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Hybrid Machine Learning Approach for Accurate Heart Disease Prediction

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Abstract: The continued prevalence of cardiovascular disease as a health problem worldwide underscores the importance of accurate models for risk prediction. Machine learning offers potential ways to increase the accuracy of predictions. To enhance the accuracy of the two-stage hybrid machine learning model used in cardiac risk prediction, this research seeks to implement brute force methods and data-driven techniques. A brute force optimization algorithm was used to improve the performance of six machine learning classifiers on two data sets, one containing 1,190 patients and the second 1,025 patients, and was compared with similar studies to produce accurate predictions of heart disease risk. The soft-voting ensemble classifier achieved an accuracy of 95.53%, while the Random Forest classifier achieved an accuracy of 96.42%; These results demonstrate the effectiveness of the proposed model. By using a brute force optimization approach to a two-stage hybrid machine learning approach the model achieved an accuracy of 97%, there is potential to aid in the rapid and accurate diagnosis of heart disease, thus making a valuable contribution to the global endeavor to reduce mortality rates from cardiovascular disease.

Keywords: Prediction of heart disease, Machine learning, Ensemble classification, Matrix performance.

1. Introduction

The data presented was supplied by the World Health Organisation (WHO). cardiovascular disease poses a significant global health risk to human beings [1]. Heart disease can be induced by a variety of factors, such as smoking, improper lifestyle choices, hypertension, obesity, and elevated cholesterol levels. abnormal cardiac rhythms, diabetes, and dietary patterns [2]. The majority of patients who develop heart disease succumb to their condition due to an insufficient initial diagnosis. As a result, to comprehend disease, it is critical to implement effective disease classification and prediction algorithms. anticipatory measure.

Conversely, the implementation of a more precise model is imperative for the prognostication of cardiovascular disease. To assess the accuracy of a model in predicting heart-related ailments, its recall performance, precision, and F1 score are taken into account. Additionally, association criteria can enhance the predictive precision of cardiac disease models. When association principles are applied to medical datasets, a variety of regulations are produced. The majority of these regulations lack any medical significance. In addition, locating them can be an impractical and time-consuming endeavor. This is because the association criteria are not derived from an independent sample, but rather from the available dataset. Therefore, to detect heart disease predictions in their early stages, search constraints are implemented on real-world datasets comprising patients who have heart disease. For the early detection of cardiac attacks, a rule-generation algorithm has been implemented utilizing search constraints [3]. Furthermore, the progression of healthcare technology in recent times has propelled the creation of machine learning (ML) systems that aim to forecast human health conditions [4-5-6]. Numerous researchers have been devoted to the development of regarding enhanced ML models. ML's principal objective is to produce computer code capable of accessing and utilizing current data to forecast future data [7]. There are a number of established methods for increasing model precision.

These processes encompass enhancing the dataset with supplementary information, managing missing and outlier values, selecting features, optimising algorithms, conducting cross-validation, and clustering. This article implements data preprocessing and utilizes a group voting classifier brute-force to enhance the machine learning model's precision. And at the end: In particular, we would like to call attention to:

- Data preprocessing Medical data often lacks adequacy, as characteristics often lack values.
- This work evaluates performance classification metrics on two IEEE Dataport and UCI Kaggle Cleveland cardiology datasets while investigating six basic machine learning algorithms and their implementation.
- Several machine learning (ML) classification techniques are trained during the initial phase, including K-nearest neighbor (KNN), random forest (RF), support vector machine (SVM), decision tree (DT), and gradient boosting (GB). And neural network (NN).
- To achieve maximum accuracy, several brute force hyperparameter optimization methods have been used along with performance evaluation through the use of accuracy metrics.
- To enhance the accuracy of the model, all classifiers were subsequently combined using the facilitated voting ensemble method.

The remainder of this paper is organized as follows. Second section Illustrates previous studies using machine learning and hybrid machine learning techniques in cardiology. In the third section,The proposed methodology is explained and the data are described in detail and pre-processed. Section Four It presents the models used in this research and the disadvantages of each model. In the fifth section,Technology improvement of algorithms and what is its impact. The sixth section focuses on comparing the proposed model with previous studies using other methods. In conclusion, the seventh section discusses this method.

2. Literature review

Machine learning and computational power advancements have facilitated the exploration of numerous innovative research opportunities within the healthcare sector. In an attempt to enhance the accuracy of disease prognosis, a multiplicity of academics have proposed machine learning and hybrid machine learning algorithms. An enormous variety of investigations and experiments have been centered on heart disease datasets. The subsequent compilation of prior investigations comprises the datasets that scholars have conducted a meticulous analysis of; these datasets have been merged through the identification of shared characteristics. The focus of this inquiry will be the merged group of data.

Heart disease is a critical ailment that ranks first among all causes of mortality across the globe [8]. However, such diseases are difficult for physicians to predict due to their complexity and high cost. The investigators of this study put forth a clinical support system as a tool to assist medical specialists in the prognosis and diagnosis of cardiovascular diseases. and arrive at optimal decisions. The present study employed various Ml algorithms to predict heart failure disease through the extraction of risk factor data from medical files. These algorithms included Nave Bayes, KNN, SVM, RF, and DT. Numerous experiments have been conducted to forecast the utilization of the HD UCI data set. Among these, split-test training and cross-validations yielded the most accurate results with NB (82.17% and 84.28%, respectively).

This research proposes a model that attempts to find the best machine learning algorithm that can predict with high accuracy in its early stages. Three parts make up the proposed model: collecting and processing patient data, followed by training on the data and testing it using machine learning algorithms (random forest, support vector machines, K-nearest neighbor, and decision tree). Random forest shows the best classification (94.958 percent), while The third step involved refining the results using a random search strategy to tune the hyperparameters. The highest accuracy rate was 95.4% [9].

Reliable diagnosis of heart diseases is achieved through the development of machine learning classifiers and a comparative analysis is performed in [10]. With the help of the Cleveland Heart Disease dataset, the effectiveness of five machine learning algorithms is comprehensively evaluated. These classifiers are Support Vector, Naive Bayes, Logistic Regression, and Naive Bayes. In addition, K-nearest neighbor is a machine. Using an 80/20 split, split the data set into training and testing parts after preprocessing.As in [11].

LR, SVM, KNN, NB, ANN, DT, the Back Propagation Neural Network (BPNN), and ensemble-based layering were implemented in addition to the CD. In [12], they examined the various ML techniques for predicting cardiac disease on a large scale using big data analysis. The extensively utilized Cleveland dataset was formerly divided by 0.90:0.10. Various algorithms, including DT, HRFLM, DT, RF, LR, KNN, SVM, AdaBoost (AB), Gradient Boost (GB), and HRFLM, were implemented. The highest achievable accuracy was 91.8% with the HGBDTLR

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ensemble algorithm. A classification and regression tree-based ensemble method for predicting HD risk was introduced by the authors of [13]. The mean values of two datasets were utilized to divide them into random numbers. Weights were assigned to the accuracy as the various CART models merged into a homogeneous ensemble classifier. The experimental findings indicated that the CD achieved an accuracy rate of 93%. The efficacy of their findings was evaluated in comparison to that of the GB, LDA, SVM, RF, LR, and KNN models. Bagging and boosting were implemented to enhance the Acc of the models. The ensemble algorithm that has been proposed achieves an Acc of 92.30% and a BPNN of 93%. A researcher put forth a model in reference [14], which underwent evaluation across multiple datasets to ascertain its efficacy in enhancing accuracy. Three datasets were utilised to evaluate the model: the Comprehensive Dataset acquired from the IEEE Dataport, the Cleveland Dataset, and the Cardiovascular Disease Dataset obtained from the Mendeley Data Centre. The accuracy ratings for the respective datasets were as follows: 88.24%, 93.39%, and 96.75% for the outcomes of the proposed paradigm.

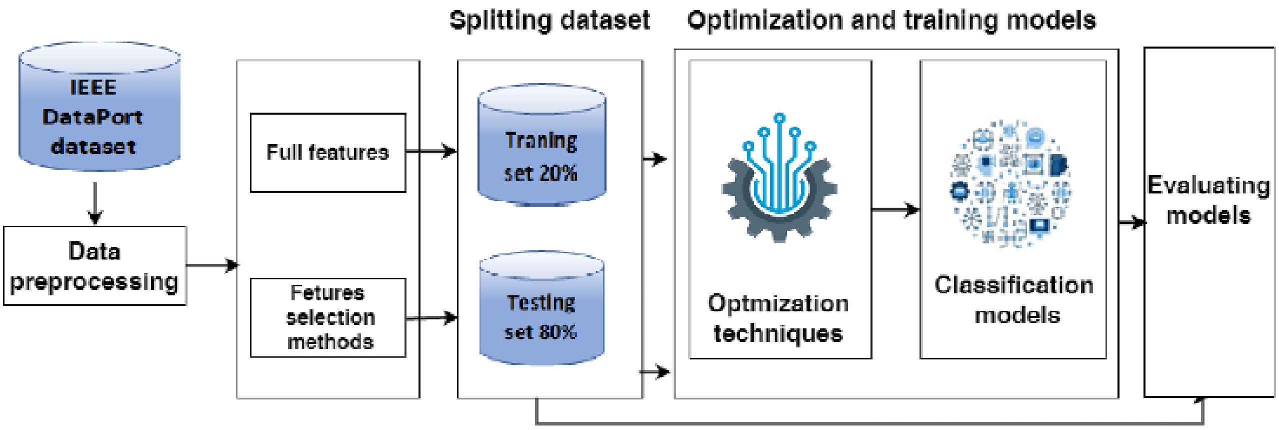

Figure. 1 The architecture of the proposed model

Table 1. Attributes for the heart disease dataset

Dataset Details		
Features	Description	Value
Age	Age is a significant factor in the provision of healthcare.	Its value is an integer.
Sex	Gender	Female=0,Male=1
Chest pain (cp)	The patient has chest pain	substernal=1. otherwise=0
Resting Blood Pressure (treetops)	High blood pressure ensues with some other factors which increase the risk.	It has either an integer or float value.
Cholesterol (chol)	serum cholesterol	It has either an integer or float value
fasting blood sugar (FBS)	The fasting blood glucose level exceeds 120 mg/dL.	true=1.false=0
RestingECG (research)	Resting Electrocardiographically	ST-T wave abnormality =2, Normal =0, Left ventricular hypertrophy =1,
Max Heart Rate Achieved (thali)	This is your greatest heart rate ever recorded.	It has either an integer or float value.
Exercise-induced angina (exam)	Angina precipitated by physical activity	no = 0, yes = 1
Oldpeak	ST depression induced by exercise as opposed to relaxation	It shows the value as either an integer or Afloat.
Slope	Slope of the maximal exercise segment ST	flat = 1, downsloping = 2, Upsloping =0
target: Heart Disease	Prognosis of heart disease	0 indicates a diameter narrowing of less

Table 2. Description of datasets I, II.

Datasets	Classes	Attributes	Instances
IEEE Dataport (dataset I)	0—>no heart disease 1—>heart disease	12	1190
UCI Kaggle Cleveland (dataset II)	0—>no heart disease 1—>heart disease	14	1000

3. Proposed methodology

Using one of the optimization methods, the objective of this research is to optimize the classification result of a model that can predict cardiac disease. This portion comprises the following: The process of gathering data, describing the dataset, preprocessing the data, engineering features, and selecting appropriate machine learning algorithms; additionally, there is a block within this section. in addition to the diagram and evaluation matrices, the procedure and methodology of the study. Fig.1 illustrates the model's architecture.

3.1 Dataset description

Dataset-I: Kaggle repository and it is a comprehensive dataset of 1190 instances which is a combination of five different datasets listed (Cleveland 303 instances, Hungarian 294 instances, Switzerland 123 instances, Long beach VA 200 instances, Stalog heart dataset 270 instances)
Dataset-II: Comprehensive UCI Kaggle Cleveland, Hungary, Switzerland, and Long Beach V. This heart disease dataset, which has 14 features, 1025 instances, and 2 classes, is contributed to by the Medical Center, the Cleveland Clinical Foundation, the Hungarian Institute of Cardiology, Switzerland, and the Long Beach V Clinical Foundation. It may also be found in the UCI repository. A summary of [16] dataset is given in Table 1

3.2 Preprocessing

Thorough checks and modifications were carried out throughout the data preparation phase of this investigation to guarantee the appropriateness and quality of the merged dataset. First, a thorough search for absent values was carried out, and the dataset was whole, lacking nothing in terms of missing info. This demonstrated the dataset's dependability and integrity. Second, a careful analysis of duplicate values was done to guarantee data consistency since the dataset was created by combining three different datasets. The lack of duplicates was verified by this study, supporting the dataset's accuracy. To find any extreme numbers that can distort the results, an outlier analysis was also performed. The fact that there were very few outliers found highlights how reliable the dataset is. To ensure consistency and enable significant feature comparisons, the data were standardized to a range of 0 to 1. The data analysis and interpretability were improved by this scaling procedure. These meticulous data pretreatment procedures laid a strong basis for trustworthy and excellent analyses in this research. To optimize the performance and precision of the heart disease prediction model, the dataset containing heart disease data was partitioned as follows: 80% was set aside for training purposes, while the remaining 20% was set aside for testing

4. Modeling implementation

The implementation of ensemble learning algorithms constituted a pivotal element of this investigation. Ensemble learning is a subfield of machine learning that leverages the capabilities of merging numerous models to enhance the precision and resilience of predictions [17]. Throughout this research, numerous A variety of ensemble learning methods were implemented, such as RF, DT, NN, GB, SVM, and KNN. Ensemble learning involves the process of aggregating the predictions of multiple individual models that were trained on the same dataset in order to produce a final prediction. wherein the predictions made by the individual classifiers are presented. By combining them, a collective prediction is generated. By means of this aggregation, ensemble models can be assessed utilising performance metrics including F1-score, accuracy, precision, and recall. The subsequent section provides comprehensive explanations of each ensemble learning technique employed in this study, including their corresponding pseudocodes and a range of hyperparameters. The algorithms were meticulously selected to capitalize on their distinct advantages and improve the precision and dependability of our model for predicting cardiac disease.

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4.1 Random forest classifier

is a strategy for classifying data that makes use of an extensive collection of decision trees. As shown in [18]. A drawback of Random Forests is that they might overfit, particularly when working with noisy or high-dimensional data. Moreover, their performance may be adversely affected by imbalanced datasets or situations involving excessive class overlap.

4.2 Dataset description

To arrive at a classification result, decision trees are hierarchical models that make successive decisions per feature. They can process both categorical and numeric data and are interpretable. C4.5 is an extensively implemented algorithm for decision trees [19]. DTs, in addition, resemble arboreal structures, which are they are utilized for managing sizable datasets. As shown in [20]. To ascertain the predicted class for a decision tree, one proceeds from the trunk of the tree. A drawback of decision trees is that they might overfit, particularly when handling noisy or imbalanced data. Additionally, they could have trouble expressing intricate connections between aspects.

4.3 K-Nearest neighbors (KNN)

KNN is a technique for passive or instance-based learning. As shown in [21]. A drawback of k-Nearest Neighbours is that, particularly when dealing with big datasets, it may be computationally costly during inference. Moreover, it is afflicted by the curse of dimensionality, which states that performance declines with increasing feature count**.**

4.4 Gradient boosting classifier (GB)

A GB Classifier As shown in [22]. A drawback of gradient boosting is that the technique may be computationally costly and prone to overfitting, particularly in cases involving complicated models or big datasets. It could also have trouble with loud or anomalous data.

4.5 Support vector machines (SVM)

A GB Classifier As shown in [22]. A drawback of gradient boosting is that the technique may be computationally costly and prone to overfitting, particularly in cases involving complicated models or big datasets. It could also have trouble with loud or anomalous data.

4.6 Methodology of ensemble classifier

The ensemble method is utilized in this proposed methodology to combine multiple machine learning models to produce a unified result that exceeds the accuracy of any of the individual algorithms. Voting ensembles average the forecasts produced by our six machine-learning models [24]. The voting classifier differentiates between two discrete ballot types. Lenient votes and hard votes are defined as follows:

• **Hard**: The final class prediction is determined by the estimator through a majority vote based on the class predictions that transpire most frequently across the ML base models.

• **Soft**: To ascertain the final class prediction, the probabilities of all predictions generated by the ML base model are averaged.

Soft voting, which calculates the mean of the probabilities, “adjusts the weight” of confident ballots, potentially leading to more favorable outcomes than hard voting. In the soft voting group, both weighted majority and average voting are taken into account as shown in [25].

SVE = argmax(1/N× (P(RF)+P(KNN)+P(NN)+P(GB)+P(DT))).

The variables “N” and “P” represent the number of base classifiers and, respectively, the probability of each base classifier. The function arg max, which maximises arguments, is applied in order to ascertain the class with the greatest probability. In this fashion, an essential probability target label can be chosen. Through this approach, specific classifiers are duly compensated for their deficiencies. The primary objective of ensemble methods is to reduce the amount of bias and variance that a model contains. By employing the SVE method and utilizing the scores of all forecasts produced by the base classifiers, we were able to categorize predictions of cardiac disease in our research. Combining the scores predicted by each of the fundamental ML classifiers [26], the SVE model, as proposed, selects the class with the highest scores. The category with the highest probability value is ascertained by our proposed SVE model.

Algorithm 1 Pseudocode of the ensemble learning algorithm

Input:
- Training dataset D
- Ensemble method (e.g., hard or soft voting)
- Base classifiers CI (RF,SVM,GB, DT,KNN, NN)
- Hyperparameters for ensemble method and base classifiers

Output:
- Ensemble model M

Procedure:

1. Initialize empty list of base classifiers: base_classifiers = []

2. For each base classifier Ci:
   a. Train base classifier Ci on training dataset D
   b. Add trained base classifier Ci to base_classifiers list

3. If ensemble method is hard voting:
   a. Initialize hard_voting_ensemble as an empty ensemble model
   b. For each instance in the test dataset:
      i. Make predictions using all base classifiers in base_classifiers
      ii. Aggregate predictions using majority voting
      iii. Assign the aggregated prediction to the instance in the test dataset
   c. Return hard_voting_ensemble

4. If the ensemble method is soft voting:
   a. Initialize soft_voting_ensemble as an empty ensemble model
   b. For each instance in the test dataset:
      i. Make predictions using all base classifiers in base_classifiers
      ii. Aggregate predictions using weighted averaging
      iii. Assign the aggregated prediction to the instance in the test dataset
   c. Return soft_voting_ensemble

5. Return ensemble model M

4.7 Performance evaluation

The performance metrics employed in this study were pivotal in assessing the classifiers' efficacy and precision. Several metrics were utilised in the analysis, such as AUC-ROC, F1-score, Cohen's kappa (κ), recall, precision and mean squared error (MSE). The aforementioned metrics contributed significant insights regarding various facets of the classifiers' efficacy. The assessment was conducted utilizing the confusion matrix presented in Table 3. As shown in [27].

Table 3. The matrix of confusion

	predicted Positive	**Predict Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)
Accuracy = $(TN + TP)/(TN + FP + TP + FN\ ) * 100\%$		
Precision =$(TP/\ )\ /\ ((TP\ +\ FP)\ \times\ 100\%)$		
Recall = $(TP)\ /\ ((TP\ +\ FN)\ \times\ 100\%)$		
κ = 2 × $(TP \cdot TN - FP\ \cdot FN)/TP + FP) \cdot (FP + TN) + (TP + F$		
F1-score = 2$*$ $Precision\ \times\ Recall/Precision\ +\ Recall$		
MSE =$\frac{1}{2}\sum_{i=1}^{n}(y_i -\ x_i)^2$		

5. A brute-force technique

A brute-force technique is a direct way to solve a problem by methodically examining every potential answer. Usually, you have to test every option until you find the right one. This strategy is often used when more effective alternatives are either unavailable or too difficult to put into practice. Brute-force methods are usually easy to comprehend and use, but because of the sheer amount of options that must be considered, they may be very inefficient, particularly for huge issue situations. A brute-force strategy, for instance, would include attempting every move combination until the one that solves the challenge is discovered, in the case of trying to solve a puzzle. Even while this approach will always ultimately discover a solution (if one exists), big issues may need an unreasonably lengthy period to solve. It was used in this research and obtained the best results.

6. Results and analysis

Using two different datasets, the study carried out a thorough comparison of the suggested heart disease prediction systems with current approaches. Table 5 presents the comparison with current prediction systems on Dataset I, which is derived from the IEEE Dataport; Table 5 shows the performance assessment on Dataset II, which is derived from the UCI Kaggle Cleveland dataset. Results for Dataset I

A comparison between the suggested cardiac disease prediction systems and current approaches using Dataset I is shown in Table 4. Especially, the suggested methods showed consistently competitive performance with different classifiers and approaches. In particular, the best accuracy of 97.32% was attained by the suggested strategy that used the ensemble soft voting method and was refined using RandomizedSearchCV and GridSearchCV. With accuracy ranging from 93.39% to 95.4%, this beat other systems, including the stacked ensemble

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classifiers [32] and ensemble soft voting techniques [30, 31]. Additionally, the suggested method using brute-force ensemble soft voting had an impressive accuracy of 98.21%, demonstrating its effectiveness in the prediction of heart disease. Results for Dataset II The assessment of the suggested methods on Dataset II of the UCI Kaggle Cleveland dataset is shown in Table 5. The outcomes show how well the suggested technique works with various classifiers and ensemble tactics. The ensemble soft voting approach, in conjunction with GridSearchCV and RandomizedSearchCV for fine-tuning, produced the greatest accuracy of 97%, which is comparable to the results in Dataset I. Furthermore, with accuracy ranging from 87.62% to 92.20%, the suggested ensemble approaches demonstrated competitive performance in comparison to the state-of-the-art methods. Comparative Evaluation Overall, on both datasets, the suggested heart disease prediction algorithms perform better than current approaches. When optimization algorithms are used in conjunction with ensemble learning approaches, the models' predicted accuracy increases. Additionally, the suggested systems' resilience is demonstrated across a variety of datasets, highlighting their potential for practical uses in risk assessment and cardiovascular health monitoring In-depth examination of the findings from contrasting the suggested heart disease prediction systems with current approaches is given in this part, along with insights into the systems' functionality and their healthcare ramifications.

Table 4. Comparison Of The Proposed System With Existing Heart Disease Prediction Systems On (Dataset I)

Ref/Year	**Dataset**	**Classifiers Used**	**Methodology Used**	**Maximum Accuracy (%)**
[28] 2022	Heart disease dataset (Dataport from IEEE)	MLPNN, NN, AB, SVM, ANN, LR, RF	An ensemble strategy in which numerous classifiers are combined.	93.39%
[29] 2023	Heart disease dataset (Dataport from IEEE)	KNN, RF, LR, NB, GB, AB, SVE classifier	Method of ensemble soft voting	95%
[30] 2024	Heart disease dataset (Dataport from IEEE)	XGB, Extra tree, RF, DT, KNN, SVM	Voting. AdaBoost, bagging, stacking	93.67%
[31] 2023	Heart disease dataset (Dataport from IEEE)	SVM, KNN, DT, RF		RF 95.4%
Proposed	Heart disease dataset (Dataport from IEEE)	RF, SVM, KNN, GB, NN, DT	Classifier (Ensemble soft voting method) brute-force	97%

Table 5. Comparison Of the Proposed Techniques (Dataset II)

Ref/Year	**Dataset**	**Classifiers Used**	**Methodology Used**	**Maximum Accuracy (%)**
[32] 2019	UCI Kaggle Cleveland	XGB, ADB, GBM, LGBM, and CatBoost	Ensemble	87.62% with XGB
[33] 2022	UCI Kaggle Cleveland	DNN, KDNN, XGB, KNN, decision tree, and random forest	Ensemble	88.65%
[34] 2021.	UCI Kaggle Cleveland	Naïve Bayes, linear model, logistic regression, decision tree, random forest, SVM, and HRFLM	Ensemble	88.40%
[35] 2023	UCI Kaggle Cleveland	XGB, ADB, and GB	Ensemble	92.20%
Proposed	UCI Kaggle Cleveland	KNN, RF, SVM, GB, NN, DT.	Classifier (Ensemble soft voting method) brute-force	97%

With brute-force optimization and ensemble soft voting, the proposed system attained its utmost accuracy of 97.21%. The proposed system consistently outperforms extant systems or achieves altitudes comparable to those reported for the utmost accuracy. In comparison to alternative approaches utilized in established systems, Ensemble Soft Voting methods exhibit superior performance when combined brute-force optimization. Ensemble technique for predicting cardiac disease are utilized to illustrate the efficacy of the proposed system, which combines multiple classifiers (KNN, RF, SVM, GB, NN, DT). About identifying optimal hyperparameters, brute-force optimization is the most accurate of all optimization techniques, underscoring its efficacy.

7. Discussion

The results of the research survey indicate: The research survey presumably yielded valuable insights regarding the present state of methodologies used to predict cardiac disease. These insights likely encompassed patterns, obstacles, and nascent strategies. Through the synthesis of the survey's principal discoveries, a groundwork can be laid for comprehending the circumstances under which the comparison is undertaken. This enables the identification of pertinent methodologies and considerations for the comparison. Objective of Comparing: The objective of comparison is to assess and contrast the efficacy of various methodologies utilized in the prediction of cardiac disease. This entails evaluating a multitude of aspects, including but not limited to predictive efficacy, computational speed, interpretability, and scalability. By correlating the comparison with the results obtained from the research survey, it is possible to guarantee that the evaluation effectively tackles relevant research inquiries and makes a scholarly contribution to the domain. The correlation between survey results and the objective of comparison: By identifying methodologies to incorporate into the comparison and gaining an understanding of the wider context of heart disease prediction research, the research survey functions as a foundation. The ability to identify trends, challenges, and voids in current approaches facilitates the process of selecting appropriate methodologies for evaluation. Furthermore, the results of the survey could potentially shed light on deficiencies in existing methodologies or indicate the necessity for innovative approaches, thereby providing direction for the comparison and the analysis of the findings.

8. Conclusion

The competitive accuracy rates of the proposed heart disease prediction system, which utilizes ensemble methods and diverse classifiers, are apparent in comparison to those of existing systems, as demonstrated in Table 5. Although the proposed system exhibits variability in the utmost accuracy achieved by various ensemble methods and voting strategies, it consistently showcases robust performance, as evidenced by accuracy scores spanning from 92% to 97%. Specifically, in terms of accuracy, the performance of the proposed system is comparable to that of existing cardiac disease prediction systems. The accuracy of 97% achieved by the proposed system, which utilizes a rigid voting mechanism, is the highest among all systems assessed on Dataset I. Furthermore, the proposed system, which employs a brute-force approach in conjunction with soft voting, attains a remarkable accuracy rate of 97%. This surpasses the highest accuracy rated by previous systems when evaluated on an identical dataset. Based on the provided dataset, these outcomes demonstrate that the proposed system is capable of precisely predicting cardiac disease. By utilizing ensemble methods and diverse classifiers, the system's dependability in clinical applications is strengthened through the provision of flexible predictions. In addition, the demonstrated flexibility of the proposed system in accommodating various prediction scenarios is exemplified through the incorporation of both hard and flexible voting methods.

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