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Machine Learning in Cardiac Surgery: A Systematic Review of ML Techniques, Applications, and the Road Ahead

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ABSTRACT

Machine learning (ML) is an accelerating force in cardiac surgery, augmenting predictive accuracy, clinical judgment, and outcomes. Addressing the deficit in traditional models, its integration provides dynamic, data-driven insights for surgical care. This work is relevant as it assesses the clinical utility of machine learning methods, shifting attention from their use in mortality prediction, complication evaluation, and resource allocation in high-risk surgeries. Awareness of these implications is critical for the uptake of AI-based technologies in intricate cardiac surgeries. A systematic review of the narrative approach was used with peer-review articles from 2000 through 2024 in databases like PubMed, Scopus, and IEEE. The choice was based on predefined inclusion criteria, MeSH keywords, and AI-augmented research tools for complete coverage. The analysis concludes that machine learning methods, primarily ensemble and deep learning models, function superior to standard scores for predicting outcomes in surgeries, favoring a shift in the direction of precision-based cardiac care. The models provide high performance in predicting complications as well as blood transfusions. Nonetheless, issues like the heterogeneity of the data, its explainability, generalizability, and integration within clinical workstreams continue. The future holds prospects for technological convergence, personalized machine learning-based tools, and multi-disciplinary collaboration for expanded adoption. This review is useful for researchers, clinicians, and data scientists as it outlines the current scope and future direction of machine learning, leading to safer, smarter, and optimized cardiac surgeries.

Keywords: *Focal seizures, epilepsy, children, neurocysticercosis, EEG, neuroimaging, tuberculoma, ILAE classification*

1. INTRODUCTION

Cardiac surgery represents one of the most complex and high-risk domains in medicine, where surgical outcomes depend on numerous patient-specific, procedural, and perioperative factors. The identification of patients at elevated risk for adverse outcomes represents a critical challenge in clinical decision-making. Over the past decade, machine learning (ML) has emerged as a promising approach to enhance risk prediction, optimize patient selection, and improve outcomes in cardiac surgery. Machine learning is a revolutionary technology that promises to change the way surgery is practiced. Spurred by advances in computing power and the volume of data produced in healthcare, ML has shown remarkable ability to master tasks once reserved for physicians (Ostberg, 2021). This literature review synthesizes current research on machine learning applications in cardiac surgery, examining methodological approaches, clinical implementations, key findings, and future directions in this rapidly evolving field.

The integration of machine learning into cardiac surgery has been propelled by limitations in traditional risk prediction models. Most established prediction models are limited to the analysis of nonlinear relationships and fail to fully consider intraoperative variables, which represent the acute response to surgery (Tseng, 2020). Currently available risk prediction models either do not provide patient-specific risk factors or only predict in-hospital mortality rates (Jalali, 2020). These limitations have created an opportunity for machine learning to provide more personalized, accurate, and comprehensive risk assessment across various cardiac surgical populations and procedures.

2. METHOD

This review study employed a comprehensive literature review methodology, focusing on peer-reviewed research articles published between January 2000 and August 2024 that explored the application of machine learning (ML) in adult cardiac surgery. Key databases including Google Scholar, PubMed, Scopus, Springer, IEEE, and ACM, along with other credible internet sources, were systematically searched. A structured keyword strategy was applied using MeSH terms such as "Cardiac Surgery," "Machine Learning," "Machine Learning Techniques," and related variations. The review was narrative in nature, and studies were initially screened based on titles and abstracts to ensure thematic relevance. Only articles published in English were included, while studies focused on congenital heart surgery, general thoracic surgery, minimally invasive procedures, and cardiac transplants were excluded. The Concordance Index (C-index) was considered as the primary metric to assess model performance across the selected studies. Additionally, AI-powered research tools like Scispace, Answerthis, and Connectedpapers were utilized to enhance the efficiency and accuracy of literature selection.
Here is the summary as a table (See Table 1), outlining the systematic approach adopted for literature selection. The table presents key parameters such as search duration, databases used, keyword strategy, inclusion/exclusion criteria, and AI-supported selection tools.

Table 1: Search-Criteria and keywords

Criteria	Description
Date of search window	12-02-2025 to 15-02-2025
Source of published articles	Google Scholar + PubMed + Scopus + Springer + IEEE + ACM + Other Internet source
Keywords for search used	"Cardiac Surgery" + "Machine Learning" + "Machine Learning Techniques" + "Machine Learning in Cardiac Surgery" + "Application of Machine Learning in healthcare"
Timeframe window	Jan 2000 to Aug 2024
Inclusion and exclusion criteria	English language and adult heart surgery are required. General thoracic, aortic, congenital heart, or thoracic transplant surgery is not allowed.
Selection process	AI tool like "answerthis" , "scispace"," connectedpapers" etc. were used to select relevant sources.

3. MACHINE LEARNING METHODS AND APPROACHES IN CARDIAC SURGERY

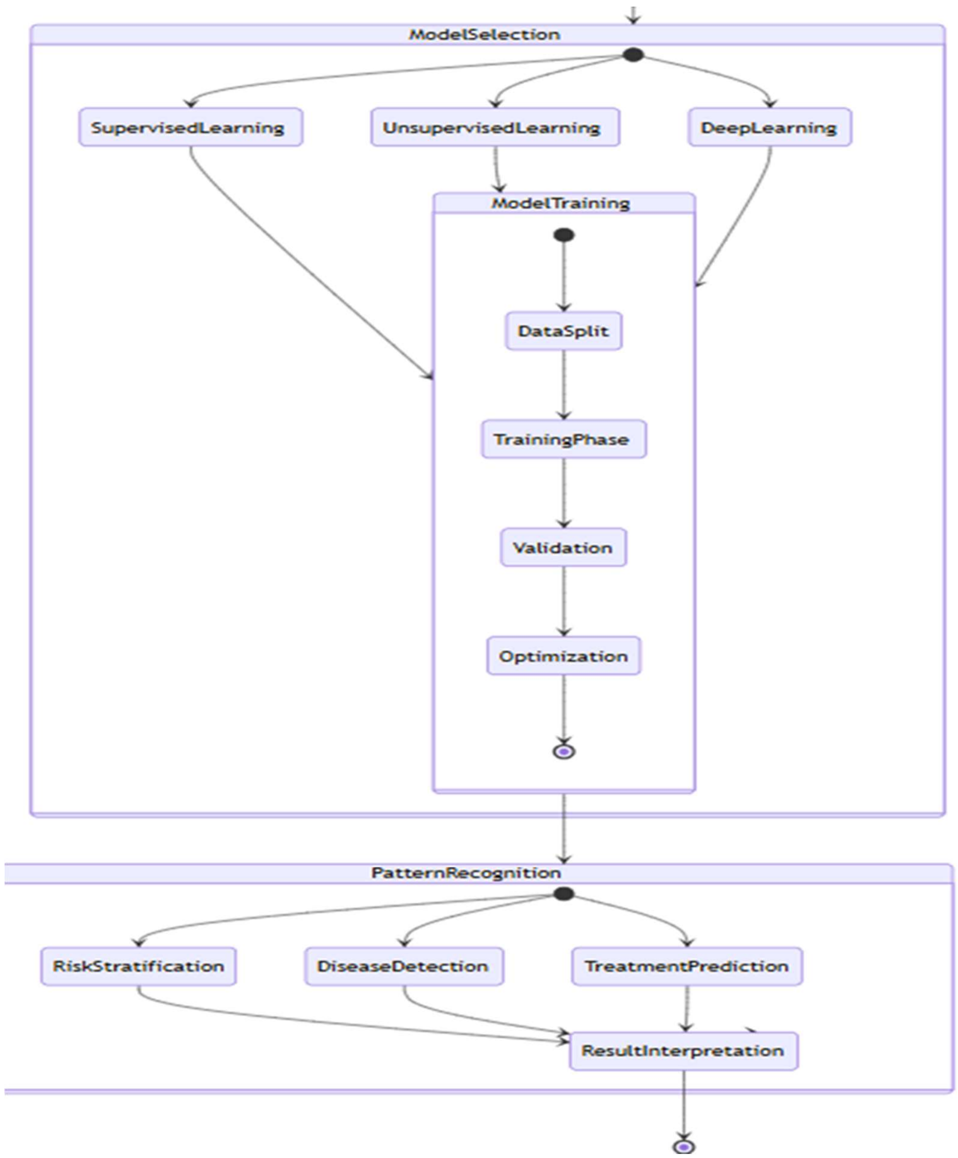
Machine learning methods such as logistic regression, SVM, Random Forest (RF), XGBoost, and ensemble models have shown significant potential in cardiac surgery outcomes prediction [Tseng, 2020]. Tree-based models, particularly RF and ensemble combinations like RF-XGBoost, have demonstrated strong predictive performance with AUCs above 0.84 [Tseng, 2020]. XGBoost combined with SMOTE has effectively addressed class imbalance issues in pediatric cardiac surgery, outperforming traditional models in sensitivity and overall AUC [Ghavidel, 2024].
Deep learning approaches, especially deep neural networks (DNN), have achieved high accuracy (up to 89%) and AUCs close to 0.95 for mortality prediction and prolonged hospital stays [Jalali, 2020; Petrosyan, 2022]. These models also surpass traditional ensemble models in metrics like precision, recall, F1-score, and balanced accuracy. Hybrid models, such as RF feature selection with logistic regression, further improve prediction quality in cases like acute kidney injury after cardiac surgery [Dong, 2023].
Ensemble learning techniques, particularly homogeneous ensembles like XGBoost and RF, show clinical superiority by integrating legacy and contemporary datasets for improved prediction accuracy [Allyn, 2017]. These ensemble strategies outperform single-time datasets by leveraging multiple data streams and modeling techniques, reinforcing the robustness and reliability of ML-based decision-making in cardiac surgical settings.
Here is the summary as a table (See Table 2) highlighting the key techniques used in the field. The table provides a concise comparison of each method's strengths and limitations to assess their clinical applicability and predictive effectiveness.

Figure 1 illustrates a Machine Learning (ML) approach for extracting useful patterns from large-scale clinical or medicinal datasets. The workflow covers model selection, training, validation, optimization, and pattern recognition for applications such as disease detection, risk stratification, and treatment prediction.

Table 2: Machine Learning Methods in Cardiac Surgery

ML Method	Description	Strength	Limitation
Logistic Regression	A statistical method using probability functions for binary classification tasks.	Easy to interpret and apply in clinical contexts; works well with small, structured datasets.	May underperform on non-linear data.
Random Forest (RF)	Ensemble of decision trees for robust predictions across variables.	High AUC (0.839), strong generalization, and good handling of complex features [Tseng, 2020].	Can be computationally intensive.
XGBoost (with SMOTE)	Gradient boosting with synthetic oversampling to manage class imbalance.	High sensitivity (0.74) and best performance in imbalanced pediatric surgery data [Ghavidel, 2024].	Complex hyperparameter tuning.
Deep Neural Networks (DNN)	Multi-layer neural networks for complex, non-linear patterns.	Achieved high AUC (0.95) and accuracy (89%) in mortality prediction [Jalali, 2020; Petrosyan, 2022].	Poor interpretability ("black-box").
Hybrid RF + Logistic Regression	Combines RF for feature selection with logistic regression modeling.	Balanced performance (C-statistic = 0.75), reliable after internal validation [Dong, 2023].	Still requires robust variable tuning.
Ensemble Learning	Combines multiple base models (homogeneous/heterogeneous).	Best overall performance (AUC up to 0.8327) using historical and updated data [Allyn, 2017].	Needs large and well-structured data.

Figure 1: Machine Learning approach after method selection



4. APPLICATIONS OF MACHINE LEARNING IN CARDIAC SURGERY

The application of machine learning in cardiac surgery has shown transformative potential, offering enhanced predictive capabilities across various clinical scenarios. From accurately forecasting mortality and adverse outcomes [Du, 2022; Yu, 2021; Parise, 2023], to identifying risks for specific complications like AKI, POAF, and infections [Tseng, 2020; Zhang, 2023; Wang, 2022], ML models demonstrate superior performance over traditional methods. Furthermore, advanced algorithms have enabled precise prediction of blood product requirements, supporting efficient resource management and preoperative planning [Sinha, 2023].

4.1 Prediction of Mortality and Adverse Outcomes

Machine learning models have consistently outperformed traditional risk scoring systems in predicting mortality and adverse outcomes in cardiac surgery, demonstrating higher AUC values and clinical utility [Du, 2022]. In pediatric cardiac surgery, XGBoost has significantly outperformed standard risk stratification methods like STS-EACTS and RACHS-1, achieving an

AUC of 0.887 [Yu, 2021]. Additionally, for long-term mortality prediction post-surgery, AdaBoost has shown superior accuracy and fit with the highest AUC among various algorithms applied [Parise, 2023].

4.2 Prediction of Specific Complications

ML methods have effectively predicted specific complications such as acute kidney injury (AKI), with key predictors including intraoperative urine output and transfused blood units [Tseng, 2020]. Prediction of postoperative atrial fibrillation (POAF) using models like Random Forest and Support Vector Machine has yielded high performance, with age and aortic cross-clamp time among top predictors [Zhang, 2023]. For postoperative infections, ML models using RF, LASSO, and other classifiers have identified critical infection-related variables, enabling construction of robust predictive models for surgical patients [Wang, 2022].

4.3 Blood Product Requirement Prediction

ML has proven effective in forecasting blood product requirements, especially red blood cell transfusions during cardiac surgery, enhancing inventory management and preoperative risk assessment [Sinha, 2023]. Hybrid models integrating regression and classification techniques like Gaussian Process algorithms have achieved strong accuracy for varying transfusion volumes (e.g., AUC = 0.826 for predicting 4+ RBC units) [Sinha, 2023]. These approaches address imbalanced datasets and optimize transfusion predictions for clinical decision-making.

.5. MODEL PERFORMANCE AND EVALUATION

Evaluating the performance of machine learning models is critical to understanding their clinical applicability and reliability in cardiac surgery. This section examines how ML models compare with traditional risk scores [Arafat, 2023; Mohammadi, 2024; Dong, 2024], addresses the challenges of performance drift over time [Zeng, 2021], and highlights the importance of model interpretability for clinical integration [Tseng, 2020; Mauricio, 2024; Gong, 2015]. These insights emphasize the need for robust, adaptive, and explainable ML systems to ensure sustained value in surgical settings.

5.1 Comparison with Traditional Risk Scores:

Machine learning (ML) models such as XGBoost and Random Forest have consistently outperformed traditional scoring systems like EuroSCORE II in predicting in-hospital mortality post-cardiac surgery, offering higher AUC and F1 scores [Arafat, 2023]. In tricuspid valve surgery, ML models like elastic net and RF also demonstrated superior performance over EuroSCORE in predicting operative mortality [Mohammadi, 2024]. For pediatric cardiac surgery, a systematic review showed that AI models provided better prediction of mortality, complications, and prolonged care outcomes compared to traditional systems [Dong, 2024].

5.2 Performance Drift and Temporal Validation:

Performance of ML models can degrade over time due to dataset drift, where the data used during model training no longer aligns with newer clinical data [Zeng, 2021]. Despite this drift, XGBoost and Random Forest maintained relatively higher clinical effectiveness metrics (CEM ~0.728), while EuroSCORE II consistently underperformed [Zeng, 2021]. Monitoring temporal shifts in variable importance and retraining models as data evolves is essential for maintaining model relevance and clinical utility [Zeng, 2021].

5.3 Model Interpretability and Explainability:

Model explainability is essential for clinical acceptance, with SHAP values helping visualize feature impact on predictions via summary and dependence plots [Tseng, 2020]. In pediatric heart surgery, interpretable ML models using k-means and SHAP helped reveal how blood pressure variability influences complication risk, aiding clinical decision-making [Mauricio, 2024]. Combining explainability tools like LIME with simulation-based scenario planning has enabled reversal of negative surgical prognoses, demonstrating real-world clinical potential [Gong, 2015].

6. CHALLENGES AND LIMITATIONS

Despite the growing use of machine learning in cardiac surgery, key challenges persist (See Table 3). A major limitation lies in the quality and availability of data, which is often limited by institutional specificity and large class imbalances in clinical datasets [Montisci, 2022]. Though Big Data sources such as EHRs and OMICS profiles offer vast potential, effectively harnessing this information for personalized risk models remains complex [Li, 2023].

Generalizability is another core concern, as models trained on institution-specific data may fail when applied elsewhere. External validation using independent datasets like MIMIC-IV is critical but not consistently performed [Leivaditis, 2025]. Ethical, regulatory, and workflow integration barriers further hinder broader model adoption in diverse clinical environments [Rellum, 2021].

Lastly, clinical implementation faces hurdles due to the lack of interpretability, fragmented data sources, and uncertain real-world effectiveness. Although promising applications exist in diagnostics, intraoperative guidance, and postoperative care, the translation of ML benefits to improved clinical outcomes remains limited [Ostberg, 2021; Khalsa, 2021]. Overcoming these limitations is vital to fully realize ML's impact in cardiac surgery.

Table 3: Summary for challenges and limitations

Challenges and Limitations	Description	Reference Number
Data Quality and Availability	ML model development is hindered by small, specific datasets and class imbalance; Big Data offers potential but is difficult to integrate effectively.	[Montisci, 2022]; [Li, 2023]
Generalizability and Validation	Models often lack external validity; testing across populations and datasets like MIMIC-IV is essential but underutilized.	[Leivaditis, 2025]; [Rellum, 2021]
Clinical Implementation	Barriers include interpretability, fragmented clinical data, ethical concerns, and uncertain translation to improved outcomes in surgical practice.	[Ostberg, 2021]; [Khalsa, 2021]

7. FUTURE DIRECTIONS

As machine learning continues to advance, its future in cardiac surgery promises to be shaped by technological integration, personalized care, and collaborative innovation. This section explores emerging trends that are redefining surgical planning and outcome prediction. Key directions include convergence with other digital health tools, development of individualized predictive models, and fostering interdisciplinary partnerships.

7.1 Integration with Other Technologies

The integration of ML with technologies like telemedicine, robotic-assisted systems, and computer vision is enhancing precision surgery, remote monitoring, and cost-efficient care [Júnior, 2020; Rellum, 2021]. These synergies promise improved intraoperative guidance, automated workflows, and accurate postoperative risk predictions.

7.2 Personalized Medicine Approaches

Machine learning is driving a shift toward personalized medicine, enabling real-time, individualized risk calculators accessible via web or mobile applications for congenital cardiac surgery [Sulague, 2023]. While this evolution challenges the dominance of RCTs, its full clinical impact remains to be seen [Li, 2023].

7.3 Interdisciplinary Collaboration

The future success of ML in cardiac surgery hinges on interdisciplinary collaboration, transparent model development, and robust validation frameworks [Rellum, 2021]. Though AI has improved preoperative risk assessment and postoperative prediction, further high-powered studies are needed to ensure clinical accuracy and safety [28].

8. CONCLUSION

Machine learning has demonstrated significant potential to transform risk prediction, clinical decision-making, and outcome improvement in cardiac surgery. The superior performance of ML models compared to traditional risk scores has been consistently demonstrated across various surgical populations and procedures. Tree-based algorithms like Random Forest and XGBoost have emerged as particularly effective, with ensemble and hybrid approaches showing further improvements. Despite the promising results, several challenges remain. These include addressing the limited availability of high-quality data, ensuring model interpretability, validating models across diverse populations, and successfully implementing these tools in clinical practice. Performance drift over time presents an additional challenge that must be addressed for the long-term utility of these approaches.

The future of machine learning in cardiac surgery will likely involve greater integration with other technologies, increasingly personalized approaches to patient care, and enhanced interdisciplinary collaboration. As the field continues to evolve, machine learning holds promise for improving risk stratification, optimizing patient selection, and ultimately enhancing outcomes in this high-risk surgical specialty.

Despite these challenges, in the future, the practice of cardiac surgery will be greatly augmented by ML technologies, ultimately leading to improved surgical performance and better patient outcomes.

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