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Efficacy of machine learning algorithms versus conventional assessment techniques in predicting postoperative complications in general surgery: a comprehensive literature review

Eficacia de los algoritmos de aprendizaje automático versus técnicas de evaluación convencionales para predecir las complicaciones posoperatorias en cirugía general: una revisión de la literatura

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ABSTRACT

We examine machine learning algorithms' efficacy and core abilities versus conventional methods in predicting postoperative complications in general surgery. Our findings revealed that machine learning algorithms generally supervised and non-supervised assessment techniques in predicting postoperative complications, offering greater accuracy and reliability, thus suggesting a shift towards integrating these advanced tools in clinical practice. This paper discusses the potential of machine learning to revolutionize postoperative care, enhancing prediction accuracy and improving patient outcomes significantly.

Keywords: machine learning, efficacy, predicting postoperative complications, general surgery, literature review.

RESUMEN

Examinamos la eficacia y las capacidades centrales de los algoritmos de aprendizaje automático versus los métodos convencionales para predecir complicaciones posoperatorias en cirugía general. Nuestros hallazgos revelaron que los algoritmos de aprendizaje automático generalmente supervisan y no supervisan las técnicas de evaluación para predecir complicaciones posoperatorias, ofreciendo mayor precisión y confiabilidad, lo que sugiere un cambio hacia la integración de estas herramientas avanzadas en la práctica clínica. Este artículo analiza el potencial del aprendizaje automático para revolucionar la atención posoperatoria, mejorar la precisión de la predicción y mejorar significativamente los resultados de los pacientes.

Palabras clave: aprendizaje automático, eficacia, predicción de complicaciones posoperatorias, cirugía general, revisión de la literatura.

INTRODUCTION

From routine to complex cases, surgical treatments persist as a common choice in the medical field; despite advancements, postoperative complications remain a notable challenge, and its financial burden cannot be ignored (Javed et al., 2023). Machine learning algorithms are advanced computational methods that analyze vast data sets to predict postoperative complications, such as random forest, predictive neural networks, decision trees, naïve Bayes, and KNearest Neighbors (KNN) are machine learning algorithm based predicting models to know complications by analyzing diverse datasets and other sources such as patient demographics, medical history, surgical details, and preoperative test results to predict complications like infections, bleeding, organ failure, and prolonged recovery in different surgical contexts (shake., 2023). The type of software selected based on the individual patients to predict complications, as each logarithm has its strengths and specifications. Conventional assessment techniques rely on traditional statistical analysis tools such as G8, Logistic Regression, Clinical Prediction Rules (CPRs), Risk Score, Nomograms, and Survival Analysis Models (Traunero et al., 2022) (Zhou et al., 2015) (Tetreault et al., 2015).

Multiple papers support that machine learning algorithms can outperform traditional statistical techniques in identifying patients at risk of developing complications after surgery (Singal et al., 2013) (Peng et al., 2024) (Qi et al., 2023). Mufti et al. (2019) stated that by analyzing preoperative and intraoperative data, machine learning models can uncover hidden patterns and risk factors that may not be apparent through conventional assessment methods. Variables are obtained before or during surgery, and based on these variables, algorithms can accurately predict postoperative complications while aiding in reducing the risk of adverse events (Zeng et al., 2021). Machine learning models have been successfully applied in diverse surgical such. They are widely being used in cardiac surgery, bariatric surgery, liver resection, spine surgery, neurological surgeries, and, in short, all surgeries that have high complication rates and risks to optimize patient outcomes (Mufti et al., 2019) (Bektaş et al., 2022) (Kang et al., 2024).

Comparative papers assess the performance of machine learning algorithms against conventional regression analyses in predicting postoperative outcomes; in results, machine learning methods offer superior accuracy in prognosticating complications after surgeries like esophageal and gastric carcinoma surgeries (Kooten et al., 2022) (Zeng et al., 2023). Other machinelearning models are developed to predict specific complications, such as pulmonary complications after emergency gastrointestinal surgery and postoperative delirium after cardiac surgery, demonstrating the versatility and effectiveness of these algorithms across various surgical scenarios (Xue et al., 2021).

METHODOLOGY

For this paper, we decided on a PICO question to focus on our inquiry to effectively compare the predictive capabilities of the latest algorithms and conventional methods.

Population (P), is a targeted population that previously underwent surgical procedures; it encompasses a diverse patient demographic with varying risk factors and health conditions.

Intervention (I), will use machine learning algorithms to predict postoperative complications. The intervention will be supervised learning models like logistic regression, decision trees, and neural networks) Alternatively, unsupervised learning models (e.g., clustering) and ensemble methods (e.g., random forests, gradient boosting).

Comparison (C), is made against traditional methods of predicting postoperative complications.

Outcome (O), will be the findings to evaluate, including the accuracy, sensitivity, specificity of both techniques and. Finally, a conclusion will be made based on the reduction in postoperative complications, the impact on patient morbidity and mortality, the efficiency of clinical decision-making, and the cost-effectiveness of predictive models.

Inclusion and Exclusion Criteria

The literature selection process must adhere to rigorous inclusion and exclusion criteria to ensure the relevance and quality of the studies reviewed. Inclusion criteria should encompass studies that:

1. Focus on the prediction of postoperative complications in general surgery.
2. Utilize machine learning algorithms or conventional assessment techniques.
3. Are published in peer reviewed journals.
4. Include quantitative data on predictive accuracy, sensitivity, specificity, or similar metrics.
5. Are published in English.

Exclusion criteria should filter out studies that:

1. Do not directly compare machine learning algorithms with conventional assessment techniques.
2. Focus on postoperative complications outside the realm of general surgery.
3. Lack sufficient data for a robust comparative analysis.
4. Are opinion pieces, editorials, or case reports without empirical data.

5. Are duplicates or retracted papers.

Databases and Search Terms Used

The databases selected for the literature search should include major repositories of medical and scientific research, PubMed, Google Scholar, and Scopus. Search terms must be comprehensive and specific to capture all relevant studies, so our search terms include:

1. (("General Surgery"[MeSH]) AND ("Postoperative Complications"[MeSH])) AND(("Machine Learning"[MeSH] OR "Algorithms"[MeSH] OR "Artificial Intelligence"[MeSH] OR "Neural Networks, Computer"[MeSH])) OR (("Risk Assessment"[MeSH] OR "Medical History Taking"[MeSH] OR "Physical Examination"[MeSH] OR "Risk Factors"[MeSH] OR "Preoperative Care"[MeSH] OR "Imaging, Preoperative"[MeSH])) AND (("Treatment Outcome"[MeSH] OR "Sensitivity and Specificity"[MeSH] OR "Predictive Value of Tests"[MeSH] OR "Patient Outcome Assessment"[MeSH] OR "Length of Stay"[MeSH] OR "Morbidity"[MeSH] OR "Mortality"[MeSH] OR "Cost Benefit Analysis"[MeSH]))

2. 'general surgery'/exp AND 'postoperative complication'/exp AND ('machine learning'/exp OR 'algorithm'/exp OR 'artificial intelligence'/exp OR 'neural network'/exp) AND ('risk assessment'/exp OR 'medical history taking'/exp OR 'physical examination'/exp OR 'risk factor'/exp OR 'preoperative care'/exp OR 'preoperative imaging'/exp) AND ('treatment outcome'/exp OR 'sensitivity and specificity'/exp OR 'predictive value'/exp OR 'patient outcome assessment'/exp OR 'length of stay'/exp OR 'morbidity'/exp OR 'mortality'/exp OR 'cost benefit analysis'/exp)

Description of Review Process

Data Extraction

The data extraction phase involves systematically collecting pertinent information from each selected study to facilitate a thorough analysis. Key data points to extract include:

1. Study title, authors, and publication year.
2. Study design and sample size.
3. Types of machine learning algorithms and conventional assessment techniques used.
4. Metrics for predictive performance (e.g., accuracy, sensitivity, specificity, AUC).
5. Key findings and conclusions.
6. Limitations and biases identified by the authors.

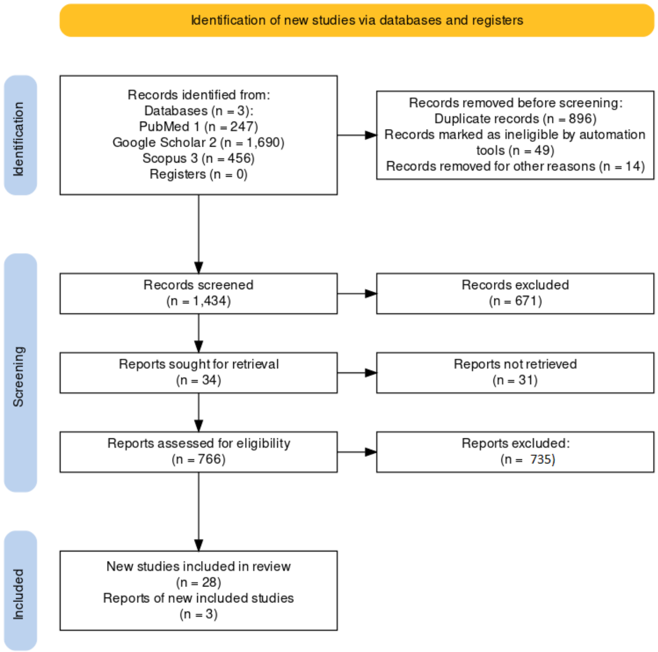
Quality Assessment of Studies

Assessing the quality of the studies is critical to ensure the reliability and validity of the review's conclusions. The quality assessment should consider the following aspects:

1. Study design robustness (e.g., prospective vs. retrospective studies).
2. Sample size adequacy and representativeness.
3. Methodological rigor in the application of machine learning algorithms and conventional techniques.
4. Clarity and transparency in reporting data and results.
5. Potential biases and conflicts of interest.
6. Reproducibility of the study findings.

Quality assessment tools, such as the Cochrane Risk of Bias tool for randomized studies or the Newcastle Ottawa Scale for observational studies, can be employed to systematically evaluate each study's methodological soundness. Here is Prisma flow diagram of selected studies:

Figure 1. identification of new studies via databases and registers



Source: the authors.

Description: The diagram outlines the systematic review process, adhering to PRISMA guidelines. Initially, 2,433 records were sourced from PubMed, Google Scholar, and Scopus. After screening for eligibility and removing duplicates, 28 studies were included from 732 assessed reports and 3 papers were selected from chrome so this paper include total 31 papers which are critically selected from papers published in last decades to keep it current.

Table 1. Findings - Machine Learning in Surgical Outcome Prediction

Authors	Title	Type of Paper	Results	Specificity	Sensitivity
Haiye Jiang, and others	Machine Learning for the Prediction of Complications in Patients After Mitral Valve Surgery	Original Research	AUROC: 0.90, ACC: 81%, Youden Index: 70%, F1score: 0.26, PPV: 15%, NPV: 99%	81%	89%
Mustafa Bektaş, Jurriaan B. and team	Machine Learning Algorithms for Predicting Surgical Outcomes after Colorectal Surgery: A Systematic Review	Systematic Review	Predictive accuracies up to 65% to 98% for ML models in colorectal surgery.	Up to 91	Up to 91
T. Wessel and others	Application of Artificial Intelligence in Predicting Complications in Patients Undergoing Major Abdominal Surgery	Systematic Review	Sensitivity: 0.060.96, Specificity: 0.610.98, Accuracy: 0.780.95	0.610.98	0.060.96
Hui Zhang et al.	Risk predictions of surgical wound complications based on a machine learning algorithm: A systematic review	Systematic Review	ML algorithms showed high 96% accuracy in predicting surgical site infections (SSI) and wound complications across various surgical specialties.	Specificity metrics varied across studies	Sensitivity metrics varied across studies
Maximilien Ravenel, et al.	Machine learning to predict postoperative complications after digestive surgery: a scoping review	Scoping Review	Identified 53 studies using ML to predict POC in digestive surgery. ML demonstrated higher performance (AUC 0.81) compared to CS in 20 out of 25 studies.	ML's AUC values: Upper-GI 0.90 (AL), Bariatric 0.75 (AL), Hepatopancreatobiliary 0.95 (POPF), Colorectal 0.83 (SSI), General Digestive 0.75 (AL).	ML sensitivity highlights: Upper-GI's AL after gastrectomy, Colorectal's AL post anterior resection, Hepatopancreatobiliary's POPF prediction, and General Digestive's AL detection.
Aman Mahajan, Stephen Esper, Thien Htay Oo, et al.	Development and Validation of a Machine Learning Model to Identify Patients Before Surgery at High Risk for Postoperative Adverse Events	Original Investigation	High accuracy in predicting mortality and MACCE (AUROC up to 0.972). Outperformed NSQIP in AUROC, specificity, and accuracy.	87%	85.3%

Source: the authors.

RESULTS

Above research shows machine learning models in various studies have shown high accuracy and potential in predicting postoperative complications, with specificities and sensitivities ranging widely across different surgical procedures. Machine learning algorithms, such as XGBoost and Gradient Boosting Machines, often outperform conventional statistical models in predicting medical outcomes due to their ability to process large datasets and identify complex patterns. For example, an XGBoost classifier achieved 83.7% sensitivity and 85.9% specificity in gastric cancer prediction, reducing hospital remissions (Afrash et al., 2023), while ML models like Support Vector Machines and Random Forests demonstrated high predictive ability for cardiovascular disease (Davis et al., 2022). In contrast, traditional statistical models, though simpler and commonly used as baselines, may not capture complex data patterns as effectively, with logistic regression achieving 90.16% accuracy in heart disease prediction, improved to 93.44% when combined with machine learning ML techniques (Chandrasekhar & Peddakrishna, 2023). Traditional methods like logistic regression are simpler and often used as baselines but are less effective in capturing complex patterns as effectively as ML algorithms, especially when dealing with large and high dimensional datasets.

Table 2. Machine Learning Applications in Predicting Surgical Wound Outcomes

Study	Title	Results
Tokgöz and Carro (2021)	Wounds classification in facial plastic surgery	ANN achieved 96% accuracy in classifying wounds in facial plastic surgery.
Prey et al. (2025)	Surgical site infections in various surgeries	SVM achieved 90% accuracy in predicting surgical site infections across multiple surgical specialties.
Pereira et al. (2018)	Surgical site infections in Cardiothoracic surgery	SVM, LDA, KNN, NB, RF, DT, LR achieved 90.1% accuracy collectively in predicting surgical site infections in Cardiothoracic surgery.
Fletcher et al. (2019)	Surgical site infections in caesarean section surgeries	CNN achieved 90.4% accuracy in predicting surgical site infections following caesarean section surgeries.
Rambhatla et al. (2020)	Burn grade diagnosis in burn plastic surgery	SVM achieved 70% accuracy in diagnosing burn grades in burn plastic surgery.
Wu et al. (2023)	Surgical site infections in laparotomy and minimal invasive surgery	CNN achieved 83.3% accuracy in predicting surgical site infections in laparotomy and minimal invasive surgery.
Sofo et al. (2022)	Surgical site infections in total abdominal colectomy	Adhoc algorithms achieved 90% accuracy in predicting surgical site infections in total abdominal colectomy.
Shenoy et al. (2024)	Assessment of various wound parameters in surgical procedures	CNN achieved 85% accuracy in assessing various wound parameters in surgical procedures.
Kuo et al. (2017)	Surgical site infection in head and neck cancer surgery	ANN and LR achieved 90% accuracy in predicting surgical site infections in head and neck cancer surgery.

Source: the authors.

Above table summarizes recent advancements in machine learning that were applied to surgical settings where various algorithms' effectiveness in predicting outcomes such as surgical site infections and wound classifications in documented. All studies demonstrate notable accuracies ranging from 70% to 96%, with SVM, CNN, and ANN flagrantly featuring across different surgical specialties, showing machine learning's potential that has revolutionize surgical care with its precise predictive capabilities while improving treatment planning and patient outcomes. Challenges remain in standardizing methodologies and ensuring robust validation across diverse surgical contexts to optimize the integration of these technologies into clinical practice effectively.

DISCUSSION

Table 3. Overall comparison of Machine Learning Algorithms and Conventional Assessment Techniques in Healthcare

Aspect	Machine Learning Algorithms	Conventional Assessment Techniques
Accuracy and Predictive Power	Higher predictive accuracy Handles large datasets and complex relationships Risk of overfitting	Reliable performance in specific contexts Less prone to overfitting May miss subtle interactions
Adaptability and Flexibility	Continuously updated and retrained Integrates various data types	Stable performance Less adaptable to new data trends
Data Requirements	Requires large, high-quality datasets Extensive preprocessing needed	Fewer data points needed Readily available clinical data
Interpretability and Transparency	Some models are "black boxes" Explainable AI is advancing	More transparent and interpretable Facilitates clinical decision-making
Implementation Challenges	Requires robust IT infrastructure Data privacy concerns Need for interdisciplinary collaboration	Easier to implement Proven track record Less technological infrastructure needed
Impact on Patient Outcomes	Potentially significant improvements Depends on successful implementation	Proven effectiveness May be limited by outdated models
Speed and Efficiency	Can process and analyze large datasets quickly Realtime decision support	Typically, faster to set up and run May not handle large datasets as efficiently
Scalability	Highly scalable with adequate computational resources Can be applied to diverse patient populations	Limited scalability Best for specific contexts and populations
Cost	High initial investment in technology and expertise Ongoing maintenance costs	Lower initial cost Less maintenance required
Regulatory and Ethical Considerations	Requires compliance with data protection laws Ethical concerns about data use and algorithmic bias	Established compliance frameworks Fewer ethical concerns
Clinical Acceptance	May face resistance due to lack of interpretability Requires training for clinical staff	High acceptance due to familiarity Minimal additional training needed
Customization and Personalization	High potential for personalized medicine Tailors predictions to individual patient profiles	Less personalized More generalizable predictions
Error Handling	Can incorporate error detection and correction mechanisms May identify outliers and anomalies	Simpler error handling May not detect subtle anomalies
Integration with Existing Systems	Requires integration with electronic health records (EHR) and other systems May face compatibility issues	Easier to integrate with existing clinical workflows Compatible with most systems
Robustness and Reliability	Potentially more robust with large datasets Sensitive to data quality and completeness	High reliability in known contexts Less affected by data variability
Training and Expertise Required	Requires expertise in data science and machine learning Continuous learning and adaptation	Requires clinical knowledge and experience Less specialized training needed

Source: the authors.

Machine learning and AI technology excel conventional methods in handling and processing large, high-dimensional data, integrating diverse types like imaging and clinical notes for a holistic analysis of patients who are subjected to surgery to estimate post-surgical risks (Zitnik et al., 2019) (Xu et al., 2024). Stam and colleagues' (2022) systematic research revealed that AI exceeds traditional approaches regarding accuracy in predicting postoperative complications since it can identify patterns missed by conventional methods. AI is dependent on robust datasets, data validity, and quality while it is associated with some limitations such as interpretability and imbalance of data. For example, there are limitations in detecting postoperative complicated risks by AI which may happen due to overcomplication modelling, lack of transparency in decision-making of machine learning algorithms known as "black box" and the challenges in ability to accurately test on different population. Challenges are data quality and ethical issues like algorithm bias that are dangerous for utilization in clinic and reliance on industrial AI-based prognosis, which cause trust issues and implementation in clinical practice as other significant barriers to translating patient management in AI as a result of large-scale data.

Mufti et al., 2019 stated conventional strategies like random forests and SVMs decide which features to use and reduce possible preprocessing manipulations in distinguishing between postoperative complications and general surgery benefits from comparing conventional learner algorithms with existing assessment methods, including several considerations. While traditional approaches involve making decisions based on clinical experience and available quantifiable measures such as the ASA Score, these strategies provide straightforward frameworks for comparison and evaluation. However, their capacity to forecast is often confined to the very subjective and, moreover, a rather rigid set of variables. ML algorithms, on the other hand, use large volumes of data such as general patient information, surgical history, specific details of the surgery process, as well as the postoperative results to come up with unique patterns that may not be noticeable when using conventional statistical techniques (Mehra et al., 2021).

It has been established that ML algorithms like random forest, support vector machines, and neural networks provide better accuracy and sensitivity than most conventional methods (Sarker, 2021). Shickel et al. (2023) also pointed out that ML models are flexible relative to traditional models, which means they are canted with new data and information and, therefore, will more or less remain ''dynamic'' in that sense. However, ML algorithms have some issues. For example, they require big data to work on, they can be overfitted, and to overcome biases, they need sound validation (Brownlee, 2019). Other issues include ethical intent regarding data privacy and the explainability of the developed ML models. In sum, even though developed ML algorithms offer relatively higher achievements in terms of predictive accuracy, implementing these algorithms and methods in clinical practice must respond to these issues to improve and expand the traditional methods of assessment (Stam et al., 2023).

CONCLUSION

From the above research, wachine learning algorithms are impressive in predicting postoperative complications. Still, specificity, sensitivity levels and accuracy vary and depend on other variables. We exemplified algorithms, like SVM, CNN, and ANN, boast accuracy ranges from 70% to 98%, and their specificity ranges from 61% to 98% and sensitivity from 6% to 96%, which means these are highly efficient. ML logarithms outperform traditional methods, such as logistic regression in complex surgical scenarios and diverse datasets. However, challenges remain, and there is a continuous need for validation across different surgical settings and the complexity of standardizing methodologies for reliable clinical integration despite their promising impact on advancing surgical care.

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