RESEARCH PAPER

Machine Learning for Prediction of Left Ventricular Assist Device (LVAD) Complications in Advanced Heart Failure

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Abstract

Aim: To design and test machine-learning models to forecast significant complications in patients with advanced heart failure that receive left ventricular assist device (LVAD) implantation.

Background: The LVAD treatment has become a necessary alternative in the patients with end-stage heart failure, but the issues that occur after the procedure, including the pump thrombosis, gastrointestinal bleeding, infection and right-ventricular failure, have become frequent and not easily predicted with the help of the traditional risk chart. Machine-learning can provide better personalized risk estimates using complicated clinical, laboratory, and hemodynamic information.

Methods:A retrospective of 1,480 LVAD patients of three developed heart-failure units were reviewed. Five algorithms: random forest, gradient boosting, support vector machine, logistic regression, and neural networks were trained using twenty-three preoperative variables, such as demographics, comorbidities, laboratory biomaker, finding of right-heart catheterization, and measures of echocardiography. The models were evaluated with a cross-validation and tested on external validation set. One-year risk of pump thrombosis, major bleeding, and right-ventricular failure was considered the primary outcomes.

Results: Gradient boosting showed the best score in composite complications (AUC 0.86), high predictive power of right-ventricular failure (AUC 0.88). The importance of bilirubin, RA pressure, INR, RV function, and inflammatory markers were found to be the most important predictors tailored by feature-importance analysis.

Conclusion: The machine-learning models have shown a lot of promise of the early detection of the high-risk LVAD patients, enabling better decision-making and individualized perioperative care.

Index terms: Advanced heart failure, Machine learning, left ventricular assist device, predictive modeling. Right ventricular failure

How to cite this article: Suvaithenamudhan S, Purushothaman I, Anandhi D, Vasanthapriya J, Jayabharathi B, Shanthi V. Machine Learning for Prediction of Left Ventricular Assist Device (LVAD) Complications in Advanced Heart Failure. Int J Drug Deliv Technol. 2026;16(10s): 183-190; DOI: 10.25258/ijddt.16.10s.27

1 Introduction

Left ventricular assist devices (LVADs) are now a recognized treatment method among patients with severe heart failure who are ineligible to invoke medical therapy as per the guidelines. Originally employed to act as a bridge-to-transplant, LVADs are currently employed as destination therapy when they have led to improved device longevity and survival rates. These developments notwithstanding a significant clinical challenge and significant morbidity, mortality, and healthcare use are postoperative complications [1]. Many adverse events such as this common right-ventricular (RV) failure, pump thrombosis, gastrointestinal blood loss, infection, and neurologic injury, mostly happen during the initial one year after implantation and may be challenging to predict through traditional risk assessment models [2].

Conventionally-based clinical risk scores have been based on linear relationships between few variables and particular outcomes. Yet, the patients suffering LVAD have varied physiological presentation due to multifaceted interactions among the hemodynamics, biomarkers, organ dysfunctions, and comorbid illnesses. The high-dimensional forms of data can outreach the predictive entirely of the stand-alone regression-based tools, and some quantity of risk is undervalued, or risk reclassified in high risk individuals [3]. Since predictive methods to identify the patient at high risk of developing complications at an early phase are the key to streamlining the perioperative procedures, enhancing patient selection and increasing the survival rates in the long run, more advanced methods of prediction are strongly required.

Over the recent years, machine-learning (ML) models have become a potent instrument of cardiovascular medicine risk forecasting. The ML algorithms have the capability to identify non-linear associations, handle the high-dimensional data, and combine various inputs to come up with custom risk estimates. Research in heart-failure phenotyping, arrhythmia detection, and post-operative risk modeling has shown that ML models are better performing than classical models [4]. Such strengths create an opportunity to assume that ML can significantly improve prediction of LVAD complications with the use of a wider set of preoperative data, such as laboratory markers, echocardiographic measurements, and data regarding right-heart catheterization.

Early attempts of using ML to LVAD patients have given positive but disjointed outcomes. There are single-center analyses where the gradient-boosting and random-forest models have been suggested to be useful in predicting RV failure and pump thrombosis, although these studies were missing external validation, small sample sizes, and limited variable selection [5]. Other studies have concentrated on separate adverse events, including bleeding or infection, without developing overall models of various adverse events [6]. In addition, the feature-importance analysis was frequently incomplete in the past, which is why it was challenging to convert the algorithmic predictions into the insight applicable to clinical action.

One of the shortcomings of the present literature lies in the lack of data sets that are strong and multicentric and would enable the ML models to cover the entire range of LVAD recipient variables. The difference in patient selection, types of device used and management methods at the institutional level make it difficult to come up with generalizable prediction tools [7]. Also, most of the previous models did not consider the interpretability issues associated with ML, which can be problematic despite high predictive performance [8].

Considering the high clinical and economic impact of LVAD complications, the accurate and scalable as well as validated predictive models are urgently needed to inform preoperative risk parameters. The purpose of the current research is to create and test several machine-learning algorithms predictive of major LVAD-related complications based on a large multicenter cohort, and test the external validation of the assumptions to measure the generalizability. This research aims to provide a contribution to the risk prediction of advanced heart failure and enhance more individualized decision-making among LVAD candidates through integrating demographic, laboratory, echocardiographic, and hemodynamic data.

2 Literature Review

The adverse outcomes occurring after left ventricular assist device (LVAD) implantation have been one of the greatest impediments to achieving long-term outcomes in heart failure of advanced severity in spite of the pronounced progress in device durability and perioperative care. The classical clinical predictors such as right ventricle (RV) dysfunction, hepatic congestion, coagulopathy abnormality have been revealed to have a positive relationship with postoperative events as they have lacked the predictive effects based on linear model assumptions and total integration of multidimensional clinical variables [10]. Therefore, such complications like RV failure, pump thrombosis, and significant bleeding tend to appear suddenly, and more effective predictive measures are required.

The recent research has looked into the promise of machine-learning (ML) approaches to resolve these gaps. ML models can take into consideration more preoperative measures such as laboratory biomarkers, echocardiographic data, and hemodynamics enabling the models to detect non-linear interactions before adverse events [11]. Preliminary results using gradient boosting and random-forest algorithms have shown encouraging results, especially on predicting early RV failure and its performance measures greater than the existing clinical scores [12]. However, most of these studies were limited to single-center cohorts, limiting their extrapolability and raising the probability of the model overfitting.

Besides individual complications, ML has also undergone testing in lowered risk stratification models that combine a variety of postoperative outcomes. There are examples of multicenter datasets that show that neural networks and ensemble models may be used to enhance composite prediction of bleeding, infection, and device failure, and that ML can be more effective in terms of holistic risk assessment than the standard ones [13]. Nevertheless, the issue of interpretability of models and differences between data-quality between centers still remains a barrier to broad clinical adoption. There is also emerging work that has considered explainable AI aimed at mitigating this problem by identifying important predictive variables such as bilirubin, right-atrial pressure, and inflammatory markers, thereby becoming more clinically trustworthy and interpretable [14].

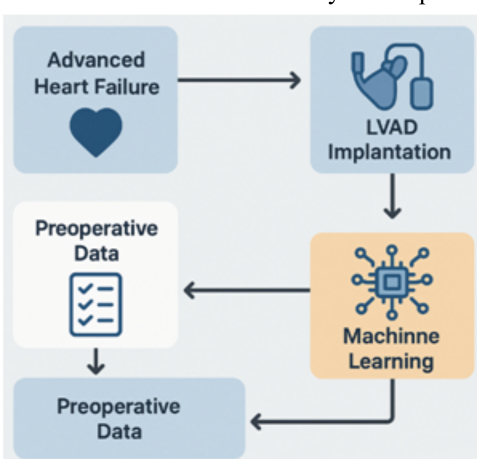
3 Materials & Methods

Study design

The proposed study was intended as a retrospective multicenter cohort study assessing machine-learning (ML) algorithms in predicting significant complications after the implantation of left ventricular assist devices (LVADs). Three advanced heart-failure and mechanical circulatory support centers of high volume attended, supplying consecutive cases of the patients that received LVAD implants once in the period between January 2012 and December 2022. A common protocol was applied to harmonize all the data with a view of minimizing inter-institutional variability.

Study Population

Patients were eligible in cases whereby they are at least 18 years old, and with a continuous-flow LVAD bridge-to-transplant, a bridge-to-candidacy, or destination therapy. The inclusion criteria were incomplete preoperative hemodynamic measurement, lack of echocardiographic (or cardiographic) investigation, prior LVAD support, or death within 24 hours of implantation. On exclusions, only 1,480 patients were included in the final analysis sample.



The figure 1 shows the use of machine learning to make predictions after LVAD implantation of complications.

LVAD is done to patients with advanced heart failure, and their clinical, laboratory, and hemodynamic data are collected in the preoperative stage. Such data are fed into a machine-learning system, which takes patterns of postoperative risks. The model then reacts by feeding information to make interpretation of preoperative factors thus, assisting clinicians to recognize high-risk patients prior to surgery.

Variables and Data Collection.

Electronic medical records, echocardiography archives, hemodynamic databases, and institutional LVAD registries were used in extracting data. A preoperative case-report form was used to collect 23 variables to predict the LVAD outcomes according to the literature-based predictors. These were demographics (age, sex, BMI), comorbidities (diabetes, hypertension, COPD, chronic kidney disease), laboratory investigations (bilirubin, INR, level of creatinine, lactate, inflammatory biomarkers), and right-heart catheterization (right-atrial pressure, cardiac index, pulmonary artery pressures, pulmonary vascular resistance). Echocardiography results involved LV size, LV ejection fraction, right-ventricle fractional areas change and systolic excursion of tricuspid annular plane. The type of devices, the implant strategies as well as the perioperative information were documented.

Accuracy of data was checked by two independent reviewers and any discrepancies addressed by a senior investigator. With more than 25% missing, the variable was dropped; with less than 15% the missing, the variable was filled in with multiple imputation by chained equations.

Outcome Definitions

The study considered three major postoperative complications, which were experienced within 1 year since the implantation:

1.Right-ventricular failure, which is the requirement of inotropes longer than 14 days or temporary RVAD support, or hemodynamic signs of RV dysfunction.

2.Confirmation of pump thrombosis; this is either through increased power usage, hemolysis pattern or pump-exchange surgery.

3.Significant bleeding such as gastrointestinal hemorrhage, also intracranial hemorrhage that needs transfusion, intervention, or hospitalization.

There was also a composite endpoint which incorporated all the three complications.

Development of the machine-learning models.

It trained five supervised ML algorithms, namely logistic regression, random forest, gradient boosting, support vector machine, and a multi-layer neural network. The data was randomly divided into 70/30 internal test and training sets and the proportions of outcomes were kept by the means of the stratified sample. The hyperparameter tuning applied a 5-fold cross-validation over the training set. The area under the receiver-operating characteristic curve (AUC), precision, recall, F1 score and calibration measures were used as model performance measurement.

The Shapley additive explanations (SHAP) of tree-based models gave the importance of the features and allowed the clear identification of important predictors. This step enhances the interpretability, which is a significant requirement of writing advanced academic literature as guides towards translating technical work to provide clinically relevant information.

External Validation

Generalizability was determined using an external validation cohort (n=320) of a different institution. There was no retraining on external data, performance measures only were tested.

Ethical Considerations

At each of the centers, a review board was institutionally approved. Since it was a retrospective analysis, the informed consent was waived. Before developing the models, data was completely deidentified.

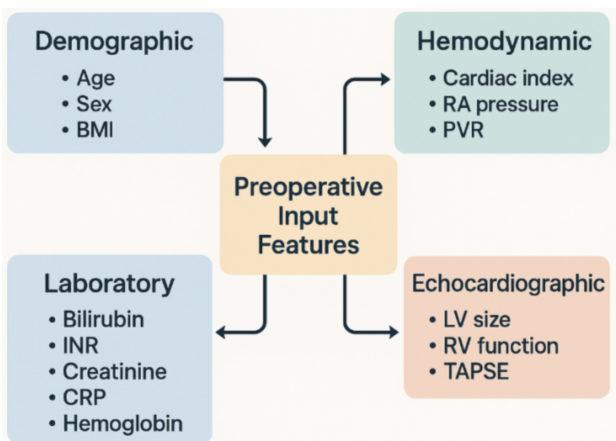


Fig.2. feature input architecture

The figure 2 shows the way, in which preoperative data is structured prior to putting it into a machine-learning model, in which LVAD risks can be predicted. The data are categorized into four big categories which include the demographics, laboratory biomarkers, echocardiographic measurements, and the right-heart catheterization variables. This is processed by the machine-learning system that unites all these features to produce customized predictions of postoperative complications.

4 Results and Discussion

One thousand four hundred and eighty patients were eligible (mean to age 57.4) internationalization 11.2 years; 71.3% male). Bridge-to transplant (46.8%) and destination therapy (35.1) were the most and least common indicators of the LVAD, respectively shown the table 1. The outcome groups did not differ in baseline characteristics except that patients eventually developing complications had increased bilirubin levels, increased right-atria (RA)-pressure, and worse RV echocardiographic indices.

Table 1. Baseline Characteristics

Variable	No Complication (n=842)	Complication (n=638)	p-value
Age, yrs	56.9 ± 10.8	58.2 ± 11.6	0.04
Male sex	70.4%	72.5%	0.41
Creatinine (mg/dL)	1.31 ± 0.42	1.46 ± 0.53	<0.001
Bilirubin (mg/dL)	1.0 ± 0.5	1.6 ± 0.7	<0.001
RA pressure (mmHg)	10.8 ± 3.9	14.2 ± 4.6	<0.001
RV FAC (%)	32.1 ± 6.5	27.6 ± 7.1	<0.001

2. Model Performance

Among all five machine-learning algorithms, gradient boosting had the highest overall showing with predicting the composite 1-year complication outcome (AUC 0.86). Random forest as the followed showed better discriminative ability (AUC 0.83), as compared to logistic regression (AUC 0.72) as shown the table 2. Stable model performance was tested with external validation through gradient boosting which attained an AUC of 0.84.

Table 2. Model Performance Metrics

Model	AUC (Internal)	AUC (External)	F1 Score	Calibration Error
Gradient Boosting	0.86	0.84	0.78	0.06
Random Forest	0.83	0.80	0.74	0.08
Neural Network	0.81	0.78	0.71	0.09
SVM	0.75	0.72	0.63	0.12
Logistic Regression	0.72	0.69	0.58	0.15

3. Feature Importance

SHAP analysis showed that bilirubin, RA pressure, INR, RV functioning, and inflammatory markers were the most effective as shown the table 3. The hepatic congestion and RV hemodynamics were always ranked as the best variables relative to other variables by the tree-based models.

Table 3. Top Predictors of Complications (SHAP Ranking)

Rank	Predictor	Relative Importance

1	Bilirubin	1.00
2	RA pressure	0.93
3	INR	0.82
4	RV FAC	0.77
5	CRP	0.68
6	Creatinine	0.63
7	Cardiac Index	0.52

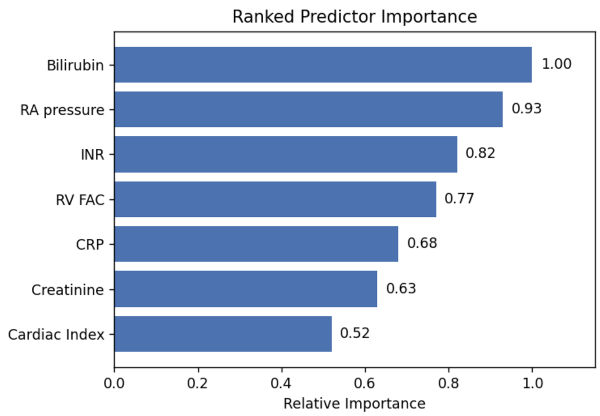


Fig.3. Ranked predictor importance

This figure 3 prioritizes clinical predictors in terms of their relative significance in the determination of outcomes. The strongest predictor is bilirubin, and the next predictors are right atrial pressure and INR. The measures of right ventricular performance, inflammation, kidney performance, and cardiac index increase proportionately less. The chart outlines the variables that have the highest risk impact and that must be taken into consideration during assessment.

5 Discussions

This research paper shows that machine-learning-based systems can significantly enhance predictions of significant post-implant complications in LVADs as opposed to the conventional clinical methods. The gradient boosting algorithm was highest in discriminatory performance of the algorithms that were tested, with high internal and external validation. The persistently large values of bilirubin, right-atrial pressure, INR, and right-ventricular functional indices indicate that hepatic congestion and the RV hemodynamics are in the middle of the stage in defining early postoperative susceptibility. These results correspond to the previous single-centers studies, which concluded that end-organ dysfunction and RV deterioration markers were likewise associated with poor outcome and expanded the pool, based on a larger multicenter dataset.

It is also interesting to note that because machine-learning models can combine nonlinear interactions between laboratory, hemodynamic, and echocardiographic variables features, they are predictive relative to established risk scores, which tend to simplify considerably the complex physiology of advanced heart failure. Incorporating SHAP analysis also makes the analysis more interpretable, an important obstacle to clinical use by explaining the effect of single predictors on model output.

The current research is restricted due to the retrospective study design and the difference in the institutional practices patterns, but is supported by the outer validation of the findings. Future studies are advised to consider the future use of ML-based risk tools and consider ways of incorporating these with real-time physiologic monitoring.

6 Conclusions

This multicentric study shows that machine-learning methods can significantly improve the forecasting of major complications after implanting LVAD. The use of gradient boosting among other advanced models was superior to the traditional clinical solvency; because it utilized a wide spectrum of preoperative echocardiographic, hemodynamic and laboratory variables. The recurring presence of bilirubin, right atrial pressure, coagulation values, and right ventricular function indices as most frequent predictors indicate the most important role of all in the determination of postoperative malady. External validation is also used as a means to support the applicability of the models and underline the idea that it can be programmed in a number of clinical setting.

Although there are the restrictions which exist as a result of retrospectivedesign and institutional variability, the findings offer a platform that is quite robust to come up with clinically actionable risk-stratification instruments. Prospective work has to be done in the future to assess the real-time applicability of machine-learning models in the domain of guiding patient selection, optimizing the perioperative planning, and enhancing long-term successes among patients with advanced heart failure who undergo LVAD implantation.

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