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Machine learning approaches to early detection of delayed wound healing following gastric cancer surgery

Kirkik D *et al*. ML for DWH in gastric cancer

Abstract

Delayed wound healing following radical gastrectomy remains an important yet underappreciated complication that prolongs hospitalization, increases costs, and undermines patient recovery. In An *et al*'s recent study, the authors present a machine learning-based risk prediction approach using routinely available clinical and laboratory parameters. Among the evaluated algorithms, a decision tree model demonstrated excellent discrimination, achieving an area under the curve of 0.951 in the validation set and notably identifying all true cases of delayed wound healing at the Youden index threshold. The inclusion of variables such as drainage duration, preoperative white blood cell and neutrophil counts, alongside age and sex, highlights the pragmatic appeal of the model for early postoperative monitoring. Nevertheless, several aspects warrant critical reflection, including the reliance on a postoperative variable (drainage duration), internal validation only, and certain reporting inconsistencies. This letter underscores both the promise and the limitations of adopting interpretable machine learning models in perioperative care. We advocate for transparent reporting, external validation, and careful consideration of clinically actionable timepoints before integration into practice. Ultimately, this work represents a valuable step toward precision risk stratification in gastric cancer surgery, and sets the stage for multicenter, prospective evaluations.

Key Words: Gastric cancer; Radical gastrectomy; Delayed wound healing; Machine learning; Decision tree; Risk prediction

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Core Tip: This letter highlights the potential of machine learning models in predicting delayed wound healing after radical gastrectomy. By leveraging routinely available clinical and laboratory parameters, interpretable models such as decision trees may

support early risk stratification and postoperative monitoring. However, external validation and the use of pre- or intraoperative variables are essential before widespread clinical adoption.

TO THE EDITOR

We read with great interest the recent study on machine learning (ML)-based risk prediction for delayed wound healing (DWH) after gastrectomy, and wish to highlight both its promise and limitations[1]. DWH after radical gastrectomy can lead to prolonged hospitalization, increased infection risk, delayed adjuvant therapy, and higher healthcare costs, underscoring the importance of early risk identification. Despite significant advances in surgical techniques and perioperative care, DWH remains a critical complication following radical gastrectomy, even if it is often underreported. This issue has serious consequences for patients, including longer hospital stays, higher healthcare costs, a greater risk of infection, and a slower overall recovery[1].

Patients who have had surgery for gastric cancer are particularly susceptible to DWH due to the extensive nature of the procedure, nutritional deficiencies, and other health conditions. While doctors continue to improve surgical and care methods, it is still difficult to identify which patients are at high risk for DWH early on. Current risk assessment methods, which often depend on a doctor's subjective evaluation or a single marker, are not very accurate[2].

In gastric cancer surgery, DWH is a problem caused by many different things, including the patient's age, nutritional status, other health conditions, and factors during and after the operation. By combining all of this data, ML models can predict an individual patient's risk, helping doctors identify those who are at high risk for DWH early in their recovery[3]. The model incorporated both clinical and laboratory variables, including drainage duration, preoperative neutrophil count, albumin level, and patient demographics, reflecting a comprehensive view of surgical and physiological risk factors. It is important that ML models can be easily integrated into a patient's care. This is

possible because they use clinical and lab data that is already routinely collected, so there is no extra work or cost involved[4,5].

Key findings and clinical implications

The study highlights how ML can be a practical tool for predicting DWH after a radical gastrectomy. Among the algorithms tested, the study reported an area under the curve of 0.951, with all cases of DWH correctly identified at the Youden threshold. It was able to correctly identify all instances of DWH at the Youden index threshold[6]. What makes this model especially useful is its reliance on easily accessible patient data, such as drainage duration, preoperative white blood cell and neutrophil counts, age, and sex. This demonstrates that ML-based risk prediction can be seamlessly integrated into routine clinical practice without requiring expensive or complicated additional tests[6].

Early identification of patients at high risk for DWH enables timely nutritional optimization, wound management, and closer postoperative monitoring, potentially reducing complications and improving recovery outcomes. Identifying patients at high risk for DWH has significant clinical benefits. Early detection enables doctors to increase monitoring, intervene promptly, and better manage resources, which could reduce postoperative complications and shorten a patient's time in the hospital[7]. Additionally, by showing which factors contribute most to DWH, these models can help create focused care strategies, like more careful infection control or improved nutritional support, leading to a faster recovery. Overall, this research demonstrates how using ML to assess risk can turn a lot of clinical data into practical, patient-focused decisions[7].

Strengths of the decision tree approach

The decision tree model used in the study provides clear interpretability, allowing clinicians to understand how each predictor contributes to the risk of DWH. Such transparency enhances clinical applicability compared to less interpretable ML models. However, while this is a key strength, the simplicity of decision trees may limit their

performance when interactions among predictors are complex, underscoring the need for external validation before clinical implementation[8].

Limitations and areas for caution

Despite its strong performance, this study and its use of the decision tree model have several limitations that should be noted. A key issue is the model's reliance on postoperative data, such as drainage duration. Because drainage duration is only known after surgery, its inclusion limits the model's ability to predict DWH preoperatively, when preventive measures would be most useful. While this information is valuable, it cannot be used for truly pre-emptive risk assessment, as it only becomes available after the surgery has already occurred, limiting the opportunity for early intervention[9].

Furthermore, the model was validated only within the single center where the study was conducted. Single-center validation restricts the generalizability of findings, as variations in surgical practice, patient populations, and data collection methods can significantly affect model performance. This raises concerns about how well it would perform in other hospitals with different patient demographics, surgical methods, or care protocols. Therefore, a broader, multicenter validation is crucial before the model can be widely adopted[10].

Other drawbacks include the relatively small sample size and possible inconsistencies in data reporting, which could affect the model's robustness. It is also important to remember that decision trees can be prone to overfitting, especially with limited data on rare outcomes like DWH. Decision trees require minimal computational resources and produce easily interpretable decision rules, making them suitable for real-time use in clinical settings. Finally, clinicians must understand that these predictive tools are not meant to replace their own judgment. They are designed to supplement an experienced doctor's decision-making, and an over-reliance on machine-generated predictions should be avoided. Acknowledging these limitations is essential for responsible and effective implementation of the model.

The importance of timing and clinically actionable variables

When creating a postoperative risk prediction model, the timing of data collection is critical. While ML can use a lot of different data, its practical value depends on whether it can identify risk factors at a time when a doctor can actually do something about them. For conditions like DWH, the most useful data comes from before or immediately after surgery, as this allows for timely actions like increased monitoring, preventive treatments, or nutritional support[11].

The inclusion of postoperative data, like drainage duration, may make a model more accurate, but it also shows a potential disconnect between a model's predictive power and a doctor's ability to take action. Clinicians need models that not only predict risk well but also provide information early enough to make a real difference in a patient's outcome. Moving forward, predictive tools should focus on using data that allows for proactive rather than reactive care, ensuring that data-driven insights lead to real-world clinical benefits.

Need for external validation and multicenter studies

While the decision tree model performed well in this study, its broader applicability is still unproven. A model developed at a single institution may not be effective in other hospitals because of differences in patient demographics, surgical methods, care protocols, or other institutional practices. Without testing the model in a variety of external settings, we cannot be sure that its strong performance is not just a result of it being "overfit" to the specific data from the original hospital.

To confirm the model's reliability and usefulness, it is crucial to conduct larger, multicenter studies. These studies would test the model on diverse patient groups, allowing researchers to refine the variables used and evaluate its real-world impact on patient outcomes[12]. This type of collaboration is also important for creating standardized data collection methods and increasing the overall size of the dataset, which makes the analysis more robust. In short, external validation is a necessary next step to

transform this promising model from a research concept into a practical tool for improving surgical care in a wider range of clinical settings.

Future directions in perioperative precision medicine

Integrating ML into perioperative care is an important step toward a future of precision medicine, where treatments and risk assessments are customized for each patient. To make these models even more accurate and useful, future research should focus on incorporating a wider range of real-time data, such as a patient's vital signs, information gathered during the operation, and trends in their lab results over time[13].

Additionally, combining ML with other new technologies, like wearable sensors, electronic health records, and telemedicine platforms, could allow for continuous patient monitoring after surgery, helping to detect complications like DWH even earlier. It is also crucial to make these tools easy for doctors to use and understand, ensuring that the insights they provide are actionable and fit seamlessly into the existing clinical workflow. Before advocating for broad clinical use, comparative analyses with conventional models such as logistic regression are necessary to demonstrate that ML offers a meaningful performance advantage rather than added complexity alone[14].

By encouraging collaboration among different fields, including surgery, data science, and nursing, we can move beyond the conceptual framework of precision medicine and make tangible improvements to patient outcomes and resource management. Integrating ML models into clinical care raises practical and ethical considerations, including potential algorithmic bias against underrepresented populations, data privacy concerns, and the need for interoperable electronic health record systems capable of supporting real-time risk scoring.

Conclusion

The study demonstrates the promise of ML, particularly interpretable decision tree models, for predicting DWH after gastrectomy. However, its reliance on postoperative variables and single-center design limits generalizability and clinical applicability. Future

studies should focus on multicenter external validation and the inclusion of preoperative predictors to enable earlier, actionable risk assessment. External validation across multiple institutions would improve robustness, detect potential overfitting, and confirm that the model maintains accuracy across diverse clinical environments.

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1	Haipeng Liu, Gary Tse. "Cutting-Edge Diagnostic Technologies in Cardiovascular Diseases - Towards Data-Driven Smart Healthcare", CRC Press, 2025 Publications	16 words — 1%
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