Editorial

Predicting Acute Kidney Injury after Cardiac Surgery by Machine Learning Approaches

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Abstract: Cardiac surgery-associated AKI (CSA-AKI) is common after cardiac surgery and has an adverse impact on short- and long-term mortality. Early identification of patients at high risk of CSA-AKI by applying risk prediction models allows clinicians to closely monitor these patients and initiate effective preventive and therapeutic approaches to lessen the incidence of AKI. Several risk prediction models and risk assessment scores have been developed for CSA-AKI. However, the definition of AKI and the variables utilized in these risk scores differ, making general utility complex. Recently, the utility of artificial intelligence coupled with machine learning, has generated much interest and many studies in clinical medicine, including CSA-AKI. In this article, we discussed the evolution of models established by machine learning approaches to predict CSA-AKI.

Keywords: acute kidney injury; AKI; cardiac surgery; machine learning; artificial intelligence; nephrology

1. Introduction

Acute kidney injury (AKI) is a common and serious complication after cardiac surgery related to a complex set of exposures, including cardiopulmonary bypass, tissue damage, cardiac dysfunction, and hemolysis [1–5]. Depending on the definition, patient characteristics, and the type of cardiac surgery, the incidence of cardiac surgery-associated AKI (CSA-AKI) varies between 7% and 40%, Table 1 [6–12]. The incremental index hospitalization cost associated with CSA-AKI is higher than USD 1 billion in the United States [13]. The development of CSA-AKI has a dramatic impact on intensive care unit (ICU) and hospital length of stay as well as on short- and long-term mortality [14–19]. In patients with CSA-AKI requiring dialysis, mortality (at hospital discharge or 30-day mortality) can be as high as 60% to 70% [20]. Risk of end-stage kidney disease (ESKD) after cardiac surgery is also substantial, especially in patients with Acute Kidney Injury Network (AKIN) stage 2 or 3 AKI, with a hazard ratio of 3.8 to develop ESKD compared with all patients [21].
Table 1. Incidence of acute kidney injury following cardiac procedures and surgeries.

| Cardiac Surgery                        | Incidence of AKI | Dialysis-Requiring AKI | Reference(s) |
|----------------------------------------|------------------|------------------------|--------------|
| CABG (off-pump)                        | 4.0–19.1%        | 2.4%                   | [22–24]      |
| CABG (on-pump)                         | 22.2–32.1%       | 1.1%                   | [23,24]      |
| TAVR (mixed)                           | 7.1–28%          | 1.0–2.8%               | [25–29]      |
| TAVR, transfemoral                     | 18.0%            | N/A                    | [30,31]      |
| TAVR, transapical                      | 38.0%            | N/A                    |             |
| SAVR                                   | 12.1–29.7%       | 3.0–4.1%               | [26,27,32,33]|
| MVR, surgical                          | 19.4%            | 2.8%                   |             |
| MV repair, percutaneous                | 18.0%            | 0%                     | [34]         |
| Heart transplant                       | 47.1%            | 11.8%                  |             |
| Combined valvular surgery and CABG     | 4.8%             | N/A                    | [36]         |
| LVAD                                   | 24.9%            | 12.6%                  |             |
| Prophylactic IABP placement            | 5.2–10.3%        | 0.0–0.9%               | [38–40]      |
| Aortic repair, open                    | 14.1–42.8%       | N/A                    | [41,42]      |
| Aortic repair, endovascular            | 3.7–27.1%        | N/A                    | [41,42]      |
| ECMO                                   | 62.8%            | 44.9%                  |             |

CABG, coronary artery bypass graft; ECMO, extracorporeal membrane oxygenation; IABP, intra-aortic balloon pump; LVAD, left-ventricular assist device; MVR, mitral valve replacement; SAVR, surgical aortic valve replacement; TAVR, transcatheter aortic valve replacement.

Several risk factors have been identified that are associated with an increased risk to develop CSA-AKI, including female sex, advanced age, left ventricular ejection fraction less than 35%, comorbidities (diabetes, hypertension, hypercholesterolemia, peripheral vascular disease, chronic obstructive pulmonary disease, congestive heart failure), preexisting chronic kidney disease (CKD), previous cardiac surgery, intraoperative (use of an intra-aortic balloon pump, more extended cardiopulmonary bypass (CPB) and prolonged aortic cross-clamping), severe bleeding requiring transfusion of blood products, a requirement for potent vasopressors, prolonged hypotension, and low cardiac output syndrome, systemic inflammatory response syndrome, more complex cardiac disease such as left main coronary disease, complex cardiac operations, and emergency surgery. Perioperative administration of nephrotoxic agents, such as angiotensin-converting enzyme inhibitors, aminoglycoside antibiotics, loop diuretics, or contrast media, may increase the risk of developing a CSA-AKI, Table 2 [20,45–47].

Table 2. Risk predictors for acute kidney injury following cardiac procedures and surgeries from multivariate analysis.

| Operative Status         | Risk Factor        | Subject          | Odds Ratio (95% CI) | Reference(s) |
|--------------------------|--------------------|------------------|--------------------|--------------|
| Pre-operative            | Age                | CABG             | 1.016 (1.002–1.030) | [48]         |
|                          | BMI (kg/m²)        | Cardiac surgery  | 4.870 (3.500–6.240) | [49]         |
|                          | Diabetes           | CABG             | 1.360 (1.022–1.809) | [48]         |
|                          | CKD                | Cardiac surgery  | 1.520 (1.070–2.160) | [49]         |
|                          | NYHA class III/IV  | Cardiac surgery  | 2.530 (1.320–4.860) | [49]         |
|                          | Hypertension       | Cardiac surgery  | 1.680 (1.440–1.970) | [49]         |
|                          | PVD                | Cardiac surgery  | 1.310 (1.090–1.570) | [49]         |
|                          | Emergency surgery  | Cardiac surgery  | 4.760 (3.050–7.430) | [49]         |
| Intra-operative          | On-pump            | CABG             | 2.630 (1.543–4.483) | [48]         |
|                          | RBC transfusion    | CABG             | 2.154 (1.237–3.733) | [48]         |
|                          | CPB time           | Cardiac surgery  | 1.094 (1.006–1.191) | [50]         |
|                          | Aortic clamping    | Cardiac surgery  | 33.780 (23.150–44.410) | [49] |
|                          | Use of IABP        | Cardiac surgery  | 13.240 (7.780–18.690) | [49] |
|                          |                    | Cardiac surgery  | 4.440 (2.370–8.300) | [49]         |
Attempts to improve AKI’s clinical outcomes have centered on early diagnosis and customized treatment [52]. Early identification of patients at high risk of CSA-AKI by applying risk prediction models allows clinicians to closely monitor these patients and start effective preventive and therapeutic approaches to lessen the incidence of AKI. Several AKI risk prediction models have been developed [14,16,17,53–59]. Risk assessment scores have been developed for CSA-AKI [14,16,17,53–60]. The Thakar Score [53], Mehta score [14], and Simplified Renal Index score [16] have been validated for predicting severe AKI that requires renal replacement therapy. The Thakar model has been examined comprehensively and found to have great discriminations. Nonetheless, dialysis events are uncommon, restricting the utility of these risk scores to prognosticate patients who do not need renal replacement therapy. Moreover, the definition of AKI and the variables utilized in these risk scores differ, making general utility complex [55]. Most of these risk scores are based on clinical factors that are accessible in the preoperative setting. These are helpful for risk stratification and counseling of patients. Nonetheless, perioperative events, including prolonged bypass, blood loss, and transfusion, can negatively influence the risk for CSA-AKI.

2. Predicting CSA-AKI by Machine Learning

The model established by machine learning approaches can effectuate early dynamic monitoring based on the actual objective data of all patients and conserve the time of clinicians. [61–64]. The rise of machine learning is driven by the ability to process “big data” and the need to deliver the best possible value- and evidence-based care. The utility of artificial intelligence (AI) coupled with machine learning, has generated much interest and many studies in clinical medicine [61,65–79]. The machine learning approach has been developed recently for advantages in performance and extensibility and has become indispensable for solving complex problems in most sciences [80–82]. This method is used to examine postoperative outcomes [83–86] and predict hypotension [87,88] and the depth of anesthesia [89–94]. Machine learning has also been applied in the fields of intensive care unit medicine [95], emergency medicine [96], and neuroimaging [97].

With the notable extension of the application of electronic health records (EHRs) in the area of big data [98–100], a substantial amount of EHR data and machine learning algorithms have advanced to fulfill an essential role in the clinical study of AKI. It is presently a relevant tool for AKI diagnosis and prediction [64]. The establishment of an AI-based clinical decision support systems (CDSS) based on a self-learning predictive model may be utilized for monitoring AKI among hospitalized patients in prospective clinical practice [101]. Compared with conventional analysis methods, recent studies have suggested that some machine learning algorithms may reach greater accuracy than the conventional logistic regression models [75,102,103]. Studies have shown that machine learning can predict AKI after general surgery, liver transplant, cardiac surgery, hepatectomy, severe burns, sepsis, and percutaneous coronary intervention [75,104–110]. Utilizing data from more than 700,000 subjects from multi-centers and stratified by an interval window of 6 hours, a recurrent neural network-based risk prediction model for AKI (AUC of 0.92) was verified [111]. AKI episodes were prognosticated within a 48-h
window. Nevertheless, the area under the precision-recall curve was only 30%, which depicts a ratio of two false alerts for each actual alert [111].

Some machine learning algorithms have also been labeled as a “black box”, where there is limited insight into how the model is basing its prediction [112]. This draws into inquiry how clinicians can mitigate certain risk factors in patients to make them a more suitable candidate for treatment without knowing what is influencing their outcome. Nevertheless, there are some machine learning algorithms, such as XGBoost (eXtreme Gradient Boosting), where the relative magnitude of variables in prognosticating a particular outcome can be computed and envisioned. This renders a level of insight comparable to a logistic regression model about individual risk factors and their prognostic significance [113]. A gradient boosting machine (GBM) is currently a widespread approach for predicting AKI onset [75,105,107,114]. Huang et al. [107] presented a hazard prediction model for AKI following a percutaneous coronary intervention (PCI) based on GBM. The investigation involved a substantial amount of data from 947,091 cases that underwent PCI to set a baseline model. Besides, temporal validation was conveyed with data from greater than 900,000 hospitalized patients. The AUC of the GBM model was 79% greater than the baseline linear regression model. Recently, Lee et al. [75,105] presented a prediction model for AKI following liver transplantation and cardiac surgery by several machine learning algorithms. GBM demonstrated the most reliable performance in both investigations [75,105].

In the setting of cardiac surgery, Lee et al. [75] recently used machine learning techniques to predict CSA-AKI among 2010 patients undergoing cardiac surgery based on data obtained from EHR and developed an internet-based risk estimator. In comparison with logistic regression analysis, decision tree, random forest, and support vector machine displayed comparable performance with regards to AUC. GBM method exhibited the best performance with the highest AUC (C-index 0.78, compared with the logistic regression model that had a C-index of 0.69) [75]. These patterns can accurately distinguish groups of cases with different risks, and their incorporation into clinical practice can reduce intricacies and improve outcomes of CSA-AKI.

3. Potential Directions and Future Scope

With the additional deepening of the investigation, machine learning-assisted monitoring may yield valuable upshots to AKI and lessen mortality and morbidity-associated CSA-AKI. The principal benefit of machine learning is in its capability to distribute with many features with multiple interactions and its specific focus on maximizing predictive performance. Nonetheless, the emphasis on data-driven prediction might dismiss mechanistic perception. Future studies are required to assess whether a machine learning model that combines AKI biomarkers (such as IL-18, NGAL, and KIM-1) [115–118] and EHR data perform better in predicting CSA-AKI than other commonly used models. Essential prerequisites are comprehensive databases with high-quality data and the evaluation and integration of AI into pragmatic clinical settings; hence, the understanding of AI and its applications in our profession is important for the present and prospective advancement of Nephrology.

4. Conclusions

In summary, CSA-AKI is a complex and multifaceted syndrome associated with significant morbidity and mortality. In the present era of using big data, the application of machine learning in Nephrology clinical practice to predict AKI, including CSA-AKI, holds great future promise.

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References

1. Chew, S.T.H.; Hwang, N.C. Acute kidney injury after cardiac surgery: A narrative review of the literature. J. Cardiothorac. Vasc. Anesth. 2019, 33, 1122–1138. [CrossRef] [PubMed]

2. Sakhjuja, A.; Kashani, K.; Schold, J.; Cheungpasitporn, W.; Soltesz, E.; Demirjian, S. Hospital procedure volume does not predict acute kidney injury after coronary artery bypass grafting—a nationwide study. Clin. Kidney J. 2017, 10, 769–775. [CrossRef] [PubMed]

3. Thongprayoon, C.; Cheungpasitporn, W.; Mao, M.A.; Srivali, N.; Kittanamongkolchai, W.; Harrison, A.M.; Greason, K.L.; Kashani, K.B. Persistent acute kidney injury following transcatheter aortic valve replacement. J. Cardiothorac. Vasc. Anesth. 2019, 33, 1122–1138. [CrossRef] [PubMed]

4. Thongprayoon, C.; Cheungpasitporn, W.; Srivali, N.; Kittanamongkolchai, W.; Sakhjuja, A.; Greason, K.L.; Kashani, K.B. The association between renal recovery after acute kidney injury and long-term mortality after transcatheter aortic valve replacement. PLoS ONE 2017, 12, e0183350. [CrossRef] [PubMed]

5. Thongprayoon, C.; Cheungpasitporn, W.; Shah, I.K.; Kashani, K.B. Association of frailty status with acute kidney injury and mortality after transcatheter aortic valve replacement: A systematic review and meta-analysis. PLoS ONE 2017, 12, e0177157. [CrossRef] [PubMed]

6. Robert, A.M.; Kramer, R.S.; Dacey, L.J.; Charlesworth, D.C.; Leavitt, B.J.; Helm, R.E.; Hernandez, F.; Sardella, G.L.; Frumento, C.; Likosky, D.S. Cardiac surgery-associated acute kidney injury: A comparison of two consensus criteria. Ann. Thorac. Surg. 2010, 90, 1939–1943. [CrossRef] [PubMed]

7. Mehta, R.H.; Grab, J.D.; O’Brien, S.M.; Bridges, C.R.; Gammie, J.S.; Haan, C.K.; Ferguson, T.B.; Peterson, E.D.; Investigators, Society of Thoracic Surgeons. Bedside tool for predicting the risk of postoperative dialysis in patients undergoing cardiac surgery. J. Cardiothorac. Vasc. Anesth. 2008, 22, 2208–2216. [CrossRef] [PubMed]
18. Metnitz, P.G.; Krenn, C.G.; Steltzer, H.; Lang, T.; Ploder, J.; Lenz, K.; Le Gall, J.-R.; Druml, W. Effect of acute renal failure requiring renal replacement therapy on outcome in critically ill patients. *Crit. Care Med.* 2002, 30, 2051–2058. [CrossRef]

19. Srivastava, V; D’Silva, C.; Tang, A.; Sogliani, F.; Ngaage, D.L. The impact of major perioperative renal insult on long-term renal function and survival after cardiac surgery. *Interact. Cardiovasc. Thorac. Surg.* 2012, 15, 14–17. [CrossRef] [PubMed]

20. Rosner, M.H.; Okusa, M.D. Acute kidney injury associated with cardiac surgery. *Clin. J. Am. Soc. Nephrol.* 2006, 1, 19–32. [CrossRef]

21. Ryder, L.; Sartipy, U.; Evans, M.; Holzmann, M.J. Acute kidney injury after coronary artery bypass grafting and long-term risk of end-stage renal disease. *Circulation* 2014, 130, 2005–2011. [CrossRef] [PubMed]

22. Seabra, V.F.; Alobaidi, S.; Balk, E.M.; Poon, A.H.; Jaber, B.L. Off-pump coronary artery bypass surgery and acute kidney injury: A meta-analysis of randomized controlled trials. *Clin. J. Am. Soc. Nephrol.* 2010, 5, 1734–1744. [CrossRef] [PubMed]

23. Cheungpasitporn, W.; Thongprayoon, C.; Kittanamongkolchai, W.; Srivali, N.; Greason, K.L.; Kashani, K.B. Incidence and risk factors of acute kidney injury following transcatheter aortic valve replacement. *Nephrology (Carlton)* 2016, 21, 1041–1046. [CrossRef]

24. Shah, K.; Chaker, Z.; Busu, T.; Shah, R.; Osman, M.; Alqahtani, F.; Alkhouli, M. Meta-Analysis Comparing Renal Outcomes after Transcatheter versus Surgical Aortic Valve Replacement. *J. Interv. Cardiol.* 2019, 2019, 3537256. [CrossRef]

25. Catalano, M.; Lin, D.; Cassiere, H.; Kohn, N.; Rutkin, B.; Maurer, G.; Berg, J.A.; Jahn, J.; Esposito, R.; Hartman, A.; et al. Incidence of Acute Kidney Injury in Patients with Chronic Renal Insufficiency: Transcatheter versus Surgical Aortic Valve Replacement. *J. Inter. Cardiol.* 2019, 2019, 9780415. [CrossRef]

26. Shah, K.; Chaker, Z.; Busu, T.; Shah, R.; Osman, M.; Alqahtani, F.; Alkhouli, M. Meta-Analysis Comparing Renal Outcomes in Open and Percutaneous Approaches for Mitral Valve Repair: A Systematic Review. *Clin. J. Am. Soc. Nephrol.* 2015, 41, 372–382. [CrossRef]

27. Thongprayoon, C.; Cheungpasitporn, W.; Kittanamongkolchai, W.; Srivali, N.; Greason, K.L.; Kashani, K.B. Transcatheter versus Surgical Aortic Valve Replacement: A Kidney’s Perspective. *J. Ren. Inj. Prot.* 2016, 5, 1–7. [CrossRef]

28. Thongprayoon, C.; Cheungpasitporn, W.; Kittanamongkolchai, W.; Srivali, N.; Ungprasert, P.; Edmonds, P.J.; Ratanapo, S.; Spanuchart, I.; Erickson, S.B. Comparison of renal outcomes in off-pump versus on-pump coronary artery bypass grafting: A systematic review and meta-analysis of randomized controlled trials. *Clin. Nephrol.* 2012, 76, 1–8. [CrossRef]

29. Thongprayoon, C.; Cheungpasitporn, W.; Kittanamongkolchai, W.; Srivali, N.; O’Corragain, O.A.; Lertjitbanjong, P.; Hansrivijit, P.; Crisafio, A.; Mao, M.A.; Watthanasuntorn, K.; Aeddula, N.R.; Bathini, T.; Kaewput, W.; Cheungpasitporn, W. Acute Kidney Injury in Patients Undergoing Cardiac Transplantation: A Meta-Analysis. *Medicines (Basel)* 2019, 6, 108. [CrossRef]
36. Ramos, K.A.; Dias, C.B. Acute Kidney Injury after Cardiac Surgery in Patients Without Chronic Kidney Disease. *Braz. J. Cardiovasc. Surg* **2018**, *33*, 454–461. [CrossRef]
37. Thongprayoon, C.; Lertjitbanjong, P.; Cheungpasitporn, W.; Hansrivijit, P.; Fulop, T.; Kovvuru, K.; Kanduri, S.R.; Davis, P.W.; Vallabhajosyula, S.; Bathini, T.; et al. Incidence and impact of acute kidney injury on patients with implantable left ventricular assist devices: a Meta-analysis. *Ren. Fail.* **2020**, *42*, 495–512. [CrossRef]
38. Wang, J.; Yu, W.; Gao, M.; Gu, C.; Yu, Y. Preoperative Prophylactic Intraaortic Balloon Pump Reduces the Incidence of Postoperative Acute Kidney Injury and Short-Term Death of High-Risk Patients Undergoing Coronary Artery Bypass Grafting: A Meta-Analysis of 17 Studies. *Ann. Thorac. Surg.* **2016**, *101*, 2007–2019. [CrossRef]
39. Ding, W.; Ji, Q.; Wei, Q.; Shi, Y.; Ma, R.; Wang, C. Prophylactic application of an intra-aortic balloon pump in high-risk patients undergoing off-pump coronary artery bypass grafting. *Cardiology* **2015**, *131*, 109–115. [CrossRef]
40. Shi, M.; Huang, J.; Pang, L.; Wang, Y. Preoperative insertion of an intra-aortic balloon pump improved the prognosis of high-risk patients undergoing off-pump coronary artery bypass grafting. *J. Int. Med. Res.* **2011**, *39*, 1163–1168. [CrossRef]
41. Nonaka, T.; Kimura, N.; Hori, D.; Sasabuchi, Y.; Nakano, M.; Yuri, K.; Sanui, M.; Matsumoto, H.; Yamaguchi, A. Predictors of Acute Kidney Injury Following Elective Open and Endovascular Aortic Repair for Abdominal Aortic Aneurysm. *Ann. Vasc. Dis.* **2018**, *11*, 298–305. [CrossRef][PubMed]
42. Tang, Y.; Chen, J.; Huang, K.; Luo, D.; Liang, P.; Feng, M.; Chai, W.; Fung, E.; Lan, H.Y.; Xu, A. The incidence, risk factors and in-hospital mortality of acute kidney injury in patients after abdominal aortic aneurysm repair surgery. *BMC Nephrol.* **2017**, *18*, 184. [CrossRef][PubMed]
43. Hansrivijit, P.; Lertjitbanjong, P.; Thongprayoon, C.; Cheungpasitporn, W.; Aeddula, N.R.; Salim, S.A.; Chewcharat, A.; Watthanasuntorn, K.; Srivali, N.; Mao, M.A.; et al. Acute Kidney Injury in Pediatric Patients on Extracorporeal Membrane Oxygenation: A Systematic Review and Meta-analysis. *Medicines (Basel)* **2019**, *6*, 109. [CrossRef][PubMed]
44. Thongprayoon, C.; Cheungpasitporn, W.; Lertjitbanjong, P.; Aeddula, N.R.; Bathini, T.; Watthanasuntorn, K.; Srivali, N.; Mao, M.A.; Kashani, K. Incidence and Impact of Acute Kidney Injury in Patients Receiving Extracorporeal Membrane Oxygenation: A Meta-Analysis. *J. Clin. Med.* **2019**, *8*, 981. [CrossRef][PubMed]
45. Coleman, M.D.; Shaefi, S.; Sladen, R.N. Preventing acute kidney injury after cardiac surgery. *Curr. Opin. Anaesthesiol* **2011**, *24*, 70–76. [CrossRef][PubMed]
46. Candela-Toha, A.; Elias-Martin, E.; Abraira, V.; Tenorio, M.T.; Parise, D.; de Pablo, A.; Centella, T.; Llano, F. Predicting acute renal failure after cardiac surgery: External validation of two new clinical scores. *Clin. J. Am. Soc. Nephrol.* **2008**, *3*, 1260–1265. [CrossRef][PubMed]
47. Thakar, C.V.; Christianson, A.; Freyberg, R.; Almenoff, P.; Render, M.L. Incidence and outcomes of acute kidney injury in intensive care units: A Veterans Administration study. *Crit. Care Med.* **2009**, *37*, 2552–2558. [CrossRef]
48. Amini, S.; Najafi, M.N.; Karrari, S.P.; Mashhadi, M.E.; Mirzaei, S.; Tashnizi, M.A.; Moeinpour, A.A.; Hoseinikhah, H.; Aazami, M.H.; Jafari, M. Risk Factors and Outcome of Acute Kidney Injury after Isolated CABG Surgery: A Prospective Cohort Study. *Braz. J. Cardiovasc. Surg.* **2019**, *34*, 70–75. [CrossRef]
49. Yi, Q.; Li, K.; Jian, Z.; Xiao, Y.B.; Chen, L.; Zhang, Y.; Ma, R.Y. Risk Factors for Acute Kidney Injury after Cardiovascular Surgery: Evidence from 2,157 Cases and 49,777 Controls—A Meta-Analysis. *Cardiovasc. Med.* **2016**, *6*, 237–250. [CrossRef]
50. Najjar, M.; Yerebakan, H.; Sorabella, R.A.; Donovan, D.J.; Kossar, A.P.; Sreekanth, S.; Kurlansky, P.; Borger, M.A.; Argenziano, M.; Smith, C.R.; et al. Acute kidney injury following surgical aortic valve replacement. *J. Card. Surg.* **2015**, *30*, 631–639. [CrossRef]
51. Wang, J.; Yu, W.; Zhou, Y.; Yang, Y.; Li, C.; Liu, N.; Hou, X.; Wang, L. Independent Risk Factors Contributing to Acute Kidney Injury According to Updated Valve Academic Research Consortium-2 Criteria After Transcatheter Aortic Valve Implantation: A Meta-analysis and Meta-regression of 13 Studies. *J. Cardiothorac Vasc. Anesth.* **2017**, *31*, 816–826. [CrossRef][PubMed]
52. Thongprayoon, C.; Hansrivijit, P.; Kovvuru, K.; Kanduri, S.R.; Torres-Ortiz, A.; Acharya, P.; Gonzalez-Suarez, M.L.; Kaewput, W.; Bathini, T.; Cheungpasitporn, W. Diagnostics, Risk Factors, Treatment and Outcomes of Acute Kidney Injury in a New Paradigm. *J. Clin. Med.* **2020**, *9*, 1104. [CrossRef][PubMed]
53. Thakar, C.V.; Arrigain, S.; Worley, S.; Yared, J.-P.; Paganini, E.P. A clinical score to predict acute renal failure after cardiac surgery. J. Am. Soc. Nephrol. 2005, 16, 162–168. [CrossRef] [PubMed]

54. Aronson, S.; Fontes, M.L.; Miao, Y.; Mangano, D. Risk index for perioperative renal dysfunction/failure. Circulation 2007, 115, 733–742. [CrossRef]

55. Birnie, K.; Verheyden, V.; Pagano, D.; Bhabra, M.; Tilling, K.; Sterne, J.A.; Murphy, G.J. Predictive models for kidney disease: Improving global outcomes (KDIGO) defined acute kidney injury in UK cardiac surgery. Crit. Care 2014, 18, 606. [CrossRef]

56. Jorge-Monjas, P.; Bustamante-Munguira, J.; Lorenzo, M.; Heredia-Rodriguez, M.; Fierro, I.; Gómez-Sánchez, E.; Hernandez, A.; Álvarez, F.J.; Bermejo-Martín, J.F.; Gómez-Pesquera, E. Predicting cardiac surgery–associated acute kidney injury: The CRATE score. J. Crit. Care 2016, 31, 130–138. [CrossRef]

57. Wong, B.; St. Onge, J.; Korkola, S.; Prasad, B. Validating a scoring tool to predict acute kidney injury (AKI) following cardiac surgery. Can. J. Kidney Health Dis. 2015, 2, 37. [CrossRef]

58. Huen, S.C.; Parikh, C.R. Predicting acute kidney injury after cardiac surgery: A systematic review. Ann. Thorac. Surg. 2012, 93, 337–347. [CrossRef]

59. Englberger, L.; Suri, R.M.; Li, Z.; Dearani, J.A.; Park, S.J.; Sundt, T.M., III; Schaff, H.V. Validation of clinical scores predicting severe acute kidney injury after cardiac surgery. Am. J. Kidney Dis. 2010, 56, 623–631. [CrossRef]

60. Nah, C.W.; Ti, L.K.; Liu, W.; Ng, R.R.G.; Shen, L.; Chew, S.T.H. A clinical score to predict acute kidney injury after cardiac surgery in a Southeast-Asian population. Interact. Cardiovasc. Thorac. Surg. 2016, 23, 757–761. [CrossRef]

61. Li, Q.; Fan, Q.-L.; Han, Q.-X.; Geng, W.-J.; Zhao, H.-H.; Ding, X.-N.; Yan, J.-Y.; Zhu, H.-Y. Machine learning in nephrology: Scratching the surface. Chin. Med. J. 2020, 120, 687–698. [CrossRef] [PubMed]

62. Molitoris, B.A. Beyond Biomarkers: Machine Learning in Diagnosing Acute Kidney Injury. J. Am. Soc. Nephrol. 2018, 29, 4570–4573. [CrossRef] [PubMed]

63. Chiofolo, C.; Chbat, N.; Ghosh, E.; Eshelman, L.; Kashani, K. Automated Continuous Acute Kidney Injury Prediction and Surveillance: A Random Forest Model. Mayo Clin. Proc. 2019, 94, 748–750. [CrossRef] [PubMed]

64. Sutherland, S.M.; Goldstein, S.L.; Bagshaw, S.M. Acute Kidney Injury and Big Data. Contrib. Nephrol. 2018, 193, 55–67. [CrossRef] [PubMed]

65. Rajkomar, A.; Dean, J.; Kohane, I. Machine Learning in Medicine. Eur. Heart J. 2017, 38, 1805–1814. [CrossRef] [PubMed]

66. Baxter, R.D.; Fann, J.I.; DiMaio, J.M.; Lobdell, K. Digital Health Primer for Cardiothoracic Surgeons. Mayo Clin. Proc. 2019, 94, 783–792. [CrossRef] [PubMed]

67. Sandler, A.; Perazella, M.A.; Garcia, J.I. Moving beyond regression techniques in cardiovascular risk prediction: Applying machine learning to address analytic challenges. Eur. Heart J. 2017, 38, 1805–1814. [CrossRef] [PubMed]

68. Szlosek, D.A.; Ferrett, J. Using Machine Learning and Natural Language Processing Algorithms to Automate the Evaluation of Clinical Decision Support in Electronic Medical Record Systems. EGEMS (Wash DC) 2016, 4, 1222. [CrossRef]
75. Lee, H.C.; Yoon, H.K.; Nam, K.; Cho, Y.J.; Kim, T.K.; Kim, W.H.; Bahk, J.H. Derivation and Validation of Machine Learning Approaches to Predict Acute Kidney Injury after Cardiac Surgery. J. Clin. Med. 2018, 7, 322. [CrossRef]
76. Rau, C.-S.; Wu, S.-C.; Chuang, J.-F.; Huang, C.-Y.; Liu, H.-T.; Chien, P.-C.; Hsieh, C.-H. Machine learning models of survival prediction in trauma patients. J. Clin. Med. 2019, 8, 799. [CrossRef]
77. Chicco, D.; Jurman, G. Machine learning can predict survival of patients with heart failure from serum creatinine and ejection fraction alone. BMC Med. Inform. Decis. Mak. 2020, 20, 16. [CrossRef]
78. Cao, Y.; Fang, X.; Ottosson, J.; Näslund, E.; Stenberg, E. A Comparative Study of Machine Learning Algorithms in Predicting Severe Complications after Bariatric Surgery. J. Clin. Med. 2019, 8, 678. [CrossRef]
79. Lee, H.-C.; Ryu, H.-G.; Chung, E.-J.; Jung, C.-W. Prediction of bispectral index during target-controlled infusion of propofol and remifentanil. Anesthesiology 2018, 129, 663–674. [CrossRef]
80. Lee, C.K.; Hofer, I.; Gabel, E.; Baldi, P.; Cannesson, M. Development and validation of a deep neural network model for prediction of postoperative in-hospital mortality. Anesthesiology 2018, 129, 649. [CrossRef]
81. Olsen, R.M.; Aasvang, E.K.; Meyhoff, C.S.; Sorensen, H.B.D. Towards an automated multimodal clinical decision support system at the post anesthesia care unit. Comput. Biol. Med. 2018, 101, 15–21. [CrossRef]
82. Lee, H.-C.; Ryu, H.-G.; Chung, E.-J.; Jung, C.-W. Prediction of bispectral index during target-controlled infusion of propofol and remifentanil. Anesthesiology 2018, 128, 492–501. [CrossRef]
83. Hatib, F.; Jian, Z.; Buddi, S.; Lee, C.; Settels, J.; Sibert, K.; Rinehart, J.; Cannesson, M. Machine-learning algorithm to predict hypotension based on high-fidelity arterial pressure waveform analysis. Anesthesiol. J. Am. Soc. Anesthesiol. 2018, 129, 663–674. [CrossRef]
84. Lee, H.-C.; Ryu, H.-G.; Chung, E.-J.; Jung, C.-W. Prediction of bispectral index during target-controlled infusion of propofol and remifentanil. Anesthesiology 2018, 128, 492–501. [CrossRef]
85. Lee, H.-C.; Ryu, H.-G.; Chung, E.-J.; Jung, C.-W. Prediction of bispectral index during target-controlled infusion of propofol and remifentanil. Anesthesiology 2018, 128, 492–501. [CrossRef]
86. Lee, C.K.; Hofer, I.; Gabel, E.; Baldi, P.; Cannesson, M. Development and validation of a deep neural network model for prediction of postoperative in-hospital mortality. Anesthesiology 2018, 129, 649. [CrossRef]
87. Olsen, R.M.; Aasvang, E.K.; Meyhoff, C.S.; Sorensen, H.B.D. Towards an automated multimodal clinical decision support system at the post anesthesia care unit. Comput. Biol. Med. 2018, 101, 15–21. [CrossRef]
88. Lee, H.-C.; Ryu, H.-G.; Chung, E.-J.; Jung, C.-W. Prediction of bispectral index during target-controlled infusion of propofol and remifentanil. Anesthesiology 2018, 128, 492–501. [CrossRef]
89. Lee, H.-C.; Ryu, H.-G.; Chung, E.-J.; Jung, C.-W. Prediction of bispectral index during target-controlled infusion of propofol and remifentanil. Anesthesiology 2018, 128, 492–501. [CrossRef]
90. Peker, M.; Şen, B.; Gürüler, H. Rapid automated classification of anesthetic depth levels using GPU based parallelization of neural networks. J. Med. Syst. 2015, 39, 18. [CrossRef]
91. Nagaraj, S.B.; Biswal, S.; Boyle, E.J.; Zhou, D.W.; McClain, L.M.; Bajwa, E.K.; Quraishi, S.A.; Oluwaseun, A.; Barbieri, R.; Purdon, P.L. Patient-specific classification of ICU sedation levels from heart rate variability. Crit. Care Med. 2017, 45, e683. [CrossRef] [PubMed]
92. Shalbaf, R.; Behnam, H.; Sleigh, J.W.; Steyn-Ross, A.; Voss, L.J. Monitoring the depth of anesthesia using entropy features and an artificial neural network. J. Neurosci. Methods 2013, 218, 17–24. [CrossRef] [PubMed]
93. Shalbaf, A.; Shalbaf, R.; Saffar, M.; Sleigh, J. Monitoring the level of hypnosis using a hierarchical SVM system. J. Clin. Monit. Comput. 2019, 1–8. [CrossRef] [PubMed]
94. Ortolani, O.; Conti, A.; Di Filippo, A.; Adembri, C.; Moraldi, E.; Evangelisti, A.; Maggini, M.; Roberts, S. EEG signal processing in anaesthesia. Use of a neural network technique for monitoring depth of anaesthesia. Br. J. Anaesth. 2002, 88, 644–648. [CrossRef] [PubMed]
95. Hever, G.; Cohen, L.; O’Connor, M.F.; Matot, I.; Lerner, B.; Bitan, Y. Machine learning applied to multi-sensor information to reduce false alarm rate in the ICU. J. Clin. Monit. Comput. 2019, 34, 339–352. [CrossRef] [PubMed]
96. Lee, S.; Mohr, N.M.; Street, W.N.; Nadkarni, P. Machine learning in relation to emergency medicine clinical and operational scenarios: An overview. West. J. Emerg. Med. 2019, 20, 219. [CrossRef] [PubMed]
97. Abraham, A.; Pedregosa, F.; Eickenberg, M.; Gervais, P.; Mueller, A.; Kossaifi, J.; Gramfort, A.; Thirion, B.; Varoquaux, G. Machine learning for neuroimaging with scikit-learn. *Front. Neuroinformatics* 2014, 8, 14. [CrossRef]

98. Abdul Salim, S.; Tran, H.; Thongprayoon, C.; Fulp, T.; Cheungpasitporn, W. Comparison of drug-coated balloon angioplasty versus conventional angioplasty for arteriovenous fistula stenosis: Systematic review and meta-analysis. *J. Vasc. Access* 2020, 21, 357–365. [CrossRef]

99. Cheungpasitporn, W.; Kashani, K. Electronic Data Systems and Acute Kidney Injury. *Contrib. Nephrol.* 2016, 187, 73–83. [CrossRef]

100. The, L. Artificial intelligence in health care: Within touching distance. *Lancet* 2018, 390, 2739. [CrossRef]

101. Laszczyńska, O.; Severo, M.; Azevedo, A. Electronic Medical Record-Based Predictive Model for Acute Kidney Injury in an Acute Care Hospital. *Stud. Health Technol. Inf.* 2016, 228, 810–812.

102. Geubbels, N.; de Brauw, L.M.; Acherman, Y.I.; van de Laar, A.W.; Bruin, S.C. Risk Stratification Models: How Well do They Predict Adverse Outcomes in a Large Dutch Bariatric Cohort? *Obes. Surg.* 2015, 25, 2290–2301. [CrossRef] [PubMed]

103. Stenberg, E.; Cao, Y.; Näslund, E.; Näslund, I.; Ottersson, J. Risk Prediction Model for Severe Postoperative Complication in Bariatric Surgery. *Obes Surg* 2018, 28, 1869–1875. [CrossRef] [PubMed]

104. Lei, L.; Wang, Y.; Xue, Q.; Tong, J.; Zhou, C.M.; Yang, J.J. A comparative study of machine learning algorithms for predicting acute kidney injury after liver cancer resection. *PeerJ* 2020, 8, e8583. [CrossRef]

105. Lee, H.-C.; Yoon, S.B.; Yang, S.-M.; Kim, W.H.; Ryu, H.-G.; Jung, C.-W.; Suh, K.-S.; Lee, K.H. Prediction of acute kidney injury after liver transplantation: Machine learning approaches vs. logistic regression model. *J. Clin. Med.* 2018, 7, 428. [CrossRef]

106. Tran, N.K.; Sen, S.; Palmieri, T.L.; Lima, K.; Falwell, S.; Wajda, J.; Rashidi, H.H. Artificial intelligence and machine learning for predicting acute kidney injury in severely burned patients: A proof of concept. *Burns* 2019, 45, 1350–1358.

107. Huang, C.; Murugiah, K.; Mahajan, S.; Li, S.X.; Dhruva, S.S.; Haimovich, J.S.; Wang, Y.; Schulz, W.L.; Testani, J.M.; Wilson, F.P.; et al. Enhancing the prediction of acute kidney injury risk after percutaneous coronary intervention using machine learning techniques: A retrospective cohort study. *PLoS Med.* 2018, 15, e1002703. [CrossRef]

108. Thottakkara, P.; Ozrazgat-Baslanti, T.; Hupf, B.B.; Rashidi, P.; Pardalos, P.; Momcilovic, P.; Bihorac, A. Application of Machine Learning Techniques to High-Dimensional Clinical Data to Forecast Postoperative Complications. *PLoS ONE* 2016, 11, e0155705. [CrossRef]

109. Mohamadlou, H.; Lynn-Palevsky, A.; Barton, C.; Chettipally, U.; Shieh, L.; Calvert, J.; Saber, N.R.; Das, R. Prediction of Acute Kidney Injury with a Machine Learning Algorithm Using Electronic Health Record Data. *Can. J. Kidney Health Dis.* 2018, 5, 2054358118776326. [CrossRef]

110. Grogan, K.L.; Goldsmith, M.P.; Masino, A.J.; Nelson, O.; Tsui, F.-C.; Simpao, A.F. A narrative review of biomarkers for predicting acute kidney injury and mortality 3 years after cardiac surgery. *J. Am. Soc. Nephrol.* 2014, 25, 1063–1071. [CrossRef]

111. Tomašev, N.; Glorot, X.; Rae, J.W.; Zielinski, M.; Askham, H.; Saraiva, A.; Mottram, A.; Meyer, C.; Ravuri, S.; Protsysuk, I.; et al. A clinically applicable approach to continuous prediction of future acute kidney injury. *Nature* 2019, 572, 116–119. [CrossRef] [PubMed]

112. Protsyuk, I.; et al. A clinically applicable approach to continuous prediction of future acute kidney injury. *J. Cardiothorac. Vasc. Anesth.* 2020, 34, 479–482. [CrossRef]

113. Parikh, C.R.; Coca, S.G.; Thiessen-Philbrook, H.; Shlipak, M.G.; Koyner, J.L.; Wang, Z.; Edelstein, C.L.; Devarajan, P.; Patel, U.D.; Zappitelli, M. Postoperative biomarkers predict acute kidney injury and poor outcomes after adult cardiac surgery. *J. Am. Soc. Nephrol.* 2011, 22, 1748–1757. [CrossRef]

114. Koyner, J.L.; Carey, K.A.; Edelson, D.P.; Churpek, M.M. The Development of a Machine Learning Inpatient Acute Kidney Injury Prediction Model. *Crit. Care Med.* 2018, 46, 1070–1077. [CrossRef]

115. Parikh, C.R.; Coca, S.G.; Thiessen-Philbrook, H.; Shlipak, M.G.; Koyner, J.L.; Wang, Z.; Edelstein, C.L.; Devarajan, P.; Patel, U.D.; Zappitelli, M. Postoperative biomarkers predict acute kidney injury and poor outcomes after adult cardiac surgery. *J. Am. Soc. Nephrol.* 2011, 22, 1748–1757. [CrossRef]
117. Arthur, J.M.; Hill, E.G.; Alge, J.L.; Lewis, E.C.; Neely, B.A.; Janech, M.G.; Tumlin, J.A.; Chawla, L.S.; Shaw, A.D. Evaluation of 32 urine biomarkers to predict the progression of acute kidney injury after cardiac surgery. *Kidney Int.* 2014, 85, 431–438. [CrossRef]

118. Koyner, J.L.; Vaidya, V.S.; Bennett, M.R.; Ma, Q.; Worcester, E.; Akhter, S.A.; Raman, J.; Jeevanandam, V.; O’Connor, M.F.; Devarajan, P.; et al. Urinary biomarkers in the clinical prognosis and early detection of acute kidney injury. *Clin. J. Am. Soc. Nephrol.* 2010, 5, 2154–2165. [CrossRef]

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