

Interpretable machine learning framework for congestive heart failure risk prediction

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ABSTRACT

Congestive heart failure (CHF) is a leading cause of morbidity and mortality worldwide and is influenced by multiple clinical risk factors, including age, sex, blood pressure, cholesterol levels, and electrocardiographic characteristics. This study employs publicly available heart disease datasets compiled from populations in Cleveland, Hungary, Switzerland, and Long Beach repositories (2015–2020) and analyzes 11 predictor attributes and one binary outcome using the cross-industry standard process for data mining (CRISP-DM) framework. Four supervised machine learning (ML) models—decision tree, random forest, gradient boosted trees, and naïve Bayes—were developed and evaluated using confusion matrix-based performance metrics, with results showing that the decision tree model offers balanced predictive performance and clear interpretability, making it suitable for heart failure risk prediction. The findings demonstrate the potential of ML approaches to support clinical risk assessment and enhance decision-making in heart failure management.

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1. INTRODUCTION

Congestive heart failure (CHF) is a leading cause of morbidity and mortality worldwide, with risk factors such as age, sex, hypertension, dyslipidemia, and diabetes that can progress to serious cardiac complications, underscoring the need for early risk identification [1], [2]. Machine learning (ML), a branch of artificial intelligence that learns from data without explicit programming [3]–[5], has shown strong potential for heart failure prediction [6]–[8]. Supervised algorithms—decision trees, random forests, gradient boosting, and naïve Bayes—predict heart failure outcomes with promising accuracy [9]–[12], yet often emphasize classification performance over interpretability and evaluation rigor [13], [14]. Explainability remains similarly underdeveloped, with few CHF studies linking input features to predictions [15], [16], or combining predictive modeling with structured data-mining and practical reporting.

This study addresses that gap with a cross-industry standard process for data mining (CRISP-DM) based ML framework for CHF risk prediction, building and comparing four supervised models—decision

tree, random forest, gradient boosted tree, and naïve Bayes—on clinical risk-factor data, alongside a dashboard that communicates results and key risk factors to support risk awareness and preventive planning.

2. LITERATURE REVIEW

2.1. Heart failure

CHF is a group of symptoms resulting from abnormal heart muscle function that impairs the heart's ability to pump or receive blood normally. It can be classified by affected side, where right-sided failure causes fluid retention, swollen feet, and an enlarged liver, while left-sided failure causes pulmonary congestion and edema, and by onset, where acute failure develops rapidly while chronic failure follows a prior diagnosis. Common symptoms include shortness of breath, fatigue, and fluid-or salt-related edema, with underlying causes ranging from myocardial ischemia to viral infection, arrhythmias, and elevated blood lipids.

2.2. Dataset

According to the World Health Organization (WHO), cardiovascular diseases (CVDs) are the leading cause of death globally, accounting for an estimated 19.8 million deaths in 2022, which represents approximately 32% of all global deaths [1]. Heart failure is a major category within CVDs, and individuals with risk factors such as hypertension, diabetes, elevated blood lipid levels, or existing cardiovascular conditions require early screening and appropriate treatment. The dataset used for ML model development in this study was obtained from publicly available heart disease datasets compiled from the Cleveland, Hungary, Switzerland, and Long Beach repositories [17]. These datasets contain 11 clinical and demographic attributes related to heart disease risk and are widely used in ML-based cardiovascular research; the attributes employed in this study are summarized in Table 1.

Table 1. Dataset characteristics

No.	Attribute	Description
1	Age	Patient's age (years)
2	Sex	Patient's gender (M: male, F: female)
3	ChestPainType	Type of chest pain (TA: typical angina, ATA: atypical angina, NAP: non-anginal pain, ASY: asymptomatic)
4	RestingBP	Resting blood pressure (mmHg)
5	Cholesterol	Blood cholesterol level (mg/dL)
6	FastingBS	Fasting blood sugar (1: fastingBS > 120 mg/dL, 0: other)
7	RestingECG	Resting electrocardiogram (Normal: normal, ST: ST abnormality, LVH: left ventricular hypertrophy)
8	MaxHR	Maximum heart rate
9	ExerciseAngina	Exercise-induced chest pain (Y: yes, N: no)
10	Oldpeak	ST depression value (0 mV: normal, 0.1-1.0 mV: mild abnormality, 1.0-2.0 mV: moderate abnormality, 2.0-4.0 mV: severe abnormality, 4.0-6.0 mV or greater: very severe abnormality)
11	STslope	ST segment slope characteristics (Up: upward, Flat: flat, Down: downward)
12	HeartDisease	Chance of occurrence (1: heart disease, 0: normal)

2.3. Machine learning

ML, a form of artificial intelligence, enables computers to learn patterns from data and make predictions or classifications without explicit programming [18], [19], with applications spanning forecasting [20] and image recognition [21]. ML is broadly grouped into supervised learning, which trains on labeled data using methods such as naïve Bayes, decision trees, and neural networks for regression or classification [22], [23]; unsupervised learning, which finds structure in unlabeled data through clustering methods; reinforcement learning, which optimizes an agent's actions toward a goal via reward feedback; and semi-supervised learning, a hybrid of the two. This study is grounded in supervised learning.

2.4. Decision tree

A decision tree is a tree-structured model in which a root node branches into child nodes, ending in leaf nodes that represent the predicted class [24], [25]. Classification proceeds by comparing input attributes against node conditions from the root down to a leaf [26], [27]. Node splits are commonly chosen using information gain, which selects the attribute yielding the highest reduction in entropy at each step [28], [29], continuing until entropy reaches zero or a stopping criterion is met [30].

2.5. Business intelligence

Business intelligence (BI) applies information technology to support accurate, data-driven decision-making [31], [32]. It provides organizations with lots of benefits, e.g., better identification of opportunities and risks, improved operational efficiency, effective performance monitoring and strategic planning. A typical BI workflow begins by identifying internal or external data sources [33], [34]. Followed by data source management and verification [35], transformation into a data warehouse via an extract, transform, and load (ETL) process, and finally analysis using tools such as online analytical processing (OLAP) and data mining to generate reports and multi-dimensional insights that support better business decisions [36]–[38].

2.6. Data visualization

Data visualization is a key component of BI that enables organizations to effectively communicate data-driven insights, identify patterns and trends, facilitate a better understanding of complex information, and support evidence-based and timely decision-making. Data visualization presents information through charts, diagrams, and graphics to make complex data easier to interpret and understand [39]. A related technique, forecasting, uses historical data to predict future trends and outcomes, enabling organizations to anticipate potential changes and make more informed decisions [40], [41].

3. RESEARCH METHODOLOGY

The CRISP-DM was mainly used for system design and website development. It is a standard process used in data analysis and dataset management for data mining [42] which helps discover knowledge or trends from data [43]. Its process is often used to support organizational decision-making and planning [44]. CRISP-DM has six main structural steps, i.e., business understanding, data understanding, data preparation, modeling, model evaluation, and deployment.

3.1. Business understanding

This study draws on four datasets—heart failure prediction data, clinical-variable heart disease prediction data, hospital mortality data with heart disease as the primary cause, and Framingham project case-study data—to identify the main risk factors for heart disease. These datasets were also used to address two research questions: i) which sex shows a higher observed prevalence of heart failure in the analyzed dataset, and ii) what are the key contributing factors associated with heart failure. The datasets, sourced from Kaggle [17] and covering populations in Cleveland, Hungary, Switzerland, and Long Beach, together comprise 4,927 cases collected from January 2015 to February 2020 across the 12 attributes summarized in Table 1.

3.2. Data understanding

Following the CRISP-DM framework, records with missing values in key clinical variables (age, sex, chest-pain type, resting blood pressure, cholesterol, maximum heart rate, and electrocardiographic indicators) were excluded to avoid potentially biased imputation. All 11 predictor attributes were retained, and HeartDisease was used as the binary target. Continuous variables (age, resting blood pressure, cholesterol, and maximum heart rate) were normalized, whereas categorical variables (sex, chest-pain type, resting ECG, exercise-induced angina, and ST-segment slope) were numerically encoded. No over-sampling or under-sampling was applied. The cleaned dataset was then divided into 70% training data and 30% testing data.

3.3. Modeling

Model development was performed in RapidMiner Studio using the Auto Model workflow on the prepared 4,927-case dataset. The cleaned data were divided using a stratified 70:30 train-test split, producing 3,449 training cases and 1,478 test cases. The same partition was used for the naïve Bayes, random forest, decision tree, and gradient boosted tree models to ensure a fair comparison. No over-sampling or under-sampling was applied. The exact RapidMiner Studio version, hardware configuration, and random seed were not retained in the original experimental record; consequently, the reported results correspond to the archived data partition used in this study.

3.4. Model evaluation

The four models—naïve Bayes, random forest, decision tree, and gradient boosted tree—were evaluated on the same held-out test set using accuracy, precision, recall, and F-measure derived from the confusion matrix. The stratified 70:30 split preserved the class distribution. RapidMiner Studio was used for

model training and prediction, Microsoft Excel files were used to transfer the outputs, and Microsoft Power BI Desktop was used for ETL processing, multidimensional analysis, and dashboard visualization. Future work will incorporate a fixed random seed, software-version reporting, k-fold cross-validation, receiver operating characteristic-area under the curve (ROC-AUC), precision-recall-area under the curve (PR-AUC), and external clinical datasets to strengthen reproducibility and generalizability.

3.5. Deployment

Deployment used Microsoft Power BI Desktop to build prediction dashboards from Excel-stored data via an ETL process through three main steps. The first step focuses on gathering system requirements and stakeholder needs, identifying key factors such as age, heart rate, and cholesterol from RapidMiner outputs. The second step involves system analysis and design. The last step is to build dashboard reports that let users filter by conditions such as heart-rate range, sex, and age to reveal risk trends. The system was then tested to validate real-user interactions under actual usage scenarios.

4. RESULTS AND DISCUSSION

4.1. Model selection

Four prediction models were developed in RapidMiner using 4,927 records collected from 2015 to 2020, comprising 3,155 male and 1,772 female records. A stratified 70:30 split assigned 3,449 records to training and 1,478 records to testing. The models were compared using confusion-matrix-derived measures. The decision tree was selected for detailed analysis because it achieved the highest recall and direct rule-based interpretability, while also reporting higher accuracy than the random forest. The decision-tree structure is shown in Figure 1.

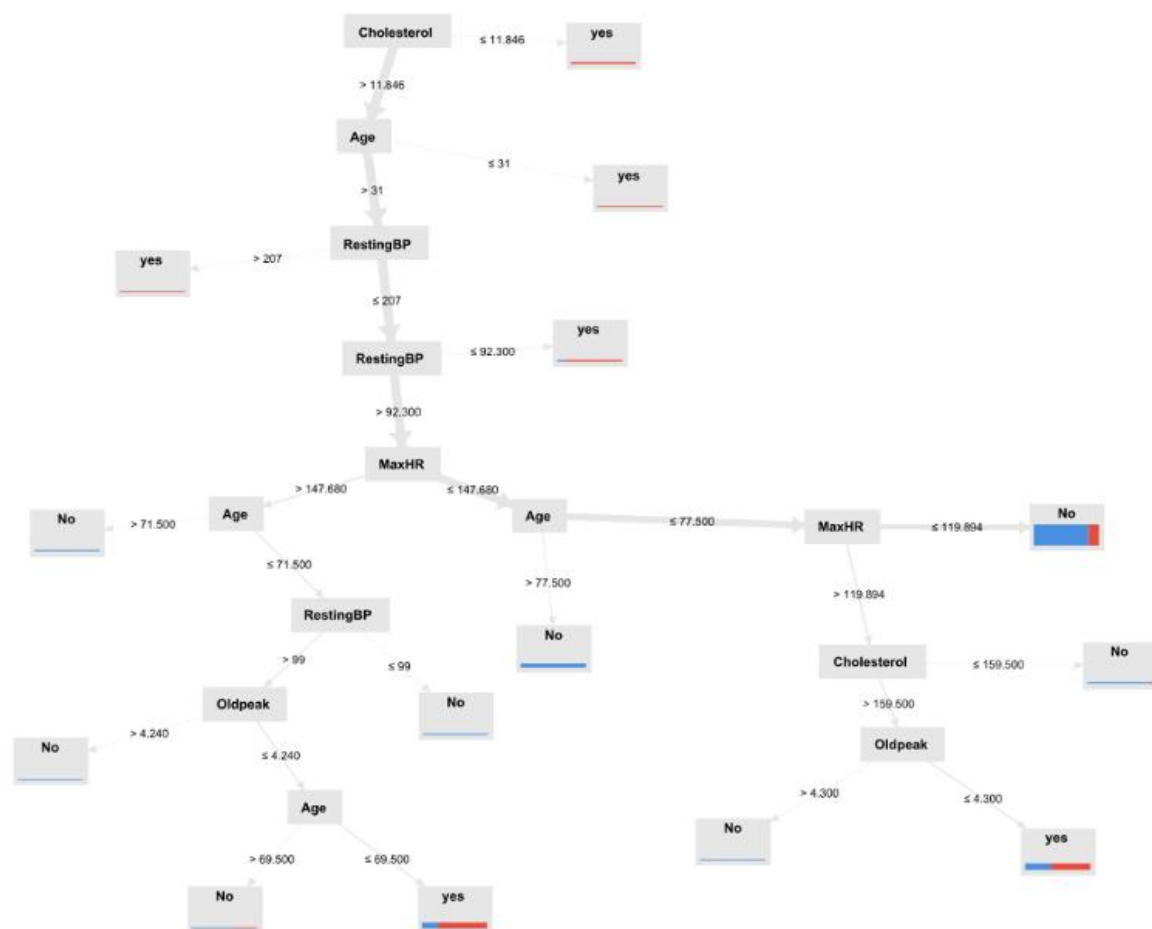


Figure 1. Decision-tree structure and rule-based paths used for heart-disease classification

In considering model efficiency based on the confusion matrix of the decision tree model, the classification results include 375 true positive (TP) cases, 816 true negative (TN) cases, 175 false positive (FP) cases, and 112 false negative (FN) cases, as shown in Table 2. These values indicate the model's ability to correctly identify both patients with CHF and those without the condition. The confusion matrix therefore provides a detailed view of classification performance and serves as the basis for calculating evaluation metrics such as accuracy, precision, recall, and F-measure.

Table 2. Confusion matrix of decision tree

Prediction	Actual negative	Actual positive
Predict negative	816	112
Predict positive	175	375

As shown in Table 2, the decision tree model achieved an accuracy of 0.8058, a precision of 0.6818, a recall of 0.7700, and an F-measure of 0.7232. The model correctly classified 375 positive cases and 816 negative cases. Overall, 1,191 of the 1,478 test cases were classified correctly, corresponding to an accuracy of 80.58% for CHF prediction.

4.2. Model efficiency analysis

A stratified 70:30 split allocated 3,449 of the 4,927 records to the training subset and 1,478 records to the testing subset. The training subset consisted of 2,181 male and 1,268 female records and was used to develop the four ML models for comparative evaluation. Model efficiency was assessed using values derived from the confusion matrix, where the decision tree model was selected based on balanced performance and interpretability, rather than relying solely on a single highest metric, as shown in Table 3.

Table 3. Results of model efficiency analysis

Model	Accuracy	Precision	Recall	F-measure
Naïve Bayes	0.7713	0.6867	0.5626	0.6185
Random forest	0.8019	0.7102	0.7146	0.7124
Decision tree	0.8058	0.6818	0.7700	0.7232
Gradient boosted tree	0.7991	0.6855	0.7207	0.7027

The decision tree model achieved an accuracy of 0.8058, a precision of 0.6818, a recall of 0.7700, and an F-measure of 0.7232, demonstrating balanced performance while maintaining clear interpretability. Based on this performance, the decision tree was selected as the final model for heart failure risk prediction. Table 4 compares the distribution of records in the training and testing subsets across selected attributes. The sex-specific summaries in subsection 4.3 show that 1,144 of 3,155 male records (36.26%) and 512 of 1,772 female records (28.89%) had heart failure.

Table 4. Distribution of records in the training and testing subsets

Attribute	Category	Training records	Testing records	Difference	Percentage
Sex	Female	1,268	504	764	60.25
	Male	2,181	974	1,207	55.34
ChestPainType	ATA	1,018	429	589	57.86
	TA	1,464	610	854	58.33
	NAP	618	155	463	74.92
	ASY	349	284	65	18.62
RestingECG	Normal	2,222	952	1,270	57.16
	ST	727	279	448	61.62
	LVH	500	247	253	50.60
ExerciseAngina	No	2,311	997	1,314	56.86
	Yes	1,138	481	657	57.73
STSlope	Flat	1,497	637	860	57.45
	Down	263	116	147	55.89
	Up	1,689	725	964	57.08

4.3. Heart failure risk prediction system using BI

The heart failure risk prediction system was implemented as a web-based platform that presents prediction reports and supporting reference data in a structured, accessible format, as shown in Figure 2. Heart failure data for 4,927 cases (January 2015 to February 2020) and RapidMiner risk-factor predictions, exported as Excel files, were imported into Power BI's ETL/OLAP pipeline to generate dashboard reports

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supporting heart failure planning. The analysis comprises two parts: data model development and dashboard report display.

The data model links internal and external sources through defined dimensions, measures, fact tables, and dimension tables in a star schema, underlying reports on heart failure probability and risk-factor predictions by sex across the five-year period, as shown in Figure 3. For the dashboard report display, analysis and presentation are divided into three parts: male, female, and combined summaries. Among 3,155 males, 1,144 had heart failure. On average, affected males were 54 years old with cholesterol 220 mg/dL, heart rate 118.6 bpm, resting blood pressure 132.98 mmHg, and mean ST-segment depression (Oldpeak) of 1.15 mV (moderately abnormal). Resting ECG was normal in 59.97% (686 cases), abnormal (ST) in 25% (286), and showed left ventricular hypertrophy in 15.03% (172); ST slope was upward in 48.43% (554), flat in 45.28% (518), and downward in 6.24% (72); chest pain was typical angina in 44.84% (513), atypical angina in 21.15% (242), non-anginal in 22.55% (258), and asymptomatic in 11.45% (131); and exercise-induced chest pain occurred in 39.16% (448) of cases.

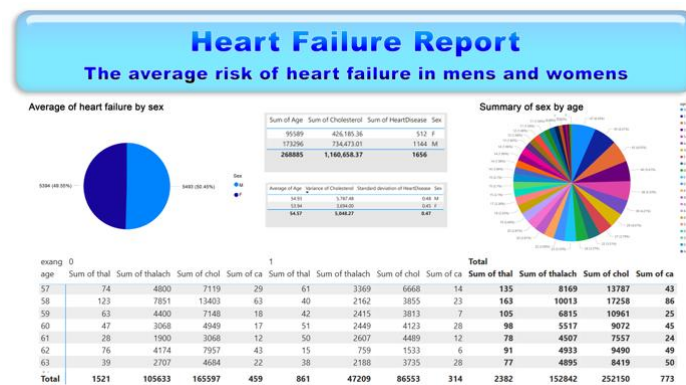


Figure 2. Summary of CHF report

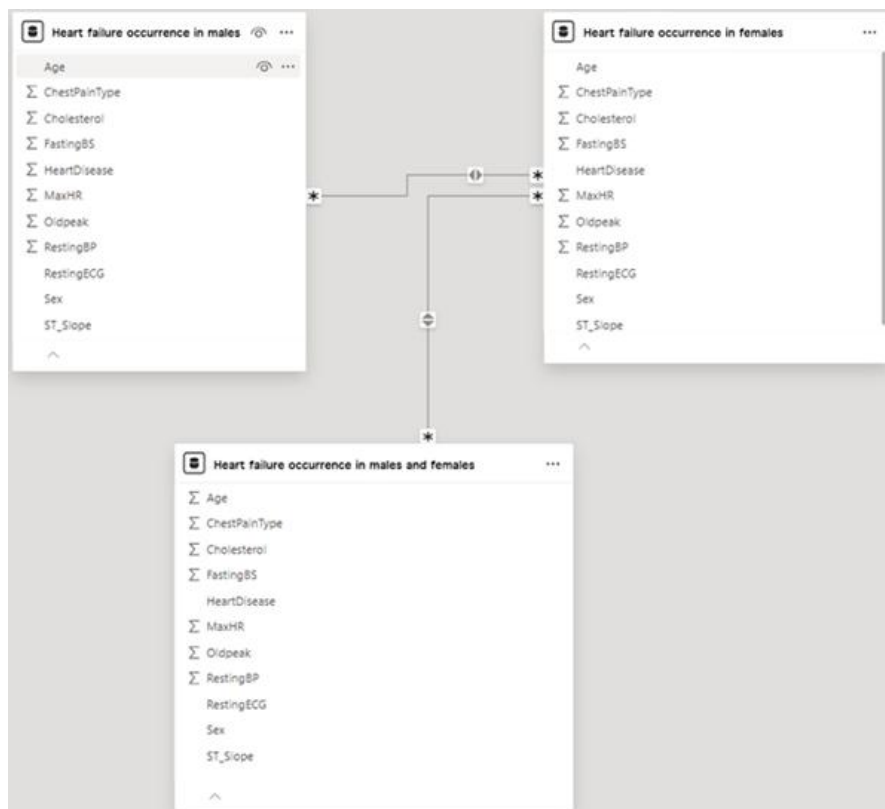


Figure 3. Star schema report presenting prediction of heart failure risk factors

Among 1,772 females, 512 had heart failure. Affected females averaged 55 years old with cholesterol 248 mg/dL, heart rate 118.6 bpm, resting blood pressure 132.98 mmHg, and mean ST-segment depression (Oldpeak) of 1.03 mV. Resting ECG was normal in 65.82% (337), abnormal in 15.82% (81), and showed LVH in 18.36% (94); ST slope was upward in 53.52% (274), flat in 39.84% (204), and downward in 6.64% (34); chest pain was typical angina in 41.99% (215), atypical angina in 25.78% (132), non-anginal in 18.75% (96), and asymptomatic in 13.48% (69); and exercise-induced chest pain occurred in 34.18% (175) of cases. Combining both sexes (1,656 patients: 69.08% male and 30.92% female), the overall profile averaged 54 years and a cholesterol level of 229 mg/dL. Resting ECG was normal in 61.78% (1,023); ST slope was upward in 50% (828), flat in 43.6% (722), downward in 6.4% (106); chest pain was typical angina in 43.96% (728), atypical angina in 22.58% (374), non-anginal in 21.38% (354), asymptomatic in 12.08% (200); and exercise-induced chest pain occurred in 37.62% (623) of cases, consistent with the sex-specific patterns above. Full breakdowns are shown in Figure 4, where Figure 4(a) shows the male heart failure report, (b) female heart failure report, and (c) prediction report of all patients.

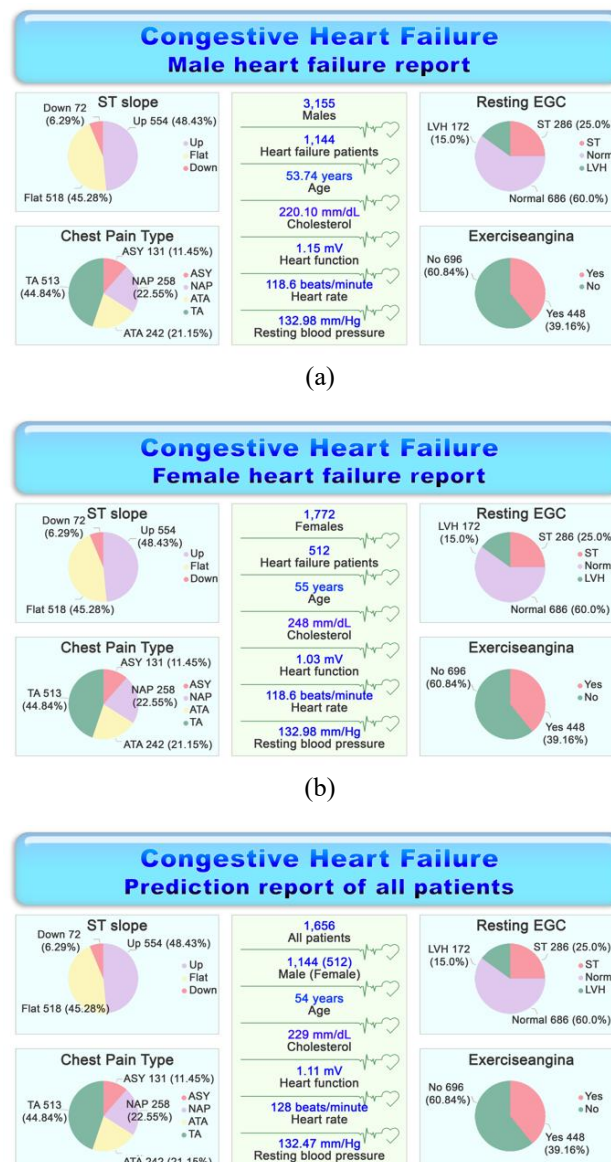


Figure 4. CHF report of (a) male heart failure, (b) female heart failure, and (c) prediction of all patients

4.4. Model interpretability and clinical implications

The training process involved developing and comparing four supervised ML models—decision tree, random forest, gradient boosted trees, and naïve Bayes—using confusion matrix-based performance

evaluation, after which the decision tree model was selected as the final prediction model based on balanced performance and interpretability. This finding is consistent with previous studies emphasizing that model selection in clinical ML should consider not only predictive performance but also interpretability and the ability to explain predictions to healthcare practitioners [11], [12], [15]. The sex-specific summaries show a higher observed prevalence of heart failure among males (1,144/3,155; 36.26%) than females (512/1,772; 28.89%) in the analyzed dataset. While the proposed approach supports timely risk analysis and promotes practical understanding of heart failure in daily healthcare contexts, potential limitations related to data quality highlight the need for regularly updated datasets and further studies to enhance predictive accuracy and clinical applicability. While the proposed framework demonstrates balanced performance and interpretability, further evaluation using ROC-AUC, PR-AUC, k-fold cross-validation, statistical significance testing, and independent external datasets is required to establish model robustness and generalizability more comprehensively [12], [13].

4.5. Discussion

The training process involved developing and comparing four supervised ML models—decision tree, random forest, gradient boosted trees, and naïve Bayes—using confusion matrix-based performance evaluation, after which the decision tree model was selected as the final prediction model based on balanced performance and interpretability. The sex-specific summaries show a higher observed prevalence of heart failure among males (1,144/3,155; 36.26%) than females (512/1,772; 28.89%) in the analyzed dataset. While the proposed approach supports timely risk analysis and promotes practical understanding of heart failure in daily healthcare contexts, potential limitations related to data quality highlight the need for regularly updated datasets and further studies to enhance predictive accuracy and clinical applicability. While the proposed framework demonstrates balanced performance and interpretability, further evaluation using ROC-AUC, PR-AUC, k-fold cross-validation, and statistical significance testing across multiple datasets is required to fully establish model robustness and external validity.

5. CONCLUSION

This study investigated heart failure risk prediction by evaluating model efficiency using accuracy, precision, recall, and F-measure derived from confusion matrix analysis implemented in the RapidMiner environment. Four supervised ML models—decision tree, random forest, gradient boosted trees, and naïve Bayes—were trained and compared using the auto model approach, and the results demonstrated that the decision tree model achieved the most balanced overall performance, leading to its selection as the final prediction model. In addition to model comparison, the sex-specific summaries showed a higher observed prevalence of heart failure among males (36.26%) than females (28.89%) in the analyzed dataset, while the developed web-based prediction system enhanced accessibility through browser-based platforms.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Siranee Nuchitprasitchai		✓		✓	✓				✓	✓	✓			
Yuenyong Nilsiam	✓			✓		✓			✓	✓		✓		✓

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**ding

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available on Kaggle, as referenced in [17].

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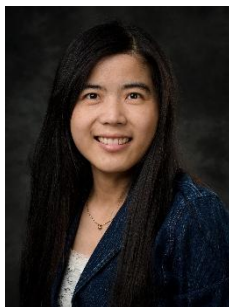
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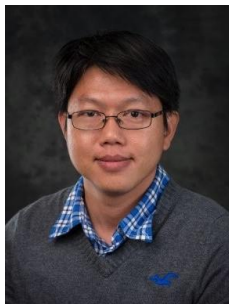
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