A Comprehensive Review with Comparative Analysis of Optimization-Driven Frameworks for Sustainable Heart Disease Prediction

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Abstract: Cardiovascular diseases (CVDs) cause over 17.9 million fatalities a year, early and precise prediction is essential for long-term healthcare systems. We conduct a review and provide a comparative analysis across algorithmic methodology, mathematical formulation, and quantitative performance with respect to sensitivity, accuracy, Area Under the Curve (AUC) specificity, F1-score, and precision. Machine learning (ML) and deep learning (DL) techniques have developed as revolutionary tools for heart disease risk stratification. In order to provide a framework for long-term heart disease prediction, our summary for the literature review aims to pinpoint the main research gaps. These results highlight the suggested Synergistic Fibroblast Optimization with Channel Attention and Multilayer Perceptron's scientific novelty and therapeutic applicability. (SFO-CAtt-MLP) framework and provide a path forward for sustainable, AI-driven cardiology research

Keywords: cardiovascular risk stratification, explainable AI, SMOTE, SHAP, synergistic fibroblast optimization, channel attention, heart disease prediction, and sustainable healthcare

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Introduction

With a predictable 17.9 million deaths per annum [1] and a disproportionate impact on low- and middle-income health systems, cardiovascular disease remains to be the foremost cause of death worldwide [2]. As health systems throughout the world shift toward sustainability, preventative treatment, and resource-efficient digital transformation, the clinical need for early, accurate, and economical prediction of cardiac disease has never been greater [3,4]. In settings with limited resources, traditional diagnostic routes that rely on coronary angiography, echocardiography, and expert consultation are expensive, time-consuming, and unavailable [5].

A new paradigm with machine learning and deep learning models that can predict cardiac events with accuracy comparable to that of skilled cardiologists [4,7,8]. Because these models were trained using electronic health records (EHRs), multi-lead electrocardiograms (ECGs), and multi-modal bio signals, they have the potential to decentralize cardiac diagnosis, reduce unnecessary invasive procedures, and improve population-level early screening [3,10].

However, the literature has significant gaps and methodological variations [4, 8]. The dataset provenance, preprocessing rigor, feature engineering strategy, model architecture, cross-validation technique, and interpretability presented by the research differ greatly. A key unsolved issue is explainability, which prevents high-accuracy black-box models from being used in clinical settings since clinicians are unable to

analyze their decision-making processes [11]. Class imbalance is a prevalent issue in clinical datasets with underrepresented problematic patients, which is frequently acknowledged but not adequately handled

Related work

This study applies a systematic methodology customized for a technical survey. The dataset consist of feature engineering technique, ML/DL methodology, mathematical formulation, performance metrics (sensitivity, accuracy, specificity, precision, AUC, F1-score), explainability provided, deployment strategy. This corpus was used to analyze the base article SFO-CAtt-MLP.

Traditional Machine Learning Approaches for Heart Disease Prediction

Gradient Boosting and Explainability

XG Boost gradient boosting and SHAP (SHapley Additive exPlanations) were implemented by Ryu, Hagyeong [3] to predict heart failure on MIMIC-III with an accuracy of 91.8% (AUC = 0.938). Equation 3 provides the XG Boost forecast.

$$\hat{y}^m = \hat{y}^{m-1} + \eta \cdot f_{m(x)}, \qquad f_m = arg\, min_f \Sigma_i L\left(y_i, \hat{y}_i^{m-1} + f(x_i)\right) \tag{1}$$

where L is the loss function, f_m is the m^{th} tree, and η is the learning rate [3]. Despite using SHAP, 3. Ryu, Hagyeong et al. [3] produce misleading sensitivity estimates because they ignore class imbalance in the MIMIC-III dataset, which has a heart failure prevalence of almost 14%.

Explainability, Fairness, and Imbalance Handling

SHAP-Based Interpretability

By calculating Shapley values, the SHAP framework, which is based on cooperative game theory, divides the prediction of a model f(x) among its input features For feature I, the SHAP value is:

$$\varphi_i = \sum\{S \subseteq F\backslash\{i\}\} \frac{[|S|!\,(|F| - |S| - 1)!}{|F|!} \,.\, [f(S \cup \{i\}) - f(S)] \tag{2}$$

where *f(S)* is the model output using just features in S, S is a subset that does not include feature i, and F is the whole feature collection.

SMOTE and Class Imbalance

Class imbalance, in which the number of positive (disease) instances is significantly lower than the number of negative cases, masks low sensitivity while inflating accuracy. In order to overcome this, SMOTE creates artificial minority-class samples along feature-space line segments [11]:

$$x_{new} = x_i + \lambda \cdot (\tilde{x} - x_i), \qquad \lambda \sim Uniform[0, 1] \tag{3}$$

Where $\tilde{x}$ is one of its *k* closest neighbours and x_i is a minority sample. On the Cleveland dataset, Latha and Jeeva [1] demonstrate that SMOTE boosts sensitivity from 84.1% to 91.2% without correspondingly raising false positives. By extending SMOTE with a conditional GAN generator (cGAN-SMOTE), Chen et al. [8] reduce overfit on minority-class borders and generate more realistic synthetic ECG feature distributions. While acknowledging SMOTE's drawback of producing noisy data when minority class clusters are scarce, Krawczyk and Haixiang et al. offer systematic assessments validating SMOTE as the most successful and extensively proven imbalance technique in cardiovascular machine learning.

Comparative Analysis: Methods, Performance, and Mathematical Modelling

In addition to the suggested SFO-CAtt-MLP framework, Table 1 shows a cross-study comparative analysis of eight exemplary research selected from this evaluation. Techniques range from transformer-based designs to classical ensembles; performance is provided on the main test set.

Table 1. Comparative Analysis of Selected Heart Disease Prediction Studies (2024–2025)

Study / Year	Dataset	Method	Accuracy (%)	AUC	Key Gap
Latha & Jeeva (2024) [1]	UCI Cleveland	RF + SMOTE	92.4	0.946	No explainability
Najia, Mechichi, and Benzarti Faouzi [6]	MIT-BIH arrhythmia	CNN-BiLSTM	93.1	0.951	Limited scalability
Wu, Zhenyan [9]	PhysioNet ECG	DL-ECG	94.7	0.963	ECG-only, no tabular
Inekwe, Trusting [10]	Multi-centre EHR	Transformer	93.9	0.956	Black-box, no XAI
Proposed SFO-CAtt-MLP	Combined Public	DL + Attention + SFO + SHAP	≥ 95.0	≥ 0.970	—

Table 2 allows readers to readily compare theoretical formulations by providing mathematical modeling of each fundamental method or element that appears in or contributes to the evaluated literature.

Table 2. Mathematical Formulation of Core Algorithms and Components

Algorithm	Core Formula / Equation	Role in Pipeline
SMOTE	$x\_new = x\_i + \lambda(\tilde{x} - x\_i), \quad \lambda \sim U[0,1]$	Synthetic minority oversampling to balance class distribution
SFO Feature Selection	$f\_score(j) = \Sigma\_i\,[w\_i \cdot \lvert r(x\_j, y\_i)\rvert] \,/\, \sigma\_j$	Selects discriminative features guided by fibroblast-inspired optimization
Channel Attention (SE)	$a = \sigma(W\_2 \cdot \delta(W\_1 \cdot GAP(F))), \quad F = a \otimes F$	Recalibrates feature channels; highlights cardiac-relevant signals
MLP Forward Pass	$h\hat{}(l) = \varphi(W\hat{}(l)\, h\hat{}(l-1) + b\hat{}(l))$	Hierarchical non-linear feature transformation for classification
Cross-Entropy Loss	$L = -(1/N)\Sigma\_n\,[y\_n \log \hat{y}\_n + (1 - y\_n)\log(1 - \hat{y}\_n)]$	Optimises binary heart-disease classification objective
SHAP	$\varphi_i = \sum\{S \subseteq F\backslash\{i\}\} \frac{[\lvert S\rvert!\,(\lvert F\rvert - \lvert S\rvert - 1)!}{\lvert F\rvert!}\,.\,[f(S \cup \{i\}) - f(S)]$	Assigns feature importance scores for explainable AI transparency
Adam Optimizer	$\theta\_t = \theta\_\{t-1\} - \alpha\, \hat{m}\_t \,/\, (\sqrt{\hat{v}\_t} + \varepsilon)$	Adaptive learning-rate optimisation for stable DL convergence

A quantitative performance comparison of the main models under consideration across seven parameters is shown in Table 3.

Table 3. Quantitative Performance Comparison Across Key Metrics

Method [Ref]	Acc. (%)	Sens. (%)	Spec. (%)	Prec. (%)	F1 (%)	AUC
RF+SMOTE [1]	92.4	91.2	93.1	91.8	91.5	0.946
CNN-BiLSTM [6]	93.1	92.3	93.8	92.7	92.5	0.951
CNN-Dense [7]	94.7	93.9	95.2	94.3	94.1	0.963
SFO-CAtt-MLP	≥95.0	≥94.5	≥95.3	≥94.8	≥94.7	≥0.97

Analysis of the Proposed SFO-CAtt-MLP Framework

Synergistic Fibroblast Optimisation (SFO) for Feature Selection

The SFO algorithm is a bio-inspired population-based metaheuristic that models the cooperative behaviour of fibroblasts in wound healing. In the context of feature selection, each fibroblast agent represents a candidate feature subset, and the population iteratively evolves toward subsets that maximise a fitness function combining classification accuracy and feature economy. The feature importance score under SFO is:

$$f_{score(j)} = \frac{\Sigma_i [w_i \cdot |r(x_j, y_i)|]}{\sigma_j} \quad (4)$$

where $r(x\_j, y\_i)$ is the Pearson correlation between feature j and class label i, σ_j is the feature's standard deviation, and w_i are class weights . Kumar and Verma demonstrate that SFO outperforms The advantage of evolutionary and swarm-based feature selection over filter-only approaches in high-dimensional clinical data is complete.

Discussion

This research demonstrates that a deep survey on a Review with Comparative Analysis of Optimization-Driven Frameworks for Sustainable Heart Disease Prediction and also highlights on the optimization-driven, explainable deep learning is the most promising approach for equitable, scalable, and sustainable cardiac disease prediction in contemporary digital health systems.

Conclusion

Thirty high-impact, peer-reviewed articles on machine learning and deep learning for heart disease prediction have been included in this systematic review, which also compares technique, mathematical formulation, and performance indicators.

The research shows a clear hierarchy: unstructured deep networks and traditional ML ensembles are outperformed by attention-augmented deep learning pipelines with strict preprocessing and explainability methods.

The six main shortcomings found in this study are addressed methodologically by the base paper's SFO-CAtt-MLP system, which integrates SFO feature selection, channel attention, MLP classification, SMOTE balance, SHAP explainability, and mobile deployment.

The outstanding concerns of federated learning for privacy-preserving multi-site training, prospective clinical validation, GAN-augmented oversampling, and deeper counterfactual explainability characterize the frontier of sustainable cardiovascular AI.

Future research should prioritize clinical co-design, regulatory alignment, and real-world deployment studies in order to bridge the gap between benchmark performance and meaningful therapeutic effect.

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