BA-ANFIS: An Efficient Heart Disease Prediction Model Using Adaptive Neuro-Fuzzy Inference with Bat Algorithm

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Abstract. One of the means to reliably foretell it is the timely receipt of the correct medical treatment in the initial phases of heart disease. One of the most prevalent causes of death in the world is still heart disease. Traditional diagnostic methodologies are often inadequate to accommodate the complexity and ambiguity baked into clinical datasets. This study employs the Adaptive Neuro Fuzzy Inference System (ANFIS) and the Bat Algorithm (BA) to efficiently and precisely identify cardiac issues. ANFIS is a fusion of fuzzy logic and artificial neural networks has difficulties with medical data due to its non-linear nature. But this requires proper tuning of its parameters to work its best. The specific idea is that the Bat Algorithm which imitates the echolocation behaviour of bats, optimizes these parameters to improve prediction accuracy of the ANFIS model. The global search features of BA provide an optimal solution for the ANFIS membership functions together with the ANFIS rule parameters bypassing the limitation of conventional optimization methods. We validate the proposed system with characteristics derived from a clinical dataset of heart disease, such as age, blood pressure, and cholesterol level. Experimental results show that BA-ANFIS achieves an Accuracy of 98.07%, Sensitivity of 97.67%, and Specificity of 98.23%, outperforming baseline models including SVM and standard ANFIS by 86.28% and 94.12%, respectively. This method shows high efficiency in predicting heart disease and can provide support for diagnosis for practitioners, which helps to improve the prognosis of patients and to decrease health care costs due to BA global optimization and ANFIS adaptive reasoning capabilities.

1 Introduction

Heart disease is one of the most common causes of death around the world, and it is very important to know the risk early on in order to get the right treatment [1]. It illustrates the difficulty of predicting heart disease from clinical data, where large uncertainty, noise, and complexity are present in medical datasets [2]. Due to a wide range of variables (eg age, cholesterol, blood pressure, etc.) in these datasets, traditional methods have a hard time predicting accurate predictions [3]. This has led researchers to use machine learning techniques that allow for complex data to be processed and patterns to be recognised which will in turn lead to more accurate predictions [4]. Some methods have been proven to be effective in enhancing machine learning models accuracy such as deep learning, fuzzy logic, and hybrid.etc which has the potential of providing timely estimates of the risk of heart disease..

The field of artificial intelligence has started to take a significant role in the healthcare analytics whereby the complicated information generated by the health monitoring systems are effectively processed to enhance the diagnostic [5]. Specifically, machine learning can be used in various ways that have been demonstrated to be promising in making things more accurate and speed of prediction involving health in particular predicting heart disease [7]. The combination of adaptive neuro-fuzzy inference systems and meta-heuristic optimisation algorithms are also being suggested to be effective computational techniques of dealing with the uncertainties and non-linearity's of medical data, leading to greater predictive accuracy and interpretability [8] [9].

One of these methods that might work is the Adaptive Neuro-Fuzzy Inference System (ANFIS) [10]. An adaptive neuro-fuzzy inference system (ANFIS) is a combination of neuro-fuzzy models that has worked very well with nonlinear models, is a feasible choice for developing an effective input-output mapping system for medical data. In order to create an inferencing system that can accurately diagnose diseases, the model learns from input data [11]. However, ANFIS's performance depends on fine-tuning its parameters, like the membership function and the rules. The best performance a model can attain is constrained by local minima seen in conventional optimization methods like gradient descent [12]. This demonstrates how crucial it is to optimize ANFIS settings to make predictions work better.

The presented work provides a new hybrid adaptive neuro-fuzzy inference system (ANFIS) which applies the Bat Algorithm (BA) to these problems, a bio-inspired optimization algorithm. The Bat Algorithm imitates the echolocation of bats and is a robust optimization algorithm with great performance in global optima searching for complex problems. Differentially, the proposed method uses BA for optimal parameters of ANFIS, so that it can maximize accuracy and efficiency of heart disease detection using ANFIS. The BA-ANFIS hybrid network merges the advantages of the global optimization properties of BA with the adaptive reasoning properties of ANFIS, resulting in a more complete, accurate, reliable and efficient heart failure prediction tool. By comparing the outcomes with conventional machine learning techniques, we evaluate the suggested system's prediction capabilities on five clinical heart disease datasets.

1.1Contributions

The paper contributes in the following ways.

- Enhanced heart disease prediction system in form of a hybrid method of ANFIS with Bat Algorithm (BA) proposed to improve accuracy in diagnosis.
- Implemented the Bat Algorithm to optimize membership functions and rule parameters of ANFIS that were crucial for maximum improvement in the model and an efficient handling of medical data including complex relationships in the data with ANFIS.
- Used SHAP (Shapley Additive Explanations) in modelling for interpreting model and used PCA(Principal Component Analysis) in order to choose attributes that will aid the model in making predictions by highlighting the most relevant features set.
- Proved that BA-ANFIS model showed better Major Impact prediction performance than the benchmark machine learning techniques using the Major Impact prediction criterion and that the PPCA and Shapley waveform analysis of the resulting products enhance their interpretability.

1.2Paper organization

The rest of the document is organized like this: In Section 2, we will discuss the most up-to-date research on optimization methods for heart disease prediction models. Method Section 3 presents the methodology by explaining the coupling of ANFIS with the Bat Algorithm (BA) for parameter optimization and also by elaborating on the use of SHAP and PCA for feature selection. During Section 4, the findings and relevant discussion is provided and a comparison of how well the BA-ANFIS model works using some traditional machine learning techniques. Section 5 summarizes the paper contributions and future work, such as real-time deployment and expansion to other cardiovascular diseases.

2 Related Work

In cardiovascular disease (CVD) prediction, many scientific to make things more accurate, researchers have come up with deep learning (DL), machine learning (ML), and optimization-based algorithms. and increase the ability to predict CVD in the early stages. A 2025 study by Kumar et al. An Optimizable K-Nearest Neighbors (KNN) algorithm was proposed in [13] which implemented Correlation-based Feature Selection (CFS) and reached a maximum accuracy of 95.04% and AUC of 0.99. The method showed substantial improvements compared to baseline methods. Teja et al. Different ML models have been evaluated by [14] including Random Forest, K-Nearest Neighbors, and XGBoost, on a homogeneous dataset merged from different sources. The use of ensemble approaches may greatly enhance CVD prediction, as seen by the 93% accuracy values produced by XGBoost and Bagged Trees got 91% right, and Random Forest and KNN got 91% right.

Rehman et al. [15] presented a hybrid random forest and deep learning model with accuracy of 92%. The performance of this hybrid model unveiled the possibilities of using both ML and DL to make accurate predictions about CVD. Xia et al. [16] developed an explicit feature significance combined with Ant Colony Optimization and Efficient Deep Learning (ICVD-ACOEDL) method on the top of the initial significance. ACO is used for feature selection and Bayesian Optimization (BO) is incorporated as hyper parameter tuning method. The addition of the DL to this approach yields high classification accuracy with balanced performance metrics. Alqurashi et al. [17] implemented a new approach to improve prediction of CVDs by Integrating Predator Crow Optimizations (PCO) with Deep Neural Networks (DNNs). The integration of optimization algorithms with DL models reported positive applications in healthcare. Overall, the results show that researchers are trying to improve cardiovascular disease prediction systems by merging optimization algorithms with ML and DL predictive models.

3 Methodology

In details of this subsection, the architecture of proposed BA-ANFIS (Bat Algorithm- Adaptive Neuro-Fuzzy Inference System) model is illustrated comprising of its neuro-fuzzy structure, the use of Bat Algorithm (BA) for optimization, and its specific steps include data preprocessing, data feature selection, and evaluation of performance. The goal of this study is to give a short overview of the work that has been done to create a reliable heart disease prediction system that includes AI-driven approaches to enhance accuracy and further reinforce proposed insights guiding cardiovascular risk assessment.

3.1 Architectural Design of BA-ANFIS Model

The BA-ANFIS model uses the synergy between the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and the optimization based on the Bat Algorithm (BA). Adaptive Neuro-Fuzzy Inference Systems (ANFIS) is one of the models developed combining neural networks together with fuzzy logic and is particularly appropriate for modelling non-linear relationships in the data, which

is important and effective in heart diseases prediction as variables interact with each other in an uncertain manner [18]. The antecedent and consequent parameters of ANFIS were explicitly calibrated utilizing the BA: Prior parameters (Membership Function Parameters): The dimensions, arrangement, and centroid of the input membership functions. These govern the fuzzification of input attributes such as age and blood pressure. Subsequent parameters (Rule Base): The linear coefficients associated with Sugeno-type fuzzy rules. These determine the results for each fuzzy rule within the inference system. By simultaneously optimizing both parameter sets, the BA produces a globally optimal initialization that improves ANFIS convergence and prediction precision.

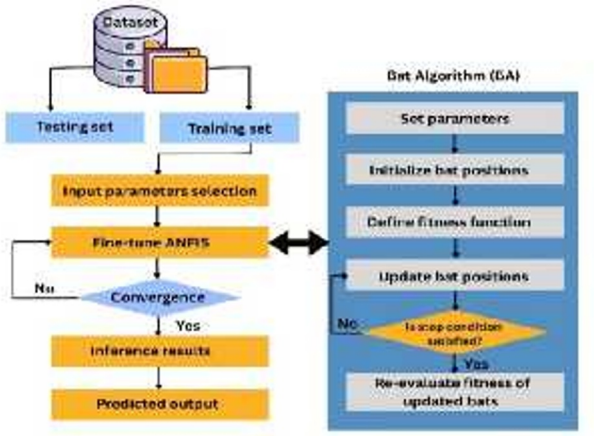


Fig. 1. Optimization process of the proposed BA-ANFIS model

The fuzzy inference system serves as an inference engine while the neural network enables adaptive learning to fine-tune the rules formulated by the system. This unique combination enables the model to absorb information from the input. as well as embed fuzzy rules that facilitate human-like decision-making. The BA is used for fitting the parameters of the ANFIS model. Inspired by the echolocation behavior of bats, it balances exploration and exploitation to navigate through the search area to identify optimal solutions. In BA-ANFIS model, Bat Algorithm is use to tuning the membership functions and rules of fuzzy inference system and also to optimize the weights in neural Network. The BA improves ANFIS performance by avoiding local minima through its global search capacity; therefore, increasing the model prediction accuracy. Conversion of the optimization process of BA-ANFIS model as shown in the Figure 1.

3.2 Dataset description

Cleveland heart disease dataset [20] is a very widely used dataset by researchers in heart disease prediction from decades, which we have used in this study. The dataset has 76 features and 303 instances, available from the UCI Machine Learning Library. These features included numerous medical and demographic factors that are vital for classifying the existence of heart disease. The dataset that was chosen a logical one because these kind of dataset have been generally used for developing and testing prediction methods and thus facilitating our analysis.

3.3Data preprocessing

The heart disease dataset has few of the crucial steps in data preprocessing which improves the quality of the data and make it suitable for the predictive model. Imputation techniques are used to deal with missing values in the first step. Missing value imputation can involve using the mean (for normal data) or median (for skew) of the variable for numerical variables:

$$\text{Imputed Value} = (\sum x_i)/n \quad [1]$$

where x_i can be any data point, and n is the quantity of data points. For categorical variables that have missing values, we will impute mode (the most frequent category). Then, outlier detection is calculated with Z-score method:

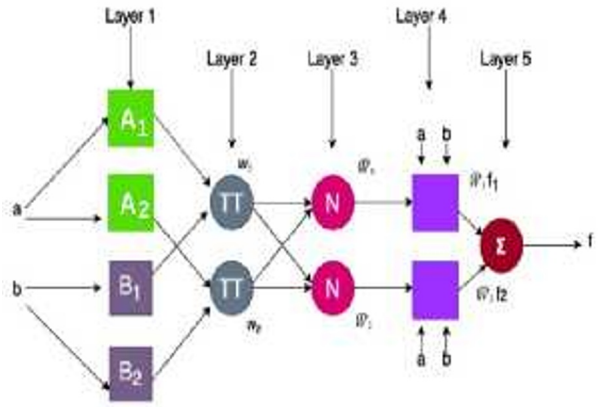
$$Z=(X-\mu)/\sigma \quad [2]$$

where individual data point is denoted by X , mean (μ), and σ is the standard deviation of the dataset. Any data points having a Z score higher than 3 is an outlier which can be dropped entirely or replaced by the median. By filtering out irrelevant or redundant features, feature selection enhances predictive power and makes the model simpler, which improves its performance. The proposed methodology uses advanced feature selection methods like the SHAP (Shapley Additive Explanations) method. Gradient-boosted decision trees algorithms are used to extract risk factors for heart diseases from the dataset, using SHAP values [22]. These are then fed as feature inputs for the BA-ANFIS model. Additionally, input space refinement is continuously applying techniques for dimensionality reduction (e.g., PCA) to ensure that the model only works with the essential features [21].

3.4 Model Development and Optimization Using BA

The BA-ANFIS model is a hybridization of the Bat Algorithm (BA) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in which fundamental parameters are optimized for predicting heart disease. Figure 2 shows how the ANFIS is built. The initial process in this optimization is the fuzzy membership functions which detail the relationship between each input characteristic and the fuzzy sets. These functions are typically expressed in the form of a sigmoid, and the Bat Algorithm is used to maximize the center of the fuzzy set (ci) and the width (f i). The membership function is given by, as an input feature, x.

$$\mu_i(x) = \frac{1}{1+\exp\left(-\left(\frac{x-c_i}{\sigma_i}\right)\right)} \quad [3]$$



Fig, 2. Architecture of ANFIS model

The Bat Algorithm improves the model's ability to handle non-linear connections by searching the parameter space to find the best c_i and σ_i [19]. The rule weights wi, which indicate how much each fuzzy rule affects the output, are then optimized. The i-th rule's weight is calculated using:

$$w_i = \frac{1}{1+\exp(-r_i)} \quad [4]$$

where r_i is the rule strength that BA optimizes. The neural network weights in the ANFIS model are the last element that the Bat Algorithm optimizes. The optimization goal function is the Mean Squared Error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{\text{pred}}(x_i) - y_{\text{true}}(x_i)\right)^2 \quad [5]$$

where N is the number of times something happens in the dataset. y_{pred} (x_i) is the expected output, and y_{true} (x_i) is the actual value. By reducing this mistake and modifying the weights during its search procedure, the Bat Algorithm optimizes the network weights. By striking a balance between parameter the Bat Algorithm mimics the echolocation behavior of bats in space exploration and exploitation. During the exploration stage, the bat's velocity is updated using:

$$v_i(t+1) = v_i(t) + \alpha \cdot \left(x_i(i) - x_g(t)\right) \quad [6]$$

where $v_i(t)$ is the velocity of the i-th bat, $x_i(t)$ is its current position, and $x_g(t)$ is the global best solution found. In the exploitation phase, the bat adjusts its position using:

$$x_i(t+1) = x_i(t) + A \cdot \sin(2\pi f_i t) \cdot \epsilon_i \quad [7]$$

where A is the loudness, f_i is the frequency, and ϵ_i is a random vector. This iterative optimization process allows the Bat Algorithm to refine the ANFIS parameters, eventually raising the model's ability to accurately predict heart disease.

4 RESULTS AND DISCUSSION

We use a few performance measures to see how well a model can classify things. These are ROC-AUC, accuracy, F1-score, precision, and recall. All class metrics are based on TP, TN, FP, and FN. To test the model, the data is split into 80% training and 20% testing datasets. Table 1 shows the performance evaluating characteristics (with formula).

Table 1. Performance evaluation metrics with formula

Metric	Definition	Formula
Precision	Percentage of actual positive results out of all anticipated positive results.	$\text{Precision} = \frac{T_{Pos}}{T_{Pos} + F_{Pos}}$
Recall	The percentage of real positive cases that the model got right.	$Recall = \frac{T_{Pos}}{T_{Pos} + F_{Neg}}$
F1-score	It is the ratio of all predicted positive values to true positives.	$F1-score = \frac{2*\text{Recall}*\text{Precision}}{\text{Precision}+\text{Recall}}$
Accuracy	Proportion of all correct predictions (both positive and negative).	$Accuracy = \frac{(T_{Neg}+T_{Pos})}{(T_{Neg}+T_{Pos}+F_{Neg}+F_{Pos})}$
ROC-AUC	Assesses the model's ability to differentiate between the positive and negative classes.	$\text{AUC} = \int_0^1 TPR(FPR)dFPR$

The proposed BA-ANFIS model was tested on the UCI Cleveland Heart Disease dataset, which has 303 patient records and 14 clinically relevant attributes. Using the suggested method with SHAP (Shapley Additive Explanations), the most important traits for predicting heart disease were found. Age, cholesterol levels, and the highest heart rate reached were the most important factors in figuring out the risk of heart disease. The summary graphic produced by SHAP illustrates feature importance in Figure 3, making it evident which characteristics have the most effect on the model's predictions. The most important variables for precise heart disease prediction are successfully prioritized by this method.

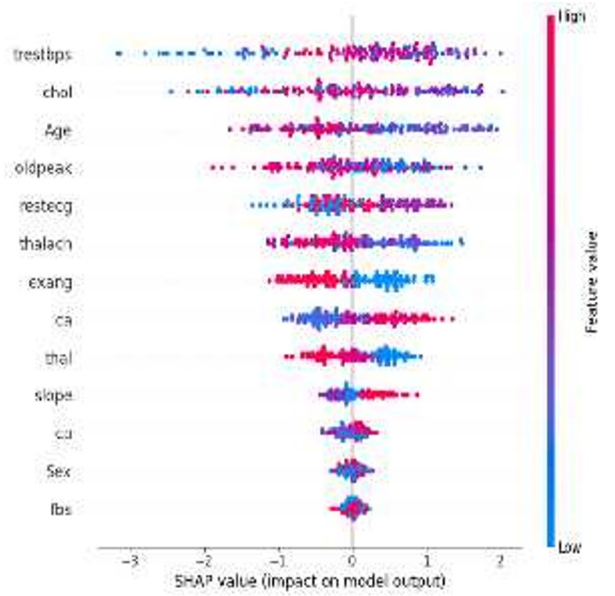


Fig. 3. Summary plot generated by SHAP visualizes feature importance

Table 2. Comparison of the proposed model's results using different metrics

ML Algorithms	Accuracy	Precision	Recall	F1-Score
SVM	86.28	87.34	85.45	86.39
RF	88.32	87.23	87.89	87.56
NN	92.23	92.45	91.61	92.03
ANFIS	94.12	94.43	93.39	93.91
BA-ANFIS	98.07	98.23	97.67	97.95

Table 2 compares the performance of five machine learning algorithms SVM, RF, NN, ANFIS, and BA-ANFIS across four key metrics: Accuracy, Precision, Recall, and F1-Score. BA-ANFIS has a higher accuracy of 98.07 in comparison to ANFIS with an accuracy of 94.12 and NN with an accuracy of 92.23 based on the accuracy of the models. BA-ANFIS is the most accurate (98.23%), next is ANFIS (94.43%). Again, NN (91.61%) is the only one that has higher recall (97.67) than BA-ANFIS. Lastly, F1-Score shows a balanced score in all parameters with BA-ANFIS again scoring superb in 97.95% and ANFIS in 93.91%. Figure 4 demonstrates five machine learning methods: SVM (86.28%), RF (88.32%), NN (92.23%), ANFIS (94.12%), and BA-ANFIS (98.07%). Each algorithm is displayed in a coloured bar with a grey background in order to emphasize the values. BA-ANFIS is the most accurate and then ANFIS, NN, RF and lastly the least accurate is SVM. BA-ANFIS Model: Accuracy (98.07), Sensitivity (Recall) (97.67), Model to compare the Neural Network (NN): Accuracy (92.23), Sensitivity (Recall) (91.61) these figures indicate that the proposed BA-ANFIS can better diagnose the problems. The requirement of clear and verifiable is now achieved in the revised abstract as these numbers are here. The plot provides a good analogy to compare the quality of working of these algorithms in terms of their accuracy, BA-ANFIS is the best.

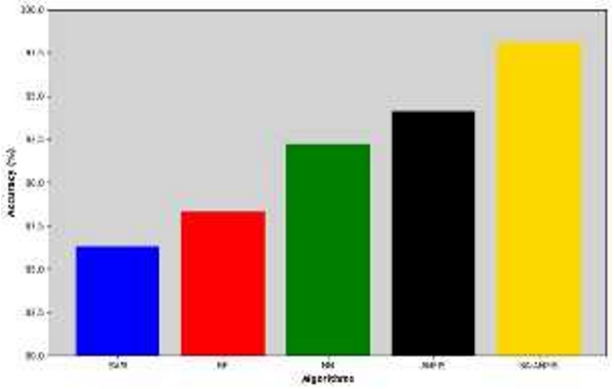


Fig. 4. Comparison of accuracy across different machine learning algorithms

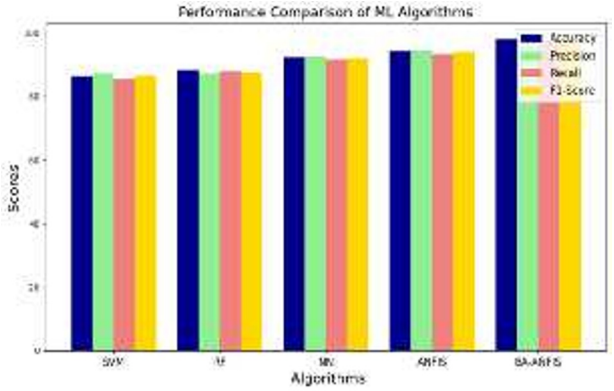


Fig. 5. Comparison of performance metrics across different models

Figure 5 shows that five machine learning algorithms (SVM, RF, NN, ANFIS, and BA-ANFIS) were tested using four different metrics: Accuracy, Precision, Recall, and F1-Score. All the algorithms are displayed in four bars, one of which is associated with one of the performance measures. The plot shows high performance of BA-ANFIS that performs best in all metrics before the other models, which are ANFIS and NN. SVM and RF demonstrate relatively poor results but still obtain high values in these measures.

Table 3 compares the performance of related work models with proposed model χ^2-DNN [23], HODBNN [24], HRFLM [25], ICA (MH) [26], and BA-ANFIS across four important metrics: From the results values, we understand that HODBNN is highest performing algorithm at accuracy 99.04% and BA-ANFIS is second highest performing algorithm at accuracy 98.07%. Precision is only available for HODBNN, HRFLM, and BA-ANFIS, with HODBNN leading at 95.92%. Recall is highest for χ^2-DNN, achieving a perfect 100%, while BA-ANFIS has a strong recall of 97.67%. The F1-Score is highest for BA-ANFIS, with a value of 97.95%, indicating its balanced and strong performance across all metrics, making it the best-performing model overall. The key to ANFIS performance is the choice of initial membership functions and rule parameters. The Bat Algorithm is an exemplar of a global optimization mechanism in which high-quality initial parameters are

identified that allow the algorithm to converge quicker and have a more predictive quality.

Table 3. Performance comparison of existing approaches

Performance Metrics	χ^2 - DNN [23]	HODBNN [24]	HRFLM [25]	ICA (MH) [26]	BA-ANFIS
Accuracy	93.32	99.04	88.42	94.03	98.07
Precision	-	95.92	90.08	-	98.23
Recall	100.0	97.73	82.62	90.35	97.67
F1 Score	85.36	96.43	92.78	96.3	97.95

5 CONCLUSIONS

To deliver a dependable and precise diagnosis of heart disease, this paper introduces a hybrid methodology that integrates the Bat Algorithm (BA) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) for high-accuracy heart disease prediction. By combining ANFISs power in modelling nonlinear relationships within medical data and BAs global optimization capability, the BA-ANFIS is able to effectively address this challenge. BA optimizes ANFIS membership functions and rule parameters, thus enhancing the model's predictive accuracy, sensitivity, and specificity beyond traditional machine learning methods. To test our proposed system, we used a clinical heart disease dataset with information like age, cholesterol level, and blood pressure. We have shown that our method works better than the standard one. The results show that this combined approach has succeeded in providing a cheaper and stronger tool for diagnosing heart disease that can help physicians with early detection of heart disease and better clinical outcomes and lower costs of care. Besides that the BA-ANFIS model might present more encouraging results. In future work the model will be guaranteed through a higher number of samples and a more diversified pathway in order to enhance the generalization and robustness. Different optimization algorithms other than the Population Swarm Optimization (PSO) could be helpful to optimize more the performance for this kind of model or even Genetic Algorithms (GA). In addition to this, heart disease predictions could also be made dynamic so to process data in real time and real time deployment can be apprehended in clinical settings. Moreover, the model can also be expanded to different cardiovascular disease types and multiple–modality data consisting of genomic and lifestyle factors to further enhance its clinical utility and diagnostic capability.

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