

Enhancing Prediction of Left Ventricular Conduction Block After Transcatheter Aortic Valve Replacement: A Machine Learning Approach with Feature Selection

Sungwoo Hur, Cheol Hyun Lee, Se Hun Kang, Daeung Ohn, SookJung Kim, Junghoon Lee, Yeon-Jik Choi, Jeong Eun Yi, Suk Min Seo, Sung-Won Jang, Won Hwa Kim, Osung Kwon

Submitted to: JMIR Medical Informatics
on: April 03, 2025

Disclaimer: © The authors. All rights reserved. This is a privileged document currently under peer-review/community review. Authors have provided JMIR Publications with an exclusive license to publish this preprint on its website for review purposes only. While the final peer-reviewed paper may be licensed under a CC BY license on publication, at this stage authors and publisher expressly prohibit redistribution of this draft paper other than for review purposes.

Table of Contents

Original Manuscript..... 5
Supplementary Files..... 40
 Multimedia Appendixes 41
 Multimedia Appendix 1..... 41



Enhancing Prediction of Left Ventricular Conduction Block After Transcatheter Aortic Valve Replacement: A Machine Learning Approach with Feature Selection

Sungwoo Hur¹ MS; Cheol Hyun Lee² MD, PhD; Se Hun Kang³ MD, PhD; Daeung Ohn⁴ MD; SookJung Kim⁴ MD; Junghoon Lee⁴ MD; Yeon-Jik Choi⁴ MD; Jeong Eun Yi⁴ MD, PhD; Suk Min Seo⁴ MD, PhD; Sung-Won Jang⁴ MD, PhD; Won Hwa Kim^{5,1} PhD; Osung Kwon^{4,6} MD, PhD

¹ Graduate School of AI Pohang University of Science and Technology Pohang KR

² Division of Cardiology, Department of Internal Medicine Dongsan Hospital Keimyung University Deagu KR

³ Department of Cardiology CHA Bundang Medical Center CHA University Seongnam KR

⁴ Division of Cardiology, Department of Internal Medicine Eunpyeong St. Mary's Hospital, College of Medicine Catholic University of Korea Seoul KR

⁵ Computer Science and Engineering Pohang University of Science and Technology Pohang KR

⁶ Cardiovascular Research Institute for Intractable Disease College of Medicine The Catholic University of Korea Seoul KR

Corresponding Author:

Osung Kwon MD, PhD

Division of Cardiology, Department of Internal Medicine

Eunpyeong St. Mary's Hospital, College of Medicine

Catholic University of Korea

1021 Tongil-ro

Eunpyeong-gu

Seoul

KR

Abstract

Background: Left bundle branch block (LBBB) remains a common complication after transcatheter aortic valve replacement (TAVR). Traditional methods to predict the occurrence of LBBB have limitations, especially as TAVR expands to low-risk patients, necessitating new approaches.

Objective: This study aims to develop a machine learning (ML)-based model to predict LBBB after TAVR, using diverse clinical and imaging data.

Methods: Data from 242 TAVR patients excluding pre-existing LBBB or prior pacemaker implantation across three centers were retrospectively analyzed. A transformer-based ML model, integrating tokenizing and classification layers, was developed to identify significant predictive features. The OURS method, which utilizes feature sets, were evaluated against traditional and domain knowledge-driven methods using key metrics: accuracy, precision, recall, and F1-score.

Results: The proposed OURS approach demonstrated balanced performance, with a gradient boosting algorithm demonstrating an accuracy of 78.05%, along with the most balanced precision, recall, and F1 scores at 47.78 ± 0.08 , 53.47 ± 0.09 , and 50.46 ± 0.08 , respectively, outperforming conventional models. This method also showed strong capability in identifying significant features suggested by medical knowledge, achieving an accuracy of 68.11%, precision of 60.00%, recall of 46.15%, and an F1-score of 52.17%. Significant features identified exclusively included height, peripheral vascular disease, Society of Thoracic Surgeons Predicted Risk of Mortality score, sinotubular junction area, diameter of the right coronary cusp, and coronary heights as measured by computed tomography.

Conclusions: This study demonstrates that ML algorithms, particularly the proposed OURS method, could effectively predict LBBB risk post-TAVR. Incorporating diverse clinical data and advanced feature selection enhances predictive accuracy, offering potential for tailored clinical strategies. Clinical Trial: Not applicable.

(JMIR Preprints 03/04/2025:75366)

DOI: <https://doi.org/10.2196/preprints.75366>

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**

Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.

Only make the preprint title and abstract visible.

No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain visible to all users.

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in [http://www.jmir.org](#)

No. Please do not make my accepted manuscript PDF available to anyone. I understand that if I later pay to participate in [https://www.jmir.org](#)

Original Manuscript

Enhancing Prediction of Left Ventricular Conduction Block After Transcatheter Aortic Valve Replacement: A Machine Learning Approach with Feature Selection

Short title: Predicting LBBB after TAVR with ML-models

Sungwoo Hur¹, MS; Cheol Hyun Lee², MD, PhD; Se Hun Kang³, MD, PhD; Daeung Ohn⁴, MD; SookJung Kim⁴, MD; Junghoon Lee⁴, MD; Yeon-Jik Choi⁴, MD; Jeong Eun Yi⁴, MD, PhD; Suk Min Seo⁴, MD, PhD; Sung-Won Jang⁴, MD, PhD; Won Hwa Kim^{1,5}, PhD; Osung Kwon^{4,6}, MD, PhD

¹*Graduate School of AI, POSETECH, Pohang, Republic of Korea*

²*Division of Cardiology, Department of Internal Medicine, Keimyung University Dongsan Hospital, Daegu, Republic of Korea*

³*Department of Cardiology, CHA Bundang Medical Center, CHA University, Seongnam, Republic of Korea*

⁴*Division of Cardiology, Department of Internal Medicine, Eunpyeong St. Mary's Hospital, College of Medicine, The Catholic University of Korea, Seoul, Republic of Korea*

⁵*Computer Science and Engineering, POSTECH, Pohang, Republic of Korea*

⁶*Cardiovascular Research Institute for Intractable Disease, College of Medicine, The Catholic University of Korea, Seoul, Republic of Korea*

Word count (excluding author metadata, references, multimedia appendices, or figures):

Conflict of interest statement: The authors have no conflicts of interest to declare.

The author wishes to acknowledge the financial support of the Catholic Medical Center Research Foundation made in the program year of 2022.

Corresponding author: Osung Kwon, MD, PhD

Division of Cardiology, Department of Internal Medicine, Eunpyeong St. Mary's Hospital, College of Medicine, The Catholic University of Korea, 1021 Tongil-ro, Eunpyeong-gu, Seoul 03312, Republic of Korea,

Phone: +82-2-2030-4332, Fax: +82-2-2030-4641

E-mail: oscaesar@gmail.com

Twitter: @osung_kwon

Co-corresponding author: Won Hwa Kim, PhD

Computer Science and Engineering / Graduate School of AI, POSTECH, 77 Cheongam-ro, Pohang 37673, Republic of Korea,

Phone: +82-54-279-2252, Fax: +82-54-279-2299

E-mail: wonhwa@postech.ac.kr

ABSTRACT

Background: Left bundle branch block (LBBB) remains a common complication after transcatheter aortic valve replacement (TAVR). Traditional methods to predict the occurrence of LBBB have limitations, especially as TAVR expands to low-risk patients, necessitating new approaches.

Objective: This study aims to develop a machine learning (ML)-based model to predict LBBB after TAVR, using diverse clinical and imaging data.

Methods: Data from 242 TAVR patients excluding pre-existing LBBB or prior pacemaker implantation across three centers were retrospectively analyzed. A transformer-based ML model, integrating tokenizing and classification layers, was developed to identify significant predictive features. The OURS method, which utilizes feature sets, were evaluated against traditional and domain knowledge-driven methods using key metrics: accuracy, precision, recall, and F1-score.

Results: The proposed OURS approach demonstrated balanced performance, with a gradient boosting algorithm demonstrating an accuracy of 78.05%, along with the most balanced precision, recall, and F1 scores at 47.78 ± 0.08 , 53.47 ± 0.09 , and 50.46 ± 0.08 , respectively, outperforming conventional models. This method also showed strong capability in identifying significant features suggested by medical knowledge, achieving an accuracy of 68.11%, precision of 60.00%, recall of 46.15%, and an F1-score of 52.17%. Significant features identified exclusively included height, peripheral vascular disease, Society of Thoracic Surgeons Predicted Risk of Mortality score, sinotubular junction

area, diameter of the right coronary cusp, and coronary heights as measured by computed tomography.

Conclusions: This study demonstrates that ML algorithms, particularly the proposed OURS method, could effectively predict LBBB risk post-TAVR. Incorporating diverse clinical data and advanced feature selection enhances predictive accuracy, offering potential for tailored clinical strategies.

Key words: machine-learning, left bundle branch block, transcatheter aortic valve replacement and prediction

ABBREVIATIONS AND ACRONYMS

CT = computed tomography

CL = classification layer

LBBB = left bundle branch block

ML = machine learning

NOP = new-onset persistent

STS-PROM = Society of Thoracic Surgeons predicted risk of mortality

TAVR = transcatheter aortic valve replacement

INTRODUCTION

Transcatheter aortic valve replacement (TAVR) for severe aortic valve stenosis has now become a viable alternative to surgery across all risk levels and is rapidly expanding to lower-risk and younger patients [1]. Despite significant advancements in experience and devices leading to high procedural success rates and excellent safety and mid-to-long-term outcomes, left bundle branch block (LBBB) remains a common complication with its incidence in the literature ranging from 4% to 65% [2-4].

Although various risk factors have been identified and considered during the procedure, the incidence of LBBB remains unchanged [3, 4], indicating the need to discovery and evaluate new risk factors. However, traditional methods have limitations in sensitivity for identifying additional risk factors from high-dimensional features. Given the rapid expansion of TAVR in low-risk patients, for whom long-term outcomes are critical, it is essential to assess the risk of new-onset persistent (NOP) LBBB before the procedure and implement strategies to minimize this risk. Therefore, this study aims to develop a machine learning (ML) algorithm to examine NOP-LBBB after TAVR, utilizing comprehensive data, including imaging information, rather than relying solely on traditional methods or limited clinical data.

METHODS

Database and study population

From 2018 to 2022, a total of 242 patients who underwent TAVR across three institutions were included in this study, after excluding those with baseline LBBB or pre-existing pacemaker implantation (Eunpyeong St. Mary hospital: 152 patients; Bundang CHA hospital: 38 patients; Keimyung Dongsan hospital: 52 patients) (**Figure 1**). The details of the variables

in each category are presented in **Table 1 and Table S1 in Multimedia Appendix I**. Data collection and preparation were approved by the institutional review boards of each center, including Eunpyeong St. Mary's Hospital, and the requirement for informed consent was waived.

Model Architecture

As shown in **Figure 2**, our method consists of three main modules: tokenizing layers, transformer layers, and a hypothesis testing and classification layer (CL). The embedding and transformer layers are used to extract meaningful feature representations for feature selection, and their design follows the standard transformer architecture [5]. Additionally, the hypothesis testing layer is adapted to perform Hotelling's T^2 test on these feature representations, while the CL is introduced to apply classification regularization to stabilize the learning process. Below, we provide a detailed explanation of the architecture.

Notation. We first define the following notations to explain our method effectively. Let

$S = \{(x_i, y_i)\}_{i=1}^N$ be a dataset of N observations, where x_i is an observation and y_i denotes its

corresponding label. Each $x_i = (x_i^{num}, x_i^{cat}) \in R^{d^{num}} \times R^{d^{cat}}$ consists of a concatenated vector of

numerical and categorical features, and x_{ij}^{num} and x_{ij}^{cat} represent numerical and categorical

features, respectively, and thus the total number of features is $d = d^{num} + d^{cat}$. For LBBB

classification $y_i \in \{0, 1\}^N$ and the cardinality of the dataset S is $N = N_0 + N_1$, where N_0 and N_1

are the number of 0-labeled and 1-labeled samples, respectively. In this work, we label positive LBBB samples as 1.

Tokenizing layers. The tokenizing layers project numeric and categorical features into a latent space with the same dimension. Specifically, D -dimensional embeddings of numerical features e_{ij}^{num} and categorical features e_{ij}^{cat} are computed as follows:

$$e_{ij}^{num} = b_j^{num} + x_{ij}^{num} W_j^{num},$$

$$e_{ij}^{cat} = x_{ij}^{cat} W_j^{cat},$$

where $b_j^{num} \in \mathbb{R}$ and $W_j^{num} \in \mathbb{R}^D$ are parameters of a linear projection layer of j^{th} numerical feature, and $W_j^{cat} \in \mathbb{R}^{C_j \times D}$ is a lookup table (embedding matrix) of j^{th} categorical feature, where C_j is the number of classes within j^{th} feature. The final embedding of an observation x_i , e_i is the concatenation of e^{cls} , $[e_{i1}^{num}; e_{i2}^{num}; e_{i3}^{num}; \dots; e_{id^{num}}^{num}]$ and $[e_{i1}^{cat}; e_{i2}^{cat}; e_{i3}^{cat}; \dots; e_{id^{cat}}^{cat}]$, where e^{cls} is an embedding vector of [CLS] token which is later used for classification task, and ; denotes concatenation of vectors.

Transformer layers. The transformer layers take the final embedding e_i compute the followings to obtain feature representations rich in semantics.

1. Linear Projections: For each head h , the input e_i is projected into three different spaces to create query, key, and value vectors.

$$Q_h = e_i W_h^Q, K_h = e_i W_h^K, V_h = e_i W_h^V$$

where $W_h^Q, W_h^K, W_h^V \in \mathbb{R}^{D \times D_k}$ are learnable projection matrices.

2. Scaled Dot-Product Attention: For each head h , the attention weights are computed by taking the dot product of the query Q_h with all keys K_h , scaling by $\sqrt{D_k}$, and applying the softmax function:

$$Attention_h(Q_h, K_h, V_h) = \text{softmax}\left(\frac{Q_h^T K_h}{\sqrt{D_k}}\right) V_h.$$

3. Concatenation of Heads: The outputs of the different attention heads are concatenated and then projected by another learnable weight matrix $W^O \in R^{HD_k \times D}$, where H is the number of attention heads.

$$MultiHead(e_i) = \bigoplus_{h=1}^H Attention_h(Q_h, K_h, V_h) W^O.$$

We denote the final output of $MultiHead(e_i)$ as $z_i \in R^{d \times D}$. Note that $z_i[0]$, the first-row vector of z_i is the [CLS] representation, and the remaining rows, $z_i[1:]$ correspond to feature representations.

Classification layer and hypothesis testing layer. The final layer consists of two fundamental layers, CL and hypothesis testing layer. As illustrated in the **Figure 2**, CL takes [CLS] representation as an input and outputs the logits for classification. Specifically, we used Layer Normalization followed by ReLU activation and a simple linear layer, as follows [6]:

$$ReLU\left(\text{LayerNorm}\left(e_i^{cls}\right)\right) W^{out},$$

where $ReLU(v) = \max(v, 0)$ for an arbitrary vector v , and $W^{out} \in R^D$.

The hypothesis testing layer computes Hotelling's T^2 statistics using $Z[1:]$ (Feature representations stacked in a matrix). The intuition behind this idea is that Hotelling's T^2 statistic can be naturally applied to define a group separation loss for vector representations, which simultaneously maximizes inter-cluster variance while minimizing intra-cluster variance [7]. For two j^{th} mean feature representations from 1-labeled and 0-labeled samples,

$\hat{z}_j^{(1)} \wedge \hat{z}_j^{(0)}$ (respectively), and for two j^{th} covariance matrices of the two different samples, $\Sigma_j^{(1)}$

and $\Sigma_j^{(0)}$, the Hotelling's T^2 statistics of j^{th} feature between the two groups, T_j is formally computed as follows:

$$T_j = \Delta_j^T \Sigma_j^{\text{pooled}} \Delta_j,$$

where $\Delta_j^T = \bar{z}_j^{(1)} - \bar{z}_j^{(0)}$ is the mean difference vector between the two groups, and Σ_j^{pooled} is the pooled covariance matrix that is computed as:

$$\Sigma_j^{\text{pooled}} = \frac{(N_1 - 1) \Sigma_j^{(1)} + (N_0 - 1) \Sigma_j^{(0)}}{N_1 + N_0 - 2}.$$

In addition, to obtain p-values from our method, F_j , the F -statistics of j^{th} feature representations, is calculated as:

$$F_j = \frac{(N_1 + N_0 - p - 1)}{(p \times (N_1 + N_0 - 2))} \times T_j,$$

and the corresponding p-value is obtained as:

$$p\text{-value}_j = 1 - P(F \leq F_j),$$

where $F \sim F(p, N_0 + N_1 - p - 1)$. Finally, as shown in **Figure 3**, we can use this p -values to obtain significant features under a certain significant level, α . i.e., the j^{th} feature is significant if $p\text{-value}_j \leq \alpha$.

Objective function

To learn meaningful feature representations and identify significant features, we propose minimizing the inverse logarithm of the sum of T_j across all group comparisons (thus, maximizing the T^2 statistic) while regularizing it with a classification task and the l_2 norm of the model parameters $l_2(\Theta)$. This loss L is formally written as:

$$L = L_{stat} + \lambda_1 l_2(\Theta) + \lambda_2 \text{CrossEntropy}(y, \hat{y})$$

$$L_{stat} = \frac{1}{\log(\sum_{j=1}^d T_j + 1)} + \lambda_1 \|\Theta\|_2^2 - \lambda_2 \frac{\sum_{i=1}^N \log P_{\Theta}(y_i \vee x_i)}{N}$$

where Θ is a set of model parameters, L_{stat} denotes the first term of L , $\frac{1}{\log(\sum_{j=1}^d T_j + 1)}$, and the term $+1$ added to the $\sum_{j=1}^d T_j$ ensures numerical stability by preventing issues with zero values when computing the logarithm, $\sum_{i=1}^N \log P_{\Theta}(y_i \vee x_i) / N$ corresponds to the Cross Entropy loss between y and predicted label $\hat{y}$ (i.e., $\text{CrossEntropy}(y, \hat{y})$). Additionally, λ_1 and λ_2 are hyperparameters that control the strength of regularization and classification task.

Experimental Design

Baseline Methods and Evaluation metric. To evaluate the feature selection capability of our method, we conducted a comparative performance analysis using the same dataset with three different feature sets: the first feature set, referred to as the ALL set, includes all available features; the second set, referred to as the DK set, consists of features selected based on domain knowledge; and the third feature set, referred to as the OURS set, contains features selected by our method. For each feature set, we searched for an optimal classification model among logistic regression, decision tree, random forest, support vector machine, linear discriminant analysis, quadratic discriminant analysis, and gradient boosting, and evaluated the quality of a feature set by comparing the best LBBB classification model that each set recorded. This assessment was conducted by comparing key metrics, including accuracy, recall, precision, and F1-score, to determine the effectiveness of a feature set.

Note that although our model is trained using cross-entropy loss for classification, this objective functions primarily as an auxiliary task. Our method initially utilizes all the features

in the dataset, which may limit its ability to fully exploit effective feature selection. Therefore, instead of directly evaluating our model based on the outputs of the classification loss, we assessed our approach by training a separate model on the significant feature set identified by our method. According to the No Free Lunch Theorem [8], no single model can universally outperform all others across all possible datasets. The effectiveness of a model is inherently dependent on the characteristics of the given dataset. Accordingly, we evaluated multiple models to identify the most suitable approach for our task.

Training-validation-test data split. We employed bootstrap resampling, which enables more efficient utilization of the available data and provides more stable performance estimates by reducing variance. Specifically, we collected data from three different hospitals and performed five bootstrap resampling iterations (**Figure 1**). The proposed method was evaluated by dividing the dataset into training and test sets at a 7:3 ratio across five fixed random seeds. For each random seed, models were trained on the entire training dataset using hyperparameters optimized through 5-fold cross-validation, and subsequently assessed on the previously separated test data.

Hyperparameters. For the transformer. We used a single transformer layer with 8 heads and set the dimension of the tokenizing layers to 32. As for the optimization, we set both coefficients of loss functions: λ_1 and λ_2 as 1×10^{-5} , and optimized total loss using Adam optimizer with a learning rate of 1×10^{-4} , while keeping all the other settings at their default values in the PyTorch [9]. In addition, we optimized our method for 3,500 epochs using full-batch training.

Clinical analysis vs. OURS. To evaluate the consistency of our method's feature selection with existing medical knowledge, we compared the feature set identified by our method with well-established significant clinical features. A confusion matrix was reported to highlight the agreement between the two feature sets.

RESULTS

Baseline Characteristics and Event Rates

The baseline characteristics of the population are listed in **Table 1 and Table S1 in Multimedia Appendix I**. The mean patient age was 82.57 ± 5.8 years; of the 242 patients, 86 (35.5%) were male. The STS-PROM score was $6.3 \pm 5.2\%$, and the EURO score II was $5.7 \pm 9.1\%$. A normal sinus rhythm was observed in 209 (86.4%) patients. NOP-LBBB occurred within the first day after TAVR in 51 (21.1%) patients. The QRS interval was significantly shorter in the NOP-LBBB group (95.6 ± 17.5 ms) compared to the no NOP-LBBB group (102.3 ± 20.2 ms, $p = 0.032$). A self-expanding valve was used more frequently in the NOP-LBBB group (54.9%) than in the no NOP-LBBB group (33.5%) ($p = 0.01$). Annular area (401.7 ± 71.2 mm² vs. 435.3 ± 87.3 mm², $p = 0.01$), annular perimeter diameter (23.0 ± 2.0 mm vs. 23.9 ± 2.3 mm, $p = 0.01$), and left ventricular outflow tract area (380.2 ± 86.2 mm² vs. 430.8 ± 105.8 mm², $p = 0.002$) were significantly smaller in the NOP-LBBB group. In addition, the left ventricular outflow tract area annular ratio was lower in the NOP-LBBB group (0.9 ± 0.1) than in the no NOP-LBBB group (1.0 ± 0.1 , $p = 0.01$). Total calcium volume was significantly smaller in the NOP-LBBB group (354.4 ± 295.1 mm³) than in the no NOP-LBBB group (507.6 ± 553.4 mm³, $p = 0.01$).

LBBB classification results

Table 2 presents the accuracy, recall, precision, and F1 score of logistic regression, decision tree, random forest, support vector machine, linear discriminant analysis, quadratic discriminant analysis, and gradient boosting across three distinct feature selection settings: ALL, DK, and OURS. In the ALL dataset, the support vector machine achieved the highest accuracy at 79.27 ± 0.03 . However, its precision, recall, and F1 score were relatively low, measuring 11.11 ± 0.11 , 50.00 ± 0.50 , and 18.18 ± 0.18 , respectively. In the DK dataset, the gradient boosting algorithm attained the highest accuracy of 76.83 ± 0.04 , while also demonstrating relatively balanced precision, recall, and F1 scores of 47.78 ± 0.08 , 50.00 ± 0.06 , and 48.83 ± 0.07 , respectively. In the OURS dataset, the gradient boosting algorithm achieved the highest accuracy of 78.05 ± 0.05 along with the most-balanced precision, recall, and F1 scores, measuring 47.78 ± 0.08 , 53.47 ± 0.09 , and 50.46 ± 0.08 , respectively.

Clinical vs. Prediction Analysis

In this experiment, we selected 26 features as clinically established LBBB-related features based on clinical observations and evidence from the clinical literature [10, 11]. The confusion matrix illustrates the alignment of our method with medical knowledge in identifying significant features. The results show that our method correctly identified 12 significant features while correctly classifying 35 features as irrelevant (Figure 4A). Assuming medical knowledge is the ground truth, this result demonstrates the strong capability of our method in identifying significant features (accuracy = 68.11%, precision = 60.00%, recall = 46.15%, and F1-score = 52.17%). Furthermore, it is particularly noteworthy as traditional methods such as logistic regression fail to identify any significant feature at 5% significance level (**Figure 4B**). In contrast, our method is trained to recognize such features without prior medical knowledge.

In addition, we compared the significant features identified by our method with those determined based on established medical knowledge in **Table 3**. Several risk factors recognized in traditional clinical knowledge align with those discovered using the OURS method. These include weight, left ventricular ejection fraction, aortic valve area measured by echocardiography, left posterior fascicular block, first-degree atrioventricular block, PR interval on electrocardiogram, prosthetic valve generation, prosthetic valve size, bicuspid valve, annular mean diameter, annular perimeter-derived diameter, and the left ventricular outflow tract /annulus ratio assessed by computed tomography (CT) scan. Meanwhile, variables such as height, peripheral vascular disease, the Society of Thoracic Surgeons Predicted Risk of Mortality (STS-PROM) score, sinotubular junction area, diameter of the right coronary cusp, and left and right coronary heights measured by CT scan were identified exclusively by the OURS method.

Discussion

This retrospective study applied ML to multicenter TAVR data to develop a risk prediction model for LBBB occurring within the first after the procedure. The gradient boosting algorithm achieved the highest performance. By employing our proposed method (OURS) which did not rely on prior medical knowledge, we were able to enhance the overall performance. In addition, while there was considerable overlap between the significant features identified based on medical expertise and those discovered via OURS, including several procedural and CT analysis variables, certain variables did not align.

It is estimated that approximately 30% of patients experience LBBB immediately after the procedure, with around 15% remaining affected at discharge [3, 4]. The onset of LBBB significantly increases the risk of high-grade conduction disorders, such as atrioventricular block, necessitating prolonged in-hospital observation and potentially

delaying discharge. LBBB has also been linked to a two-fold higher risk of permanent pacemaker implantation during follow-up [12, 13]. Long-term consequences include decreased left ventricular ejection fraction, dyssynchrony, and adverse cardiac remodeling [14, 15]. Moreover, although controversial, LBBB has been associated with increased in-hospital and long-term mortality rates [16-18]. Recent meta-analysis reported that patients with new-onset LBBB had a higher all-cause mortality risk compared to those without new-onset LBBB, across all follow-up periods [19].

Thus, multiple studies have sought to identify and stratify risk factors for conduction abnormalities after TAVR using anatomical, electrocardiographic, and procedural elements. Pre-procedural factors include pre-existing conduction abnormalities, such as right bundle branch block or first-degree atrioventricular block, severe calcification of the aortic valve or left ventricular outflow tract, prolonged QRS duration, a history of coronary artery bypass grafting, and female sex as an independent risk factor [20-22]. Procedural factors include a short membranous interventricular septum length [23], lower prosthetic valve implantation depth, with each 1mm deeper implantation increasing the likelihood of LBBB by 15-40% [24], and device-related factors such as valve oversizing and the use of self-expanding systems like the Medtronic CoreValve, which are more prone to inducing conduction disturbances [20-23].

Despite recognizing these risk factors and accounting for them during the procedure, the incidence of LBBB remains unchanged, highlighting the need to identify and evaluate additional risk factors. However, traditional methods have limitations in identifying new risk factors. Given the rapid expansion of TAVR in low-risk patients, for whom long-term outcomes are critical, it is essential to assess the risk of LBBB before the procedure and implement strategies to mitigate this risk. Hence, developing a ML model to predict post-

TAVR LBBB occurrence could significantly enhance clinical decision-making and patient management. ML models have the potential to identify complex patterns and interactions within data that traditional statistical methods might overlook, leading to enhanced predictive accuracy.

In this study, by employing the OURS method, we developed a gradient boosting model that achieved the highest accuracy and demonstrated balanced performance, even without incorporating prior medical knowledge. One of the key strengths of our algorithm is its ability to identify salient features for predicting LBBB occurrence (i.e., a binary classification task). This feature selection capability enables the model to focus on the most relevant information, thereby enhancing both interpretability and predictive performance. However, the overall performance of the evaluated models, reflected in a maximum F1-score of 50.46%, suggests that the dataset may not have lacked a sufficient sample size to adequately represent the underlying data distribution. Additionally, the limited dataset size may have constrained the models' ability to generalize effectively, potentially lacking the informative variance needed to achieve higher predictive power. Factors such as class imbalance, feature noise, and a mismatch between model complexity and dataset characteristics may also have contributed to the suboptimal predictive performance.

While there was considerable overlap with traditionally known risk factors for LBBB, the OURS method identified additional significant variables. In the CT analysis, left and right coronary heights were identified as significant predictors, while clinically, height, peripheral vascular disease, previous myocardial infarction, and the STS-PROM score were recognized as important variables. Advanced atherosclerosis, conduction system defects resulting from prior myocardial infarction, and overall risk assessed by the STS-PROM score may collectively indicate the fragility of the cardiac conduction system. Furthermore, the

identification of coronary height as a significant factor may imply that operators might have performed deeper valve implantations to avoid coronary obstruction, potentially increasing the risk of LBBB. Further validation studies are required to determine whether these variables are consistently identified as significant across alternative predictive models.

Limitations

Several limitations of this study should be noted. This study was conducted using retrospective data from three centers consisting of 242 patients, while this multicenter approach improves generalizability, the relatively small sample size may not fully represent the broader TAVR population, potentially limiting the robustness of our findings. Second, although external validation provides a more realistic assessment of model generalizability, it requires a sufficiently large and independent dataset, which was not available in this study. To address this limitation, we employed bootstrap resampling to efficiently utilize available data and reduce variance, thereby stabilizing performance estimates. Third, the incidence of LBBB in our cohort was not low, which may have impacted the predictive power of the model. Although bootstrap resampling was employed to address this issue, class imbalance remains a significant challenge in developing highly accurate predictive models. Fourth, certain procedural factors known to influence LBBB occurrence, such as implantation depth and membranous interventricular septum length may not have been fully captured in our dataset. Finally, the direct use of imaging data, such as CT or echocardiography, could have contributed to performance improvement. Developing a model that integrates imaging information, mirroring real-world clinical settings, is warranted in future work.

CONCLUSIONS

The present study demonstrated that ML algorithms, particularly the OURS method, can effectively predict the risk of LBBB occurring within the first day after TAVR. By employing data-driven feature selection, the OURS method enhances predictive performance beyond conventional models relying solely on medical expertise. This approach would enable early identification of high-risk patients, allowing for more proactive clinical decision-making and personalized post-procedural management strategies. Further prospective, multicenter external validation investigations are warranted to conform these findings and support clinical implementation.

REFERENCES

1. Spears J, Al-Saiegh Y, Goldberg D, Manthey S, Goldberg S. TAVR: A Review of Current Practices and Considerations in Low-Risk Patients. *J Interv Cardiol.* 2020;2020:2582938. PMID: 33447165. doi: 10.1155/2020/2582938.
2. Auffret V, Puri R, Urena M, Chamandi C, Rodriguez-Gabella T, Philippon F, et al. Conduction Disturbances After Transcatheter Aortic Valve Replacement: Current Status and Future Perspectives. *Circulation.* 2017 Sep 12;136(11):1049-69. PMID: 28893961. doi: 10.1161/CIRCULATIONAHA.117.028352.
3. Lilly SM, Deshmukh AJ, Epstein AE, Ricciardi MJ, Shreenivas S, Velagapudi P, et al. 2020 ACC Expert Consensus Decision Pathway on Management of Conduction Disturbances in Patients Undergoing Transcatheter Aortic Valve Replacement: A Report of the American College of Cardiology Solution Set Oversight Committee. *J Am Coll Cardiol.* 2020 Nov 17;76(20):2391-411. PMID: 33190683. doi: 10.1016/j.jacc.2020.08.050.
4. Ando T, Takagi H, Group A. The Prognostic Impact of New-Onset Persistent Left Bundle Branch Block Following Transcatheter Aortic Valve Implantation: A Meta-analysis. *Clin Cardiol.* 2016 Sep;39(9):544-50. PMID: 27431592. doi: 10.1002/clc.22567.
5. Gorishniy Y, Rubachev I, Khrulkov V, Babenko A. Revisiting deep learning models for tabular data. *Advances in neural information processing systems.* 2021;34:18932-43.
6. Ba JL, Kiros JR, Hinton GE. Layer normalization. *arXiv preprint arXiv:160706450.* 2016.
7. Ma X, Wu G, Kim WH, editors. Enriching Statistical Inferences on Brain Connectivity for Alzheimer's Disease Analysis via Latent Space Graph Embedding. 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI); 2020: IEEE.
8. Wolpert DH, Macready WG. No free lunch theorems for optimization. *IEEE transactions on evolutionary computation.* 1997;1(1):67-82.

9. Paszke A, Gross S, Massa F, Lerer A, Bradbury J, Chanan G, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*. 2019;32.
10. Sammour Y, Krishnaswamy A, Kumar A, Puri R, Tarakji KG, Bazarbashi N, et al. Incidence, Predictors, and Implications of Permanent Pacemaker Requirement After Transcatheter Aortic Valve Replacement. *JACC Cardiovasc Interv*. 2021 Jan 25;14(2):115-34. PMID: 33478630. doi: 10.1016/j.jcin.2020.09.063.
11. Yu Q, Fu Q, Xia Y, Wu Y. Predictors, clinical impact, and management strategies for conduction abnormalities after transcatheter aortic valve replacement: an updated review. *Front Cardiovasc Med*. 2024;11:1370244. PMID: 38650916. doi: 10.3389/fcvm.2024.1370244.
12. Nazif TM, Williams MR, Hahn RT, Kapadia S, Babaliaros V, Rodes-Cabau J, et al. Clinical implications of new-onset left bundle branch block after transcatheter aortic valve replacement: analysis of the PARTNER experience. *Eur Heart J*. 2014 Jun 21;35(24):1599-607. PMID: 24179072. doi: 10.1093/eurheartj/eh376.
13. Urena M, Webb JG, Cheema A, Serra V, Toggweiler S, Barbanti M, et al. Impact of new-onset persistent left bundle branch block on late clinical outcomes in patients undergoing transcatheter aortic valve implantation with a balloon-expandable valve. *JACC Cardiovasc Interv*. 2014 Feb;7(2):128-36. PMID: 24440024. doi: 10.1016/j.jcin.2013.08.015.
14. Tzikas A, van Dalen BM, Van Mieghem NM, Gutierrez-Chico JL, Nuis RJ, Kauer F, et al. Frequency of conduction abnormalities after transcatheter aortic valve implantation with the Medtronic-CoreValve and the effect on left ventricular ejection fraction. *Am J Cardiol*. 2011 Jan 15;107(2):285-9. PMID: 21129715. doi: 10.1016/j.amjcard.2010.09.015.
15. Dobson LE, Musa TA, Uddin A, Fairbairn TA, Bebb OJ, Swoboda PP, et al. The impact of trans-catheter aortic valve replacement induced left-bundle branch block on cardiac reverse

- remodeling. *J Cardiovasc Magn Reson*. 2017 Feb 22;19(1):22. PMID: 28222749. doi: 10.1186/s12968-017-0335-9.
16. Nazif TM, Dizon JM, Hahn RT, Xu K, Babaliaros V, Douglas PS, et al. Predictors and clinical outcomes of permanent pacemaker implantation after transcatheter aortic valve replacement: the PARTNER (Placement of AoRtic TraNscathetER Valves) trial and registry. *JACC Cardiovasc Interv*. 2015 Jan;8(1 Pt A):60-9. PMID: 25616819. doi: 10.1016/j.jcin.2014.07.022.
17. Regueiro A, Abdul-Jawad Altisent O, Del Trigo M, Campelo-Parada F, Puri R, Urena M, et al. Impact of New-Onset Left Bundle Branch Block and Periprocedural Permanent Pacemaker Implantation on Clinical Outcomes in Patients Undergoing Transcatheter Aortic Valve Replacement: A Systematic Review and Meta-Analysis. *Circ Cardiovasc Interv*. 2016 May;9(5):e003635. PMID: 27169577. doi: 10.1161/CIRCINTERVENTIONS.115.003635.
18. Chamandi C, Barbanti M, Munoz-Garcia A, Latib A, Nombela-Franco L, Gutierrez-Ibanez E, et al. Long-Term Outcomes in Patients With New-Onset Persistent Left Bundle Branch Block Following TAVR. *JACC Cardiovasc Interv*. 2019 Jun 24;12(12):1175-84. PMID: 31129090. doi: 10.1016/j.jcin.2019.03.025.
19. Wang J, Liu S, Han X, Chen Y, Chen H, Wan Z, et al. Prognostic Outcome of New-Onset Left Bundle Branch Block After Transcatheter Aortic Valve Replacement in Patients With Aortic Stenosis: A Systematic Review and Meta-Analysis. *Front Cardiovasc Med*. 2022;9:842929. PMID: 35463780. doi: 10.3389/fcvm.2022.842929.
20. Sharma E, Chu AF. Predictors of right ventricular pacing and pacemaker dependence in transcatheter aortic valve replacement patients. *J Interv Card Electrophysiol*. 2018 Jan;51(1):77-86. PMID: 29260369. doi: 10.1007/s10840-017-0303-1.
21. Elzeneini M, Assaf Y, Aalaei-Andabili SH, Mahmoud A, Hamburger R, Goel R, et al. Predictors of ventricular pacing burden after permanent pacemaker implantation following

transcatheter aortic valve replacement. Clin Cardiol. 2020 Nov;43(11):1334-42. PMID: 32886389. doi: 10.1002/clc.23447.

22. Zhang J, Pan Y, Wang B, Fu G. Current Opinions on New-Onset Left Bundle Branch Block after Transcatheter Aortic Valve Replacement and the Search for Physiological Pacing. Rev Cardiovasc Med. 2022 Mar 9;23(3):90. PMID: 35345257. doi: 10.31083/j.rcm2303090.

23. Phan DQ, Goitia J, Lee MS, Gupta N, Aharonian V, Mansukhani P, et al. Predictors of conduction recovery after permanent pacemaker implantation following transcatheter aortic valve replacement. J Interv Card Electrophysiol. 2021 Aug;61(2):365-74. PMID: 32671716. doi: 10.1007/s10840-020-00813-y.

24. Mangieri A, Montalto C, Pagnesi M, Lanzillo G, Demir O, Testa L, et al. TAVI and Post Procedural Cardiac Conduction Abnormalities. Front Cardiovasc Med. 2018;5:85. PMID: 30018969. doi: 10.3389/fcvm.2018.00085.

Table 1. Clinical characteristics, baseline echocardiography and electrocardiographic parameters of the study population, according to the occurrence of new-onset persistent left bundle branch block.

Clinical characteristics				
	Total population (N=242)	No NOP-LBBB (N=191)	NOP-LBBB (N=51)	P value
Age (year)	82.57 ± 5.8	82.3 ± 6.0	83.6 ± 4.9	0.14
Male	86 (35.5)	118 (61.8)	38 (74.5)	0.13
BMI (kg/m ²)	23.9 ± 4.0	23.9 ± 4.0	23.5 ± 3.9	0.50
Hypertension	187 (77.3)	144 (75.4)	43 (84.3)	0.25
Diabetes mellitus	88 (36.4)	71 (37.2)	17 (33.3)	0.73
Hyperlipidemia	101 (41.7)	83 (43.5)	18 (35.3)	0.37
NYHA classification				0.98
I-II	39 (16.1)	31 (16.2)	8 (15.7)	
III-IV	203 (83.9)	160 (83.8)	43 (84.3)	
Chronic lung disease	25 (10.3)	21 (11.0)	4 (7.8)	0.69
eGFR < 60 mL/min/1.7m ²	92 (38.0)	72 (37.7)	20 (39.2)	0.97
Coronary artery disease	125 (51.7)	105 (55.0)	20 (39.2)	0.07
Previous ischemic stroke	25 (10.3)	20 (10.5)	5 (9.8)	0.98
Peripheral vascular disease	12 (5.0)	10 (5.2)	2 (3.9)	0.98
Previous valve surgery	4 (1.7)	3 (1.6)	1 (2.0)	0.99
Previous history of MI	10 (4.1)	7 (3.7)	3 (5.9)	0.76
Previous history of PCI	88 (36.4)	70 (36.6)	13 (25.5)	0.19
Previous history of CABG	2 (0.8)	2 (1.0)	0 (0.0)	0.99
STS-PROM score (%)	6.3 ± 5.2	6.2 ± 5.0	6.5 ± 5.8	0.67
EURO score I (%)	14.8 ± 14.9	13.9 ± 14.5	17.7 ± 16.0	0.17
EURO score II (%)	5.7 ± 9.1	5.9 ± 9.7	4.9 ± 6.5	0.45
Baseline echocardiography				
LVEF (%)	56.4 ± 13.1	55.9 ± 13.5	57.9 ± 11.4	0.34
LVEF < 50%	53 (21.9)	45 (23.6)	8 (15.7)	0.31
Aortic valve Vmax (m/s)	4.4 ± 0.8	4.4 ± 0.8	4.1 ± 0.7	0.01
Aortic valve mean gradient (mmHg)	45.4 ± 17.4	47.1 ± 17.9	39.3 ± 13.9	0.001
Aortic valve area (cm ²)	0.8 ± 0.2	0.7 ± 0.2	0.7 ± 0.2	0.59
Aortic regurgitation, moderate-severe	119 (49.2)	97 (50.8)	22 (43.1)	0.42
Baseline electrocardiography				
Normal sinus rhythm	209 (86.4)	166 (86.9)	43 (84.3)	0.80
Atrial fibrillation/flutter	35 (14.4)	27 (14.1)	8 (15.7)	0.97
Left anterior fascicular block	7 (2.9)	7 (3.7)	0 (0.0)	0.36
Left posterior fascicular block	1 (0.4)	1 (0.5)	0 (0.0)	0.99
1 st degree AV block	15 (6.2)	12 (6.3)	3 (5.9)	0.99
2 nd degree AV block	2 (0.8)	1 (0.5)	1 (2.0)	0.89
PR interval (ms)	166.9 ± 57.8	165.3 ± 57.3	173.3 ± 59.6	0.39

QRS interval (ms)	100.9 ± 19.8	102.3 ± 20.2	95.6 ± 17.5	0.03
Corrected QT interval (ms)	458.1 ± 35.6	458.3 ± 35.5	457.3 ± 36.2	0.85

Data are the mean ± standard deviation or numbers (%).

Abbreviations: AV, atrioventricular; BMI, body mass index; CABG, coronary artery bypass graft; eGFR, estimated glomerular filtration rate; LBBB, left bundle branch block; LVEF, left ventricular ejection fraction; NOP, new-onset persistent; MI, myocardial infarction; NYHA, New York Heart Association; PCI, percutaneous coronary intervention; STS-PROM, Society of Thoracic Surgeons Predicted Risk of Mortality.

Table 2. Performance of left bundle branch block classification

The ALL setting utilizes all available features from the dataset, while DK includes features selected based on domain knowledge. In contrast, OURS trains each model using features selected by our method. The best-performing score is highlighted in italics.

Model	Method	Accuracy	Recall	Precision	F1-score
		(%)	(%)	(%)	(%)
Logistic Regression	ALL	74.39 ± 0.02	11.11 ± 0.11	25.0 ± 0.25	15.38 ± 0.15
	DK	63.41 ± 0.00	26.67 ± 0.07	23.61 ± 0.07	24.81 ± 0.04
	OURS	60.98 ± 0.02	26.67 ± 0.07	21.83 ± 0.00	23.57 ± 0.03
Decision Tree	ALL	56.10 ± 0.07	16.11 ± 0.06	13.39 ± 0.01	13.88 ± 0.02
	DK	48.78 ± 0.02	16.11 ± 0.06	10.05 ± 0.02	12.24 ± 0.03
	OURS	56.10 ± 0.02	11.11 ± 0.11	8.33 ± 0.08	9.52 ± 0.10
Random Forest	ALL	76.83 ± 0.01	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
	DK	68.29 ± 0.02	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
	OURS	75.61 ± 0.00	5.56 ± 0.06	16.67 ± 0.17	8.33 ± 0.08
Support Vector Machine	ALL	79.27 ± 0.03	11.11 ± 0.11	50.00 ± 0.50	18.18 ± 0.18
	DK	63.41 ± 0.00	10.56 ± 0.01	13.39 ± 0.01	11.76 ± 0.00
	OURS	62.20 ± 0.01	10.56 ± 0.01	12.70 ± 0.02	11.44 ± 0.00
Linear Discriminant	ALL	76.83 ± 0.01	0.00 ± 0.00	0.0 ± 0.00	0.00 ± 0.00
	DK	52.44 ± 0.01	21.67 ± 0.12	13.37 ± 0.04	16.30 ± 0.07
	OURS	54.88 ± 0.04	32.78 ± 0.23	18.06 ± 0.10	23.06 ± 0.14

Analysis Quadratic Discriminant	ALL	78.05 ± 0.02	15.56 ± 0.04	75.00 ± 0.25	24.29 ± 0.04
	DK	67.07 ± 0.04	20.56 ± 0.09	25.00 ± 0.13	22.55 ± 0.11
	OURS	75.61 ± 0.02	16.11 ± 0.06	41.67 ± 0.08	23.08 ± 0.08
Analysis Gradient Boosting	ALL	74.39 ± 0.01	5.00 ± 0.05	16.67 ± 0.17	7.69 ± 0.08
	DK	76.83 ± 0.04	47.78 ± 0.08	50.00 ± 0.06	48.83 ± 0.07
	OURS	78.05 ± 0.05	47.78 ± 0.08	53.47 ± 0.09	50.46 ± 0.08

Figure 1. Study diagram

CT, computed tomography; CV, cross validation; ECG, electrocardiography; LBBB, left bundle branch block; TAVR, transcatheter aortic valve replacement; TTE; transthoracic echocardiography.

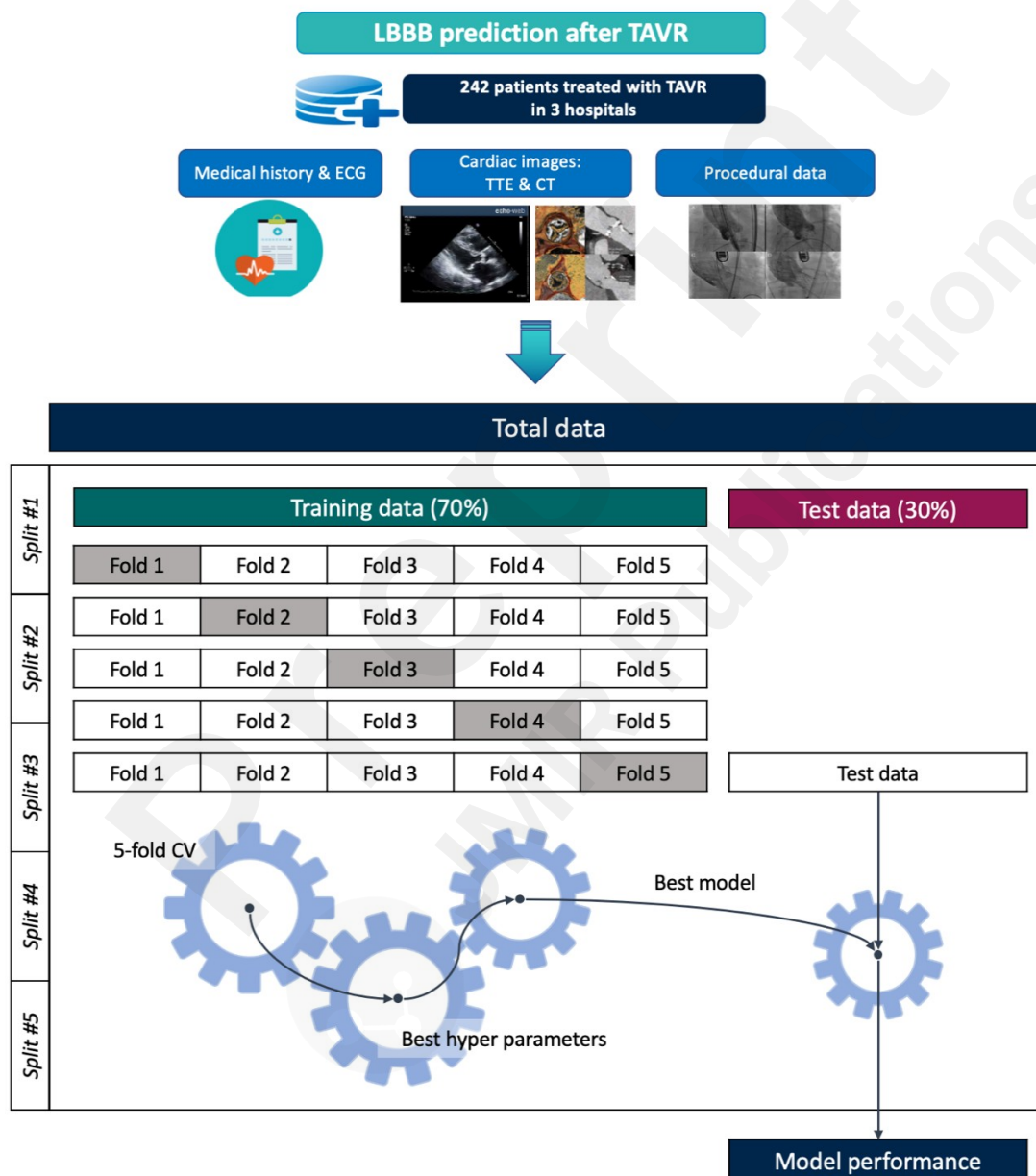


Figure 2. Overall model architecture.

The model tokenizes input data using dedicated layers for categorical and continuous variables to generate feature tokens and a global CLS embedding. These embeddings are refined by transformer layers into rich semantic representations. A hypothesis testing layer evaluates the significance of each feature, while a classification layer leverages the enhanced CLS embedding to produce the left bundle branch block (LBBB) logit. The model is trained using a full-batch training scheme that incorporates both negative and positive LBBB samples, simultaneously minimizing the LBBB classification loss (L_{cls}) and statistical loss (L_{stat}). Additionally, the black box represents a set of N_0 negative LBBB samples, while the red box corresponds to a set of N_1 positive LBBB samples.

CL, classification layer.

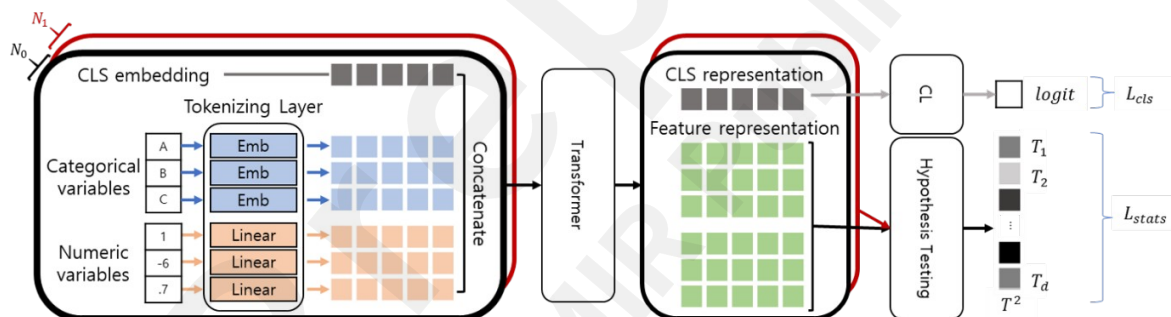


Figure 3. α -level Hotelling's T^2 test. In this step, significant features are determined by applying the Hotelling's T^2 test to the statistical representations derived from the transformer layers, as illustrated in Figure 2.

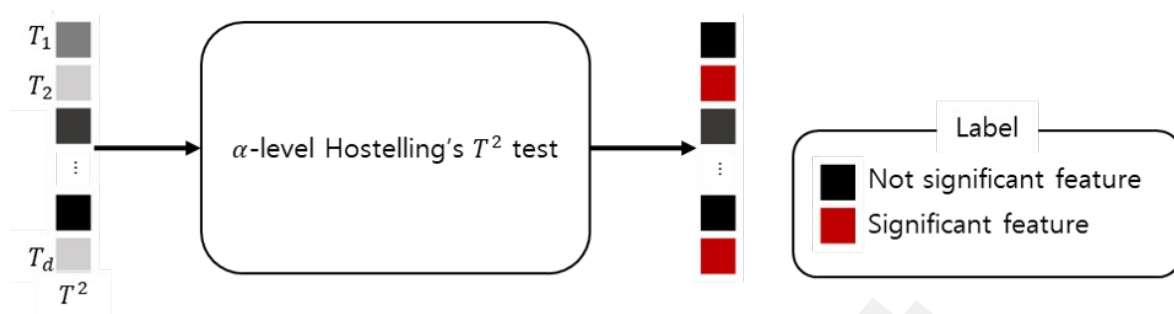
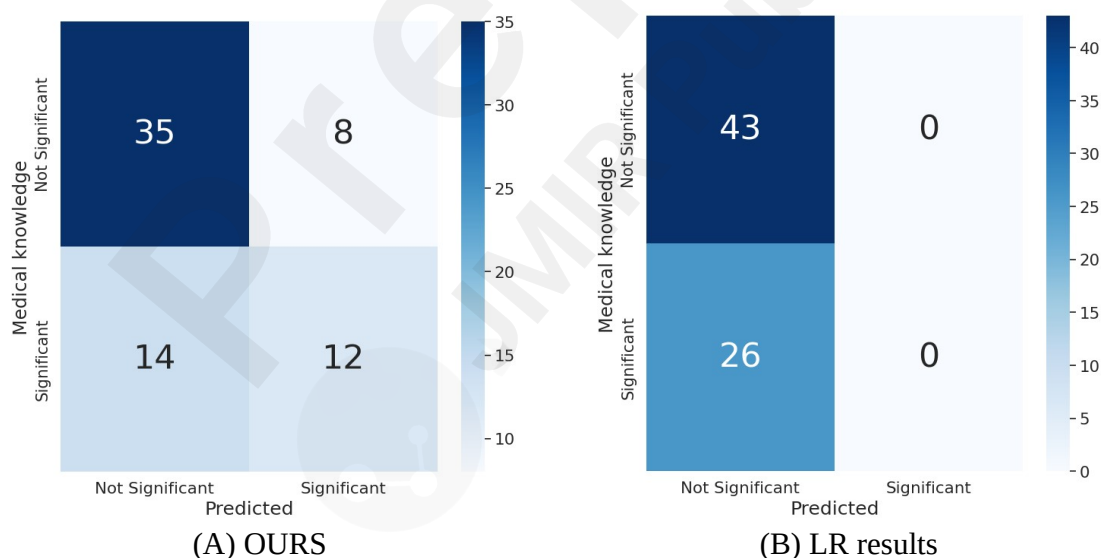


Figure 4. Confusion matrices comparing feature selection approaches. (A) Confusion matrix comparing features identified by medical knowledge and those selected by the OURS method. (B) Confusion matrix comparing features identified by medical knowledge and those selected by logistic regression. The Y- axis of matrices represents the clinically significant features, determined based on medical knowledge, while the X- axis represents the model's predicted significant features. The significance level (α) was set at 5% in both cases.

LR, logistic regression.



Multimedia Appendix I

S Her et al. “Machine learning algorithms for prediction of left ventricular conduction block after transcatheter aortic valve replacement”

Supplementary Table S1. Procedural and computer tomography parameters of the study population, according to the occurrence of new-onset persistent left bundle branch block.

This supplementary material was provided by the authors to provide readers with additional information of their work.

Table S1. Procedural and computer tomography parameters of the study population, according to the occurrence of new-onset persistent left bundle branch block.

Procedural variables				
	Total population	NoNOP-LBBB	NOP-LBBB	P value
Prothesis valve type				0.01
Balloon-expandable	150 (62.0)	127 (66.5)	23 (45.1)	
Self-expanding	92 (38.0)	64 (33.5)	28 (54.9)	
New generation valve				0.02
(Sapient 3/Ultra or Evolut R/Pro)	188 (77.7)	155 (81.2)	33 (64.7)	
Prothesis valve size				0.74
20	11 (4.5)	10 (5.2)	1 (2.0)	
23	83 (34.3)	64 (33.5)	19 (37.3)	
26	82 (33.9)	65 (34.0)	17 (33.3)	
29	63 (26.0)	49 (25.7)	14 (27.5)	
34	3 (1.2)	3 (1.6)	0 (0.0)	
Prothesis valve over sizing	12.0 ± 7.0	11.5 ± 6.9	13.9 ± 7.4	0.05
Balloon pre-dilatation	84 (34.7)	73 (38.2)	11 (21.6)	0.04
Balloon post-dilatation	19 (7.9)	16 (8.4)	3 (5.9)	0.77
Computer tomography parameters				
Bicuspid valve	12 (5.0)	10 (5.2)	2 (3.9)	0.98
Annular short diameter (mm)	20.6 ± 2.2	20.9 ± 2.2	19.7 ± 2.0	0.001
Annular long diameter (mm)	26.4 ± 2.7	26.6 ± 2.7	25.6 ± 2.7	0.02
Annular mean diameter (mm)	23.5 ± 2.3	23.7 ± 2.4	22.8 ± 2.1	0.01
Annular area (mm ²)	428.1 ± 85.1	435.3 ± 87.3	401.7 ± 71.2	0.01
Annular area diameter (mm)	23.3 ± 2.2	23.5 ± 2.3	22.5 ± 2.0	0.01
Annular perimeter (mm)	74.6 ± 7.3	75.2 ± 7.5	72.4 ± 6.3	0.02
Annular perimeter diameter (mm)	23.8 ± 2.3	23.9 ± 2.3	23.0 ± 2.0	0.01
SOV area (mm ²)	776.1 ± 152.7	779.0 ± 151.8	767.6 ± 157.0	0.67
Sinus annular ratio	4.6 ± 36.0	5.5 ± 41.6	1.9 ± 0.3	0.33
Diameter of NCC (mm)	32.6 ± 13.5	32.9 ± 15.2	31.4 ± 3.5	0.22
Diameter of LCC (mm)	31.2 ± 3.5	31.4 ± 3.5	30.8 ± 3.3	0.29
Diameter of RCC (mm)	30.3 ± 3.5	30.5 ± 3.6	29.6 ± 3.0	0.12
STJ area (mm ²)	638.0 ± 126.3	641.5 ± 126.9	627.6 ± 125.2	0.53
STJ annular ratio	1.5 ± 0.3	1.5 ± 0.3	1.6 ± 0.4	0.10
STJ mean diameter (mm)	28.0 ± 3.3	28.1 ± 3.4	27.6 ± 2.9	0.34
LCC-STJ height (mm)	20.9 ± 2.8	21.1 ± 2.8	20.2 ± 2.5	0.05
LVOT area (mm ²)	419.93 ± 103.85	430.8 ± 105.8	380.2 ± 86.2	0.002
LVOT annular ratio	1.0 ± 0.1	1.0 ± 0.1	0.9 ± 0.1	0.01
LVOT short diameter (mm)	20.0 ± 2.9	20.3 ± 2.9	18.8 ± 2.6	0.001
LVOT long diameter (mm)	26.8 ± 3.1	27.0 ± 3.2	26.0 ± 2.7	0.04
Total calcium volume (mm ³)	474.6 ± 512.2	507.6 ± 553.4	354.4 ± 295.1	0.01
LCC calcium volume (mm)	126.8 ± 153.8	141.3 ± 167.0	74.1 ± 70.2	<0.001
RCC calcium volume (mm)	130.0 ± 179.7	140.9 ± 194.8	90.5 ± 100.8	0.02
NCC calcium volume (mm)	221.1 ± 242.3	230.4 ± 259.2	187.5 ± 165.2	0.17
Left coronary height (mm)	13.8 ± 9.8	13.4 ± 3.0	15.3 ± 20.6	0.52

Right coronary height (mm)	16.7 ± 2.6	16.7 ± 2.6	16.6 ± 2.9	0.75
----------------------------	------------	------------	------------	------

Data are the mean ± standard deviation or numbers (%).

Abbreviations: LBBB, left bundle branch block; LCC, left coronary cusp; LVOT, left ventricular outflow tract; NCC, non-coronary cusp; NOP, new-onset persistent; RCC, right coronary cusp; SOV, sinuses of Valsalva; STJ, sinotubular junction.

Supplementary Files

Multimedia Appendixes

Untitled.

URL: <http://asset.jmir.pub/assets/8df9dac6f5992aa3fa4d87890adfd98b.docx>