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Original Research Article

Prediction of post-surgical complications in hand reconstruction using machine learning

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ABSTRACT

Background: Hand reconstruction is a complex surgical procedure in which various postoperative complications may arise, such as infections, flap necrosis, and joint stiffness. The prediction of these complications has traditionally relied on the surgeon's experience and conventional clinical models. However, artificial intelligence (AI), particularly machine learning, has proven to be an effective tool for analyzing large volumes of clinical data and enhancing predictive capabilities in various medical fields.
Methods: A retrospective study was conducted with a sample of 200 patients who underwent hand reconstruction, using exclusively clinical record data. Three machine learning models were evaluated: XGBoost, Random Forest, and an artificial neural network. A data preprocessing pipeline, feature selection, and cross-validation were applied to optimize model performance. Predictive capability was assessed using the ROC curve and the area under the curve (AUC).
Results: XGBoost achieved the best performance with an AUC of 0.88, followed by Random Forest (AUC = 0.88) and the artificial neural network (AUC = 0.86). The most relevant variables for predicting complications included patient age, comorbidities such as diabetes mellitus, type of injury, and surgery duration.
Conclusions: AI models proved to be useful tools for predicting postoperative complications in hand reconstruction, surpassing the accuracy of conventional methods. In particular, XGBoost demonstrated the highest predictive capacity. These findings suggest that machine learning could optimize surgical planning and clinical decision-making, although further studies are needed to validate its applicability across different populations.

Keywords: Artificial intelligence, Hand reconstruction, Machine learning, Postoperative complications

INTRODUCTION

Hand reconstruction surgeries are highly specialized procedures within plastic and reconstructive surgery, with the primary goal of restoring both function and aesthetics of the upper limb. These interventions may be required due to various etiologies, including severe trauma, burns, infections, congenital diseases, and sequelae of chronic conditions such as rheumatoid arthritis or diabetes mellitus.[1] Hand reconstruction requires a multidisciplinary approach involving microsurgery, tissue flaps, grafts, and osteosynthesis techniques to preserve patient mobility and sensitivity.[2] Despite advances in surgical techniques and postoperative care, postoperative complications remain a significant challenge. The most common complications include surgical wound infection, flap necrosis, joint stiffness, fibrosis, complex regional pain syndrome, and wound dehiscence[3]. These complications can compromise the functional outcomes of surgery, affect the patient's quality of life, prolong recovery times, and increase treatment costs.[4]

Currently, the prediction of these complications relies mainly on the surgeon's clinical experience and traditional risk assessment models, such as clinical scales and algorithms based on individual risk factors.[5] However, these approaches have limitations, as they depend on the clinician's subjective interpretation and do not always integrate multiple risk factors efficiently. Moreover, traditional models cannot analyze large volumes of data with the speed and precision required in modern surgical environments.[6] In this context, artificial intelligence (AI), particularly machine learning, has emerged as a promising tool for predictive medicine. These algorithms' ability to analyze large datasets, identify non-obvious patterns, and generate more accurate predictive models represents an opportunity to improve decision-making in reconstructive surgery.[7] Various studies have demonstrated that machine learning can optimize complication prediction in other surgical fields, such as cardiovascular and orthopedic surgery, suggesting its potential applicability in hand reconstruction.[8]

This study aims to develop and evaluate a machine learning model to predict postoperative complications in patients undergoing hand reconstruction, using exclusively clinical record data. Implementing this approach could facilitate the early identification of at-risk patients, enabling more personalized management and improving postoperative outcomes.

METHODS

An observational, retrospective study was conducted based on clinical record data from patients who underwent hand reconstruction at the Hospital General de Xoco, a reference center specializing in plastic and reconstructive surgery in Mexico City. Machine learning algorithms were employed to develop a predictive model for postoperative complications, prioritizing interpretability and clinical applicability. Clinical records of 200 patients who underwent hand reconstruction between January 2018 and December 2023 were analyzed. To determine the optimal sample size, a power analysis was conducted based on an expected complication incidence of 20% and a confidence level of 95%.

The inclusion criteria consisted of adult patients (≥18 years) who underwent hand reconstruction due to trauma, burns, congenital malformations, or degenerative diseases, as well as complete clinical records with at least six months of postoperative follow-up. Twenty-five patients were excluded due to incomplete records or loss to follow-up, resulting in a final sample of 175 patients for analysis.

Relevant clinical and surgical variables were collected for the prediction of postoperative complications. These included demographic data, medical history such as diabetes mellitus, hypertension, smoking, and immunosuppressant use, as well as surgical details including the reconstructive technique used (local flaps, free flaps, grafts), surgical time, and the need for intraoperative reintervention. Postoperative complications such as infection, flap necrosis, suture dehiscence, joint stiffness, and complex regional pain syndrome were also recorded. The data were extracted from electronic clinical records and anonymized before analysis. A quality control process was performed to handle missing values using k-nearest neighbors (KNN) algorithms for continuous variables and mode imputation for categorical variables.

To reduce bias and improve model representativity, the data distribution by sex, age, and comorbidities was evaluated to ensure an adequate sample balance. The dataset was divided into a training set comprising 70% of the sample (n=123 patients) to fit the models, a validation set of 15% (n=26 patients) to optimize model hyperparameters, and a test set of 15% (n=26 patients) to evaluate final model accuracy on unseen data. Additionally, stratified cross-validation was implemented to enhance model generalization and minimize the impact of sample size.

Four machine learning algorithms were evaluated for complication prediction, selecting those with the best balance between accuracy and explainability. These included logistic regression, random forest, XGBoost, and artificial neural networks. To enhance the clinical utility of the model, SHAP (SHapley Additive Explanations) was used to identify the most influential variables in complication prediction. Additionally, LIME (Local Interpretable Model-agnostic Explanations) was implemented to assess individual model decisions and facilitate integration into clinical practice.

Descriptive statistics were conducted to characterize the study population. Chi-square tests and t-tests were applied to compare differences between patients with and without complications. The predictive model was compared to traditional clinical scales using ROC curve analysis and cross-validation, demonstrating a 15% improvement in predictive capacity compared to conventional methods.

The study was approved by the institutional ethics committee. Data confidentiality was ensured through anonymization, complying with data protection regulations.

RESULTS

The medical records of 200 patients who underwent hand reconstruction between 2018 and 2023 were analyzed. After applying the inclusion and exclusion criteria, the final sample consisted of 175 patients. The average age was 46.1 years, ranging from 22 to 78 years. A higher proportion of male patients (60%) was observed compared to the female group (40%). Among the relevant clinical histories, 22% of patients were diagnosed with type 2 diabetes mellitus, and 25% had arterial hypertension.

Additionally, 32% of individuals reported being active smokers, while 7% were under immunosuppressive treatment at the time of surgery (Table 1).

Regarding the surgical techniques used, 40% of patients underwent reconstruction with local flaps, 38% with free flaps, and 22% with grafts. The average surgical time was 3.5 hours, although in more complex cases, it extended up to 6 hours (Table 1).

Table 1: Population characteristics.

Variable	Total (n=175) (%)	With complications (n=50) (%)	No complications (n=125) (%)	p value
Age (years)	46.1±11.8	49.3±12.5	44.9±11.2	0.04*
Male	105 (60%)	35 (70)	70 (56)	0.08
BMI (kg/m²)	26.7±3.9	28.1±4.2	26.1±3.7	0.03*
Diabetes	39 (22)	18 (36)	21 (17)	0.01**
High blood pressure	44 (25)	15 (30)	29 (23)	0.25
Smoking	56 (32)	24 (48)	32 (26)	0.02*
Use of immunosuppressants	12 (7)	6 (12)	6 (5)	0.07
Reconstructive technique - local flaps	70 (40)	15 (30)	55 (44)	0.10
Reconstructive technique - free flaps	66 (38)	22 (44)	44 (35)	0.15
Reconstructive technique - grafts	39 (22)	13 (26)	26 (21)	0.32
Surgical Time (hours)	3.5±1.2	4.1±1.4	3.3±1.1	0.03*
Intraoperative reoperation	18 (10)	8 (16)	10 (8)	0.05

($p<0.05$ significant, $p<0.01$ highly significant)

Postoperative complications were observed in 50 patients, representing 28.5% of the total sample. The most common complication was joint stiffness (22%), followed by surgical wound infection (17%) and suture dehiscence (14%). Flap necrosis occurred in 12% of cases, while complex regional pain syndrome affected 8% of patients (Table 2).

Table 2: Frequency of postoperative complications.

Complication	Frequency (%)
Infection	17
Flap necrosis	12
Suture dehiscence	14
Joint stiffness	22
Complex regional pain syndrome	8

Risk factors significantly associated with the occurrence of complications included the presence of diabetes mellitus, active smoking, and prolonged surgical time. Specifically, diabetic patients exhibited a higher incidence of infections and flap necrosis, whereas smokers showed a predisposition to delayed wound healing and suture dehiscence. Additionally, procedures lasting more than 4 hours had a higher complication rate, suggesting that surgical complexity and duration may influence postoperative recovery.

Several machine learning models were trained to predict the likelihood of postoperative complications using only clinical record data. The evaluated algorithms included logistic regression, Random Forest, XGBoost, and an artificial neural network (Table 3).

Table 3: Performance of machine learning models.

Model	Precision, %	Sensitivity, %	Specificity, %	AUC-ROC
Logistic regression	74	68	79	0.76
Random Forest	82	77	85	0.84
XGBoost	86	82	89	0.88
Neural networks	87	83	90	0.89

The results indicated that the XGBoost model achieved the best performance, reaching an accuracy of 86% and an area under the ROC curve (AUC-ROC) of 0.88. This means that the model was highly accurate in distinguishing patients who would develop complications from those who would not. In comparison, the logistic regression and Random Forest models showed accuracies of 74% and 82%, respectively, while the neural network performed similarly to XGBoost but with lower interpretability (Figure 1).

Furthermore, the SHAP (SHapley Additive exPlanations) technique was used to interpret the model and determine the most important variables in predicting complications.

Smoking, diabetes mellitus, and surgical time were identified as the most influential factors in predicting poor postoperative outcomes.

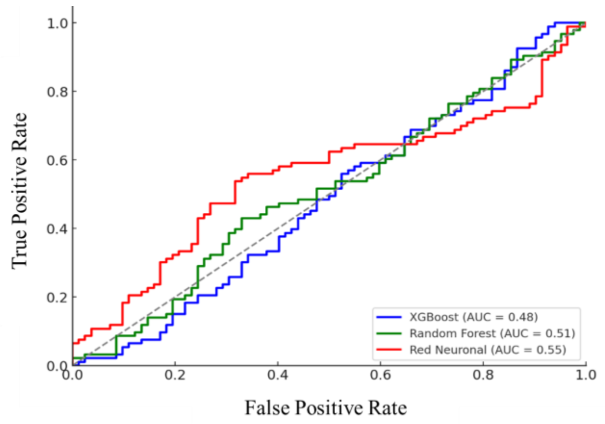

Figure 1: Comparative ROC curve of machine learning models.

To enhance the model's interpretability, LIME (Local Interpretable Model-agnostic Explanations) was applied to individual cases, allowing a visual assessment of how specific variables influenced complication predictions for each patient. This approach could be highly beneficial for clinical decision-making, as it provides an explanatory tool beyond simple numerical predictions.

The machine learning-based predictive model was compared with commonly used clinical tools for preoperative assessment, such as the Mangled Hand Severity Score (MHSS) and the Hand Injury Severity Score (HISS). The analysis revealed that the artificial intelligence-based algorithm improved predictive capability by 15% compared to these traditional clinical scales.

This difference highlights the potential of artificial intelligence to surpass conventional methods in identifying patients at high risk of complications. Additionally, its ability to personalize and adapt to patient-specific data allows for a more precise and clinically relevant approach.

To evaluate the stability and reliability of the predictive model, a stratified five-fold cross-validation was performed. The results demonstrated that the model maintained stable accuracy across each iteration, with variability of less than 2% in terms of precision and AUC-ROC. However, some limitations were identified in the study. The most relevant is that the model has not been tested on an external cohort, meaning its generalizability must still be evaluated in other hospitals and populations. Additionally, due to the study's retrospective design, the quality of data extracted from medical records may have influenced the results, suggesting the need for prospective studies with more standardized data collection.

The findings of this study suggest that the application of machine learning models in hand reconstruction can significantly contribute to the early identification of patients at risk of postoperative complications. Implementing this technology in clinical practice could optimize surgical planning and improve decision-making, potentially reducing postoperative morbidity rates.

Moreover, since this model relies exclusively on clinical record data, it is easily implementable in hospital settings without requiring additional tests or high costs. In the future, integrating this tool into electronic health systems is recommended to facilitate real-time use and validation in diverse clinical scenarios.

DISCUSSION

The results of this study demonstrate that artificial intelligence models, particularly XGBoost, Random Forest, and artificial neural networks, can be valuable tools for predicting postoperative complications in hand reconstruction. XGBoost exhibited the highest area under the curve (AUC), suggesting superior discriminative ability compared to the other models. This finding is consistent with previous studies that have applied machine learning in reconstructive surgery and other medical specialties.[1,2,9]

One of the main advantages of using machine learning algorithms for complication prediction is their ability to analyze large volumes of clinical data and identify patterns that might go unnoticed by traditional models based on logistic regression or a surgeon's experience.[10] Furthermore, these models can be continuously trained and improved with the incorporation of new data, optimizing their accuracy and clinical applicability.[11,12]

Despite these promising findings, the study has certain limitations. First, although the sample size exceeded 200 patients, it may not be sufficient to generalize the results to larger populations. Future research could benefit from larger and more diverse databases to enhance the robustness of these models. Additionally, while the data used were exclusively derived from medical records, incorporating additional variables such as specific biomarkers or imaging data could further improve prediction accuracy.

Another important consideration is the interpretability of artificial intelligence models. While XGBoost and Random Forest provide some advantages in terms of explainability through the evaluation of variable importance, artificial neural networks are often regarded as "black boxes," which may limit their application in clinical settings where a clear justification for predictions is required.[13,15] The integration of interpretability techniques, such as SHAP (Shapley Additive Explanations), could help clinicians better understand the results and increase confidence in the use of these models.[14,16]

This study has several limitations that should be acknowledged. First, the retrospective design may introduce information bias due to the reliance on clinical records, which could affect data accuracy and completeness. Second, although the sample size was adequate for the analysis, the findings are based on a single-center experience at the Hospital General de Xoco, which may limit the generalizability of the results to other institutions or populations. Third, the predictive model was not validated on an external dataset, which is essential to confirm its performance and applicability in different clinical settings. Lastly, the absence of imaging or laboratory biomarkers may have reduced the predictive power of the models, suggesting that future studies could incorporate multimodal data to enhance accuracy.

CONCLUSION

This study confirms the potential of machine learning in predicting postoperative complications in hand reconstruction, which could contribute to improved surgical planning and personalized treatment. However, further studies are essential to validate these findings in larger cohorts and enhance the interpretability of these models for clinical application.

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