, RF, SVM	SVM and LR performed best Creatinine level (max) Mechanical ventilation International normalized ratio maximum Potassium level maximum Prothrombin time minimum
Tomasev et al., 2019 [29]	703,782	Inpatient, outpatient	ANN	Deep learning (ANN) exhibited 55.8 % sensitivity for AKI prediction (48 h), 2 false positives
Tran et al., 2019 [30]	50	Burn	KNN	for 1 true positive KNN is effective at AKI prediction in burn patients. • Neutrophil gelatinase associated lipocalin • N-terminal B- type natriuretic peptide • Creatinine • Urine output
Zhang et al., 2019 [31]	6,682	Low UO (0.5 ml/kg/h) for 1 st 6 h after ICU admission	LR, GB	Extreme GB was superior to LR for volume responsive/ unresponsive AKI prediction  • Urinary creatinine  • BUN (max)  • Age  • Albumin (min)  • Body temperature (max)
Zimmerman et al., 2019 [32]	23,950	ICU - critical care inpatients	LR, ANN, RF	All 3 models performed well with ANN performing slightly better than LR and RF.
Zhou et al., 2020 [33]	27	Thoracoabdominal aorta aneurysm	LR, RF, SVM	RF and SVM (linear) performed best. • Lactic acid (postop)

Table 1 (continued)

Author, year	N	Subject characteristics	Model type	Outcomes (top models/ predictors)
				BMI Infused RBCs Age Bleeding (surgery) Serum creatinine (preop)

LR = logistic regression; AB = adaptive boosting; ANN = artificial neural network; BN = Bayesian network; DT = decision tree; ENS = ensemble; GB = gradient boosting; RF = random forest; SVM = support vector machine; BP = blood pressure; NSAID = non-steroidal anti-inflammatory drug; GFR = glomerular filtration rate; BUN = blood urea nitrogen; RBC = red blood cell; SvO2=mixed venous oxygen saturation; SOFA = Sequential Organ Failure Assessment; HR = heart rate; BMI = body mass index.

Table 2 Model Type.

Model	Number of tests (% total
Logistic regression (LR)	21/82 (25.6 %)
LR	14
LASSO	4
LR, L-1 penalized	1
LR, L-2 penalized	1
LR, L-1/L-2 penalized	1
LR w/ stepwise variable selection	1
Random forest (RF)	16/82 (19.5 %)
RF	15
RF, IDEA	1
RF, SMOTE	1
Artificial neural network (ANN)	11/82 (13.4 %)
ANN	3
ANN, backpropagation	1
ANN, convolutional	1
ANN, deep belief network	2
ANN, deep learning	1
ANN, multilayer perceptron	2
ANN, recurrent	1
Support vector machine (SVM)	9/82 (11.0 %)
SVM	4
SVM, gaussian	1
SVM, linear	1
SVM, classifier	1
SVM, least square	1
SVM, SMOTE	1
Gradient boosting (GB)	7/82 (8.5 %)
GB	4
GB, extreme	3
Bayesian network (BN)	7/82 (8.5 %)
BN, bayes net	1
BN, naive bayes	6
Decision tree (DT)	5/82 (6.1 %)
DT	3
DT, CART	1
DT, ROSE	1
Ensemble	3/82 (3.7 %)
K-nearest neighbor	2/82 (2.4 %)
Adaptive boosting	1/82 (1.2 %)

Data are n/N (%). LASSO = Least Absolute Shrinkage and Selection Operator; IDEA = Intraoperative Data Embedded Analytics; SMOTE = Synthetic Minority Oversampling Technique; CART = Classification And Regression Tree; ROSE = computeRized prOlaps Syndrome dEtermination.

studies were selected for full-text review (PubMed 32, Embase 17). Studies classified as review (3), abstract (8), commentary (2), or grant proposal (1) were not investigated. Furthermore, studies (2) that failed to provide area under the curve (AUC) or significant predictor data were not included. Four studies were excluded as they did not pertain to the

**Table 3**Model Output Variables.

Variable	Number of tests
AUC	79/82 (96.3 %)
Sensitivity (recall)	27/82 (32.9 %)
Precision	23/82 (28.0 %)
Accuracy	20/82 (24.4 %)
F1	20/82 (24.4 %)
Error rate	13/82 (15.9 %)
Specificity	11/82 (13.4 %)
Positive predictive value (PPV)	9/82 (11.0 %)
Brier score	6/82 (7.3 %)
Negative predictive value (NPV)	6/82 (7.3 %)
Net benefit	2/82 (2.4 %)
Resolution	2/82 (2.4 %)
Reliability (x10-2)	2/82 (2.4 %)
Accuracy (across K values [%])	1/82 (1.2 %)
Negative likelihood ratio (NLR)	1/82 (1.2 %)
Net reclassification improvement - w/ AKI	1/82 (1.2 %)
Net reclassification improvement - w/o AKI	1/82 (1.2 %)
Overall net reclassification improvement	1/82 (1.2 %)
Positive likelihood ratio (PLR)	1/82 (1.2 %)

Data are n/N (%).

AUC = area under the curve; AKI = acute kidney injury.

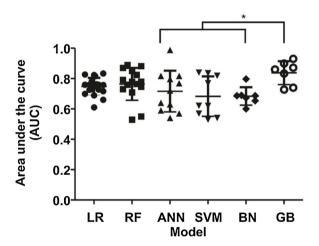


Fig. 2. Scatter plot of model performance. Gradient boosting (GB), consisting of both gradient boosting and extreme gradient boosting models, was significantly more effective at predicting AKI compared to all other ML models (artificial neural network, ANN; support vector machine, SVM; Bayesian network, BN; p < 0.05) with the exception of random forest (RF; p = 0.152).

topic of machine learning prediction or diagnosis of AKI or AKI-related mortality. Four studies, 2 related to ML diagnosis of AKI and 2 related to ML prediction of AKI-related mortality, were not analyzed due to insufficient group sizes. The remaining 24 studies were included in the present analysis (Fig. 1, Table 1) [10–33].

Among these 24 studies, there were a total of 82 models described, of which 25.6 % (21/82) were categorized as logistic regression with the remaining 74.4 % (61/82) categorized as ML (Table 2). An ML model was defined as any method that utilizes an algorithm to learn from the data in order to improve performance (i.e., AKI prediction) [34].

AUC data was provided in 96.3 % (79/82) of the models and were included in subsequent model performance comparisons. Table 3 contains a full list of variables used to describe model performance.

# 3.1. Model performance

To investigate model performance of LR and ML to predict AKI, mean AUC was calculated per group and analyzed. There was no difference in model performance between LR and ML as determined by AUC (LR:  $0.748 \pm 0.057$ , ML:  $0.736 \pm 0.116$ ; p=0.538). We next examined model

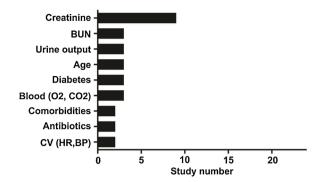


Fig. 3. Frequency of the most common predictors for machine learning models. Creatinine (blood or urine) was the most common significant predictor across the included studies.

performance of ML models to determine if one or more models exhibited greater performance. The following model groups had insufficient numbers for statistical comparison and were excluded from the analysis (AUC): decision tree (0.698  $\pm$  0.136), ensemble (0.746  $\pm$  0.083), knearest neighbor (0.824, only 1 study reported AUC), and adaptive boosting (0.715). Gradient boosting (0.838  $\pm$  0.077), consisting of both gradient boosting and extreme gradient boosting models, was significantly more effective at predicting AKI as compared to all other ML models studied (p < 0.05) with the exception of random forest (0.764  $\pm$  0.106, p = 0.152) (Fig. 2).

#### 3.2. AKI predictors

Data were examined further to determine variables that possessed the greatest predictive power in machine learning models. The number and type of predictive variables were diverse and included demographic, medical history, administrative/chart, laboratory (blood, urine, etc.), and surgical data. Seven studies (29.2 %) did not clearly indicate the most important predictors for their respective models. In cases where multiple models were performed, authors presented data on predictive variables for the best performing models. Creatinine (either blood or urine) was the most common, significant predictor observed appearing in 9 (37.5 %) studies (Fig. 3). Blood urea nitrogen (BUN), urine output, age, and diabetes were significant predictors, albeit to a lesser degree, appearing in 3 (12.5 %) studies. While creatinine was the most common predictor across studies, it represented only 16.9 % of total predictor variables (71) utilized in the studies. A list of the most common predictors for machine learning models is provided in Fig. 3.

# 4. Discussion

Here, we examined the performance of ML models to predict AKI and contrasted the performance of those ML models to LR, a conventional statistical approach used for clinical prediction models [35–37]. On average, ML models performed the same as LR models at predicting AKI with ML models displaying substantial variability across models. An in-group comparison of ML models revealed that gradient boosting, consisting of gradient boosting and extreme gradient boosting models, possessed superior performance at predicting AKI as compared to artificial neural network, support vector machine, and Bayesian network models. Variables related to creatinine were the most common, significant predictive variables described, while representing a relatively small amount of total significant predictive variables. Collectively, these data suggest that ML and LR models are effective at predicting AKI, however the specific type of model as well as variables included in the model weigh heavily on model performance.

Our finding that ML and LR models perform equally well to predict AKI was consistent with previous studies [36–38]. Christodoulou et al. found similar overall performance between LR and ML methods for

clinical risk prediction in a meta-analysis consisting of 71 studies, and they noted a high risk of bias in studies that reported better performance with ML [36]. Nusinovici et al. observed equivalent performance between LR and ML methods to predict risk of cardiovascular diseases, chronic kidney diseases, diabetes, and hypertension in an Asian cohort. LR, gradient boosting, and neural networks were ranked as the best performing models overall [38]. Lynam et al. investigated model performance of LR and 7 ML methods to discriminate between types I and II diabetes using a small set of 7 predictor variables [37]. There was no difference in type I and II diabetes classification performance between LR and ML methods. Taken together, the present results for AKI prediction along with results from the aforementioned studies suggest that LR and ML perform equally well to classify a variety of clinical conditions.

While ML and LR performed similarly overall in the present study, specific ML models demonstrated exceptional performance in predicting AKI. Gradient boosting, which in our study consisted of gradient boosting and extreme gradient boosting, performed better than all ML models studied with the exception of random forest. Although ML algorithms have inherent structural differences, the variables included in the model can drastically alter the quality of prediction. Creatinine and urine output, two variables that are utilized in AKI staging (KDIGO, AKIN), were noted to be significant predictors in multiple studies that utilized various ML models. Other variables related to kidney function such as BUN and diabetes were also noted in multiple studies. However, the majority of important predictors in the present study were unique possibly due to the nature of the subjects in the study (cardiac surgery, burn, etc.). For example, creatinine, while the most common variable observed in the models, represented a small proportion (16.9 %) of the total number of significant predictors listed. Therefore, other classes of variables, such as those related to cardiovascular and pulmonary function as well as certain medications (e.g., antibiotics, antiemetics), should be examined in more detail to determine their value to improve ML performance.

It is unclear if ML is being incorporated into the clinical setting for AKI prediction. The abundance of algorithms and variations in data type and handling can lead to a wide variety of predictive scores as evidenced by the present study. Moreover, significant challenges to the value of ML lie in the ability to predict AKI in a time frame that would be sufficient to initiate therapeutic interventions for AKI prevention. The work by Tomasev and his colleagues at DeepMind yielded the highest ML performance scores observed in the present study [29]. In this retrospective study, the artificial neural network was designed to predict disease 48 h prior to the onset of AKI. The model was able to predict 55.8 % of AKI cases at any stage with 2 false positives predicted for every 1 true positive. While measures related to creatinine were critical features of the model, the model could classify patients at a time point (48 h) prior to pathological changes in creatinine, which illustrates the potential value of such a model. Indeed, the value of ML for AKI prediction lies in the ability to handle large amounts of data and to identify seemingly benign relationships with those data as it relates to disease onset.

While not the highest performing model observed in the present study, the AKIpredictor is a public, online calculator (www.akipredictor.com) that utilizes serum creatinine as well as other patient information (age, diabetes, admission information) to calculate, upon admission to the ICU, a risk of developing AKI (stages 2 or 3) during the first week of an ICU stay [24,39]. There are other data (APACHE II score, bilirubin, maximum lactate, etc.) [24] that can be entered in on the first morning of ICU stay and after 24 h that can contribute to the model's performance. This model was prospectively evaluated and is easy to use, although it would require validation on a larger population before implementation in a clinical setting. The purpose of any ML model for AKI prediction in the clinic would be to serve as an adjunctive measure to perform real-time risk assessment of AKI and to act as an early warning system for clinicians to enhance patient care and resource management.

ML models vary in complexity from older Bayesian networks to elaborate artificial neural networks such as deep learning. In order for a ML model to successfully predict AKI, the model must be trained, validated, tested, and calibrated. All 15 studies that directly examined LR with other ML methods clearly described appropriate model training techniques (e.g., cross-validation methods), and there were no overt differences noted in the application of LR and ML methods. None of the included studies examined external validity of the models.

LR assumes that data conform to certain characteristics (e.g., independence of observations, low correlation between variables), of which violations can impact the quality of analysis. Similarly, some ML methods may perform better when applied to data that exhibit specific characteristics (e.g., large margin assumption in learning SVM models). The present results would suggest that potential violations of assumptions with respect to LR may not meaningfully impact the quality of performance as LR performed equally well to that of ML. In this case, LR models might be more advantageous than ML methods due to transparency and interpretability of LR.

AUC was the most often reported performance variable across models. However, there were 18 other performance variables that appeared in less than a third of models performed with over half of these appearing in less than 8 % of models performed. The wide variety of performance variables expressed precludes a thorough comparison of model performance aside from AUC. Future studies would add greater value by calculating other basic performance variables (e.g., accuracy, specificity, sensitivity, etc.) to allow for comprehensive model comparisons.

The limitations of the study stem from the heterogeneity of the included studies. We grouped gradient boosting and extreme gradient boosting as both models are fundamentally similar, and treated individually, could not be statistically evaluated due to insufficient numbers. Nevertheless, extreme gradient boosting is considered an enhanced model that utilizes a gradient boosting method, and it may be superior to gradient boosting in model performance for AKI prediction. More studies are needed to better characterize the performance of extreme gradient boosting algorithms to predict AKI. Support vector machine and Bayesian network models performed poorly (AUC: <0.7), although support vector machine data were highly variable. An important caveat to the results is that studies differed substantially in the quantity of data used to train the algorithm as well as the methods selected for data pre-processing. Thus, methods related to feature selection as well as the handling of missing or invalid data could have impacted model performance regardless of the type of model deployed. Moreover, potentially important variables may not always be collected and can depend on patient condition. A challenge moving forward is identifying meaningful variables for AKI prediction that are routinely collected. Similar to conventional statistical approaches, ML models are only as strong as the variables included in the model.

#### 5. Conclusions

In conclusion, interest in ML for clinical prediction has increased due to widespread availability of both ML algorithms as well as EHR. ML performed similarly to LR in predicting AKI, while gradient boosting exhibited superior performance as compared to other ML models with the exception of random forest. Important variables associated with AKI staging such as creatinine and urine output were found to be important predictors for AKI across multiple studies. There remains substantial heterogeneity in variables included in the model, model set-up (training, validation, testing, calibration), and model application (specific condition; e.g., burn vs. general inpatient). Nevertheless, our data suggest that ML and LR are equally effective at predicting AKI.

# Ethics approval and consent to participate

Not applicable.

#### What was already known on the topic

- Logistic regression has been used to predict acute kidney injury in critical care settings.
- Interest in machine learning algorithms to predict acute kidney injury has grown; however, optimal algorithms and predictor variables are poorly understood.

## What this study added to our knowledge

- Machine learning performance to predict acute kidney injury is variable and depends on the predictor variables included in the model as well
  as the type of algorithm deployed.
- While common biomarkers (creatinine, BUN) for acute kidney injury were important for model performance, there are a large number of predictor variables that have been identified and are currently being used in machine learning models.
- Machine learning performance is comparable to conventional logistic regression models in predicting acute kidney injury.

# Consent for publication

Not applicable.

#### Availability of data and materials

All data generated or analyzed during this study are included in this published article.

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# Authors' contributions

CW had conception and design, XS, XL and FL performed the literature review, XS drafted the manuscript, XL performed statistical analysis. All authors critically revised the manuscript. All authors read and approved the final manuscript.

# Summary table

#### **Declaration of Competing Interest**

The authors report no declarations of interest.

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