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Analysing the Performance of Various Machine Learning Techniques in Heart Disease Prediction

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Abstract:
One of the leading causes of death in the modern world is heart disease. One of the biggest problems in clinical data analysis is the prediction of cardiovascular disease. Making judgments and forecasts from the vast amounts of data generated by the healthcare sector has been demonstrated to be aided by machine learning (ML). Early detection of heart failure can be prevented with the accurate and prompt diagnosis of human heart disease, which also increases the prognosis of the patient. Manual methods to diagnose cardiac disease are prone to bias and interexaminer variability. Machine learning algorithms are effective and trustworthy tools for identifying and classifying heart disease patients and healthy individuals. According to various research, only a small portion of heart disease may be predicted using ML approaches. In this research, we suggest a unique approach that seeks to improve the accuracy of the prediction of cardiovascular illness by utilising machine learning approaches to identify key traits. We introduce SVM- with linear random forest for efficient prediction.

Key terms: Machine learning, diseases prediction, health care, hybrid ML, heart rate detection.

1. Introduction

According to a World Health Organization (WHO) estimate, 17.9 million fatalities worldwide in 2019 were attributable to cardiovascular diseases (CVDs) [1], accounting for 32% of all deaths worldwide [2]. The annual mortality rate for CVDs was higher than 17.7 million. According to the Australian Institute of Health and Welfare (AIHW), cardiovascular disease

(CVD) accounted for 42% of all fatalities in Australia in 2018 and was the top cause of death [3]. Because current approaches for diagnosing heart disorders are not accurate or computationally efficient for early detection, researchers are working to develop a system that will enable the prompt identification of heart diseases [4]. The diagnosis and management of cardiac disease are extremely difficult when cutting edge technologies and medical professionals are not available [5].

Due to a number of contributing risk factors, including diabetes, high blood pressure, excessive cholesterol, an irregular pulse rate, and many more, it is challenging to diagnose heart disease. A number of data mining and neural network techniques have been used to determine the severity of cardiac disease in humans. Numerous techniques, including Decision Trees (DT), Genetic Algorithm (GA), K-Nearest Neighbor Algorithm (KNN), and Naive Bayes (NB) [11], [13], are used to classify the severity of the condition. Because heart illness has a complicated character, it needs to be treated properly. Failure to do so could damage the heart or result in an early death. The different types of metabolic syndromes are discovered by the application of data mining and the medical science perspective.

Machine learning (ML) in the prediction of heart diseases leverages advanced algorithms to analyze a wide array of data—from patient demographics and clinical records to lifestyle choices and genetic markers. By applying techniques such as logistic regression, decision trees, and neural networks, ML models can discern complex patterns and risk factors associated with cardiovascular conditions. This not only aids in early diagnosis and personalized treatment plans but also enhances the overall effectiveness of healthcare interventions. As this technology evolves, it holds the promise of transforming cardiac care, ensuring better patient outcomes through predictive analytics and data-driven insights

We also discuss the use of Computer Aided Decision Support Systems (CADSS) in research and medicine. Previous research has demonstrated that the application of data mining techniques in the healthcare sector can forecast disease more accurately and in a shorter amount of time [16]. We suggest using the GA to diagnose cardiac disease. Effective association rules for crossover, tournament selection, and mutation—which yields the new suggested fitness function—are inferred using the GA in this method. We employ the well-known Cleveland dataset, which is gathered from a UCI machine learning repository, for experimental validation. Later on, we'll see how our findings stand out in comparison to some of the well-known supervised learning techniques [5].

Important risk factors that current models do not fully account for. Our research will concentrate on combining the conventional clinical signs with a wider range of variables, such as environmental and socioeconomic factors. It is expected that this integration will produce a more complete model than the existing models, one that better reflects the subtleties driving heart disease risk. In addition, we want to utilize sophisticated machine modeling methods like deep learning and ensemble learning to enhance the precision and dependability of our forecasts. Our goal is to close these gaps so that our study can improve ML models' predictive power while also lessening the biases and inconsistencies that come with manual diagnostic procedures. In the end, this might result in actions that are more accurate and timelier, greatly enhancing patient outcomes in cardiovascular care.

For the purpose of predicting heart disease, we developed a machine learning classifier in this study that combines several machine learning techniques, such as logistic regression (LR), logistic discriminant analysis (LDA), random forest (RF), XGBoost (XGB), decision trees (CART), support vector machine (SVM), multinomial Na¨ıve Bayes (MNB), and extra trees classifier (ET). To choose the ideal value for the hyperparameters for the best machine learning classifier, +e standardization and hyperparameters are carried out using the GridSearch CV method. Aside from that, the machine learning classifier's performance is assessed using a range of performance evaluation metrics, including F-measures, sensitivity, recall, accuracy, and precision. The Cleveland HD dataset has been used to test the suggested approach. Additionally, the accuracy of the suggested machine learning classifiers has been contrasted with current state-of-the-art techniques in the comparison.

1. Literature survey

In the fields where this study is directly relevant, there is a wealth of related work. In order to provide predictions with the highest level of accuracy in the medical field, ANN was introduced [6]. Heart illness is predicted by the backpropagation multilayer perception (MLP) of ANN. When the acquired findings are contrasted with those of previous models in the same field, they show improvement [10]. NN, DT, Support Vector machines SVM, and Naive Bayes are utilized to find patterns in the patient data from the UCI laboratory related to heart disease. With these algorithms, the accuracy and performance of the outcomes are compared. In terms of F-measure, the suggested hybrid approach competes with the other current techniques,

yielding values of 86.8% [7]. Previously, a significant quantity of data produced by the medical sector was not utilized efficiently. The novel methods offered here reduce costs and enhance heart disease prediction in a simple and efficient manner. The numerous research approaches taken into consideration in this work for the deep learning (DL) and machine learning (ML)-based prediction and classification of heart disease are quite accurate in demonstrating the effectiveness of these approaches [15].

A thorough prediction of heart disease based on an analysis of some of the most well-liked machine learning classifiers was employed in a different study carried out in [16] Just 14 features—out of the 303 records in the Cleveland (UCI) datasets—are used for training and testing. Following the completion of data preparation, a dataset of 296 records was produced. The accuracy of the SVM classifier findings was greater, at 90.00%. In a study to predict cardiac disease, [12] used hybrid approaches of data mining classifiers. The UCI machine learning repository provided the datasets, which have 76 attributes and 303 records. Testing and training of the model were done on 14 attributes.

The [9] description of the current and prospective state of AI-enhanced electrocardiograms (ECGs) in at-risk communities' heart disease diagnosis, summary of its implications for patients' healthcare decisions, and evaluation of its possible downsides. A novel health information system was presented in [10] to prescribe exercise to individuals with heart disease. Their preliminary research indicates that physicians are unsure of how to create an exercise prescription. Mobile Information Systems 39071, 2022, 1, retrieved [13/06/2024] from https://onlinelibrary.wiley.com/doi/10.1155/2022/1410169, Wiley Online Library. For usage guidelines, refer to the Wiley Online Library's Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions); for patients with multiple CVD risk factors, OA publications are subject to the relevant Creative Commons License.

2. Proposed Methodology

In this work, we classified heart diseases in the Cleveland UCI repository using a R studio rattle. It offers a user-friendly visual depiction of the dataset, the workspace, and the process of developing predictive analytics. The machine learning method begins with pre-processing the data, then moves on to feature selection using DT entropy, classification of modeling

performance evaluation, and better accuracy results. The process of selecting features and modelling never ends for different sets of attributes.

3.1 Data collection

The most well-known dataset that the researchers have utilized is the Cleveland heart disease dataset, which is accessible through the University of California, Irvine (UCI) online machine learning repository. There are 303 records total, and 6 samples lack values. The original version of the +e data contained 76 features; however, only 13 of these are likely to be mentioned in published work, with the remaining feature detailing the disease's effect. +e Z-Alizadeh Sani dataset is another well-liked dataset that researchers used in the prediction procedure. It contains the data of 303 patients with 55 input parameters and a class label variable for each patient. The researchers also employed Hungarian, Long Beach VA, Kaggle Framingham, and StatLog Heart datasets in their prediction process[13-15].

Table 1: Dataset details and samples.

Datasets	**Samples**	**Risk factors**	**reference**
UCI	303	13	[13]
Z-Alizadeh Sani	303	55	[14]
StatLog	270	13	[15]

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3.2 Data standardization

We improved and standardized the data sets that were gathered. These datasets had inaccurate values and were not collected in a controlled setting. For this reason, data preparation is a crucial stage in the analysis of data and machine learning. Data normalization refers to the process of a dataset's risk factors having distinct values. For instance, the temperature can be measured in multiple ways using Celsius and Fahrenheit. Scaling the risk variables and allocating numbers that illustrate the variation between standard deviations from the mean value constitute the process of standardizing the data. To enhance the performance of machine learning classifiers with a mean (μ) of 0 and a standard deviation (σ) of 1, it rescales the risk factor value. (1) provides the standards in mathematical form.

$$Data\ standardization\ X = \frac{X - Mean\ of\ X}{Standard\ deviation\ X} \quad (1)$$

3.3 Parameter processing with SVM-Linear Random forest

To achieve high precision, hyperparameter tuning is used to determine the ideal value for the hyperparameters. We employed the GridSearchCV technique for this. To improve the effectiveness of machine learning classifiers, we modify their hyper parameter values before to using them. The fit method of the Scikit-learn GridSearchCV class offers a grid of tweaking classification methods. It makes it possible to train any machine learning algorithm in a single, reliable environment and to modify the corresponding hyperparameters. Once the appropriate values for the hyperparameters have been found, the full training dataset is used to create an accurate model.

As was already noted, a number of (ML) techniques—NB, GLM, LR, DL, DT, RF, GBT, and SVM—are employed in this experiment. All 13 attributes were used in the experiment, which was conducted again using every ML technique.

Although it's more often employed for classification problems, Support Vector Machine (SVM) is a strong, adaptable supervised machine learning technique utilized for regression as well. The idea behind SVM is to identify the ideal hyperplane for classifying data into distinct groups. The hyperplane that maximizes the margin between the closest points in each class—a.k.a. support vectors—is the ideal one. The algorithm seeks to maximize this margin, which is thought of as a separating zone. The decision line in the feature space that divides several classes is called a hyperplane. This hyperplane can be seen as a line in two dimensions. The data points that are closest to the hyperplane are the support vectors. These points play a crucial role in determining the hyperplane's position since they directly affect its orientation and shape. On the nearest class points, this is the distance between the two lines. A higher margin suggests that the classifier's generalization error is smaller.

When working with non-linear boundaries in SVM, the kernel technique is a crucial idea. It entails converting data into a higher dimension where class separation can be achieved with

just a linear separator. Typical kernels consist of: Ideal for data that can be divided linearly, the linear kernel requires no change.

Model Trees, in which linear regression models are fitted at the leaves rather than utilizing the mean or mode of the target variable, could be one method if by "Linear Random Forest" you imply integrating linear models within a Random Forest-like framework. This approach is more frequently linked to machine learning methods such as M5 trees, in which the data space is partitioned using decision trees and linear models are fitted to each partition.

Partitioning: A decision tree structure is used to divide the data, but a linear regression model is fitted rather than a prediction of the outcomes at each leaf.

Data splitting: Splits are made using standard criteria, such as variance reduction (for regression jobs).

3. Results and Discussion

After gathering the dataset from an online machine learning repository, we cleaned, standardized, and improved it. Following standardization, we used machine learning classifiers and hyperparameter optimization. Ten-fold cross-validation is used for training and testing all of the classifiers. Additionally, classifier accuracy is examined both before and after standardized datasets. Plotting the accuracy of the chosen classifiers is done for evaluation purposes. The classifiers' accuracy before and after the normalization of the data is displayed in Figure 2. Figure 2 shows that on the standardised dataset, the majority of machine learning approaches (RF, CART, LDA, AB, LR, ET, and XGB) increased accuracy. while MNB and SVM classifiers lowered accuracy. On the standardized dataset, several classifiers, including CART, ET, and AB, shown notable gains in accuracy.

The precision or correctness of a machine learning or classifier model's predictions is evaluated using the accuracy metric.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The projected positive cases that are actual or true positives are measured by precision. In terms of math, it is provided by

$$Precision = \frac{TP}{TP + FP}$$

The overall number of true or actual positive cases as impacted by the total number of false negative instances is analyzed by recall.

$$Recall = \frac{TP}{TP + FN}$$

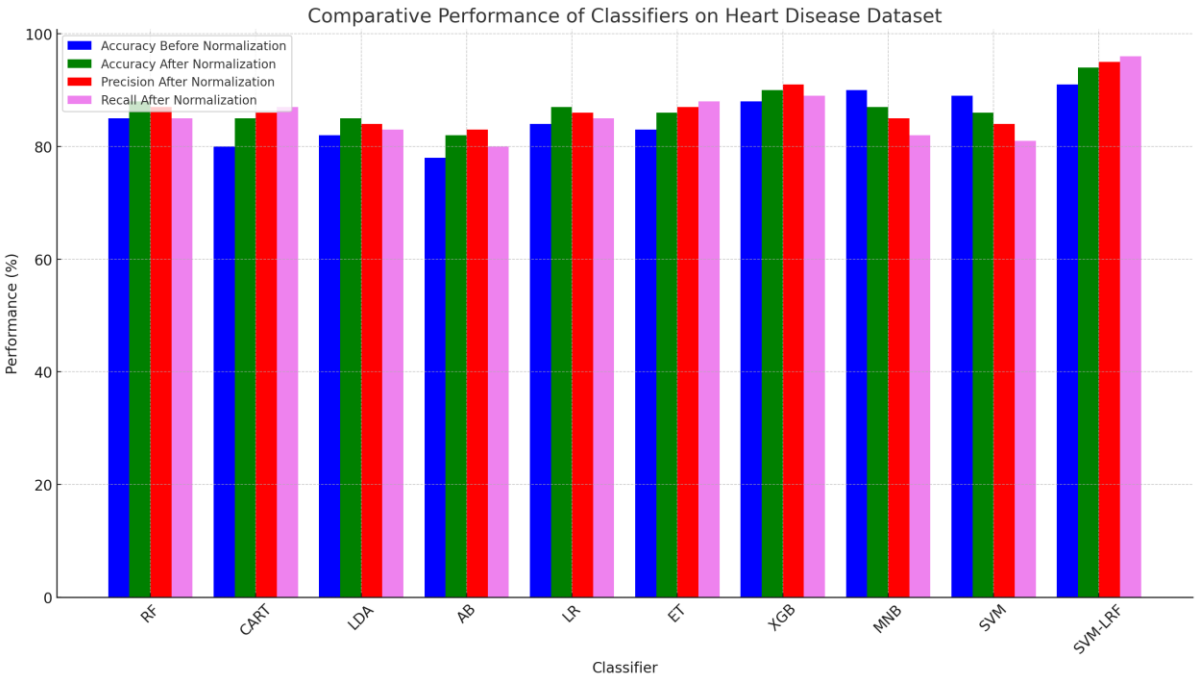

Figure 1: comparison of Various ML with proposed SVM-LRF

4. Conclusion

Long-term life preservation and the early identification of anomalies in cardiac conditions can be facilitated by understanding the processing of raw healthcare data related to cardiac information. In this study, raw data was processed using machine learning techniques to produce a fresh and innovative diagnosis of heart disease. Predicting heart disease is difficult yet crucial in the medical sector. However, if the condition is identified early and preventative actions are taken as soon as feasible, the mortality rate can be significantly reduced. In order to focus the research on real-world datasets rather than only theoretical approaches and simulations, it is highly desirable that this study be extended further. The suggested hybrid HRFLM technique combines Random Forest features with linear method.

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