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Hybrid ML–DL Framework for Heart Disease Prediction

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Abstract

Due to the complex nature of cardiovascular disease and the complexity of early symptoms, early and effective detection of cardiovascular disease continues to be a major issue in clinical practice. In order to increase diagnostic accuracy and resilience, this study suggests a hybrid ensemble learning architecture that combines Machine Learning (ML) and Deep Learning (DL) models. The method uses two DL models, Feed forward Neural Networks (FNN) and Simple Recurrent Neural Networks (RNN), in addition to four ML classifiers, a K-Nearest Neighbour (KNN), a random forest (RF), Decision Tree (DT) and Extreme Gradient Boosting (XGB). In order to ensure cleaner and more dependable input data, the system also includes sophisticated pre-processing, such as outlier detection utilizing Isolation Forest and Modified Z-Score techniques. The benefits of base learners are combined using a weighted voting ensemble technique based on stacking. The suggested ML-DL ensemble outperforms individual classifiers and traditional model ensembles with an accuracy of 94.22%, according to experimental evaluation using a publicly accessible Kaggle heart disease dataset. The findings verify that integrating ML and DL into a single ensemble structure greatly improves model stability, prediction reliability, and applicability for early cardiovascular disease identification.

Keywords: Cardiovascular Disease, Deep Learning, Ensemble Learning, Outlier Detection, Stacking Model, Weighted Voting.

Introduction

The cardiovascular system consists of the heart, arteries, veins, and pulmonary circulation, which together are responsible for transporting blood and oxygen throughout the body (1). Although the circulatory system represents one of the most important organ systems of the human body, its well-being cannot be guaranteed because it is also vulnerable to disease and accidents. The adverse impacts of heart illness on the coronary artery blood flow lead to heart muscle weakness. This circulatory impact is what ultimately leads to cardiac dysfunction (2). Cardiovascular disease symptoms may include fatigue, collapse, swollen extremities (like toes) and a feeling of oxygen deprivation. A bad diet and cigarette are severe precursors for cardiac events and strokes (3). According to the World Health Organization, cardiovascular disease remains the leading cause of mortality worldwide, accounting for about 18 million deaths yearly or over 37% of mortality worldwide (4). While serious issues like stroke and cardiovascular disease impact the entire population, obstruction of the heart artery is a less common cause of cardiac arrest. Clinicians commonly use angiography to diagnose cardiovascular disease. However, this testing process is expensive and time-consuming due to the need to evaluate multiple factors. This challenge is particularly acute in developing nations with limited access to specialists, diagnostic equipment and other necessary resources. In the past several years, heart failure is now an increasingly important medical issue due to the rising death rate from arterial diseases. Identifying the best type of treatment consequently depends on prompt diagnosis and assessment (5).

Ensemble Method Types

Bagging: The "bagging" strategy necessitates teaching numerous models. Concurrently on random parts of the instruction set generated by random sampling with replacement, or bootstrapping (6). Each model generates a forecast and the outcomes are aggregated, typically by the median for regression or the over whelming vote for classification. Bagging reduces variance and prevents over fitting, which is very advantageous

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for decision trees and other high-variance models. The Random Forest is a popular example that uses several decision trees trained on bootstrapped parts of the data.

Boosting: This method involves training each model to correct the mistakes of its predecessors in a sequential fashion. By assigning greater weights to instances that were mispredicted, the process compels subsequent models to focus more on those challenging examples. By combining weak models to produce a strong model, boosting lowers bias and variation (7). XGBoost, AdaBoost and Gradient Boosting Machines (GBM) are popular boosting methods.

Stacking (Stacked Generalization): The best method for integrating projections from many foundation models is in stacking using a meta-model. The meta-model uses each base model's forecasts as features to determine its final prediction for an input instance (8). Because stacking can mix models of many types, it offers more opportunities to reduce bias and variation than bagging or boosting.

Advantages of Ensemble Learning

Improve Accuracy and Robustness: Learning in groups improves model accuracy by utilizing the benefits of various models and it is often helpful for managing complex, high-dimensional datasets.

Decreased Over fitting: By averaging or aggregating several models, ensemble approaches like bagging reduce the danger of over fitting, which is especially advantageous for high-variance models like decision trees.

Enhanced Stability: Because ensembles are less vulnerable to noise and minute changes in the data, they generate forecasts that are more trustworthy.

Improved Generalization: Ensemble learning improves model performance on test data and other out-of-sample scenarios, allowing models to generalize more successfully on unknown data. An ensemble learning approach using numerous classifiers and a voting-based method for making choices is recommended for the detection of heart failure.

This paper discusses the three main types of ensemble methods: stacking, boosting and bagging. Well-known ensemble methods, including XGBoost, LightGBM, Random Forest, AdaBoost and CatBoost, have been emphasized (9). To address the imbalanced class issue, Hybrid Reinforced AdaBoost and Enhanced AdaBoost techniques were applied and it was observed that adjusting weighted vote parameters for weaker classifiers improves the positive class accuracy rate (10). A layered ensemble strategy integrating multiple classifiers was adopted to construct an effective projection model, achieving an F1-score of 88.07%, recall of 86.27%, and precision of 89.95% and accuracy of 88.33% for cardiovascular disease prediction (11). An integrated ensemble approach combined with a genetic algorithm was employed for heart disease classification, where performance was evaluated using specificity, sensitivity and accuracy through cross-validation (12). Ensemble-based solutions have increasingly been recognized as state-of-the-art approaches for addressing challenges such as computational complexity, over fitting and under fitting in machine learning, with a HistGradient Boost classifier achieving an F1-score of 92.7%, recall of 95.2%, and dependability of 91.5% and precision of 90.4% (13). A hybrid strategy incorporating pre-processing and adaptive algorithm selection was implemented to enhance data processing effectiveness, demonstrating improvements through hybrid methodologies (14). A hybrid cardiac disease prediction technique using Decision Tree and Random Forest classifiers demonstrated competitive predictive performance (15). Multiple ensemble learning techniques were utilized for cardiac disease detection, employing mixed-learning models to enhance prediction precision, while considering factors such as emissions, sleeplessness and stress management across large-scale datasets (16). A correlation value of 0.79 was observed between empirical evaluations and satisfaction metrics, indicating the potential of machine learning algorithms (17). An ensemble-based approach for cardiac failure risk evaluation was developed, achieving an accuracy of 95.08% (18). Several machine learning techniques, including Random Forest, K-Nearest Neighbors, Decision Tree, and Naive Bayes, have been explored for heart disease prediction, with KNN showing promising results (19). A multi-classifier ensemble framework combining neural networks, support vector machines, decision trees and Bayesian networks was implemented, resulting in high cardiovascular disease detection accuracy (20). An ensemble deep learning architecture for cardiac disease identification was proposed to improve diagnostic accuracy in remote and real-time clinical environments (21). A multilayer dynamic ensemble framework was proposed for cardiovascular disease prediction and showed superior discriminative capability compared to baseline models (22). It was demonstrated that bagging reduces model instability through averaging predictions, while AdaBoost improves accuracy by iteratively minimizing errors under low-noise conditions (23). A novel ensemble learning method employing Decision Tree, Support Vector Machine, Random Forest and adaptive boosting, along with feature selection strategies, achieved a consistency of 0.91 on the Z-Alizadeh Sani dataset and an average accuracy of 0.83 on the UCI dataset (24).

Methodology

A five-phase plan is suggested for the suggested approach in Figure 1. Selecting a dataset for the model construction is the first step in the suggested methodology. The preceding chapter discusses a number of pre-processing procedures. DT, RF, Extreme gradient enhancement (XGB), KNN are the four artificial neural predictors used to determine whether heart failure is present. Additionally, heart failure was predicted using deep learning techniques. FNN and RNN are used to assess the performance of deep learning models on certain datasets.

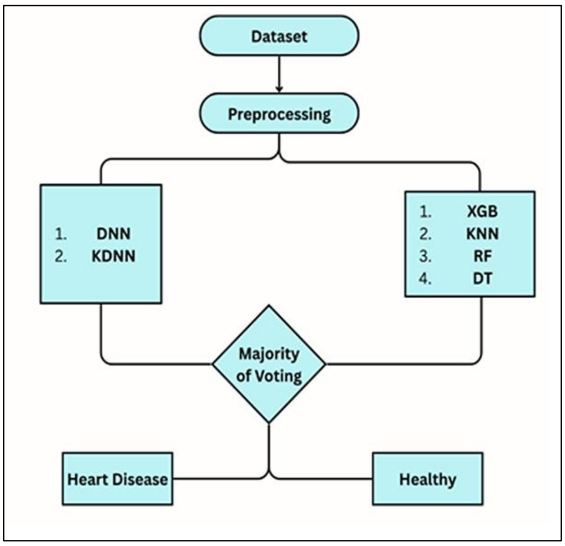

Figure 1: Proposed Method for Ensemble Methods

Dataset

The Kaggle collection of heart failure dataset is used in this investigation. 70,000 details and 13 attributes make up the selection. Thirty percent of the data is used to evaluate the method's efficacy, while seventy percent is used to train the tools. A 70/30 train–test split was adopted to ensure sufficient training data while preserving an independent test set for unbiased evaluation. Given the relatively large dataset size, this split provided stable and consistent performance.

Pre-Processing Methodology

Processing of empty values pre-processing includes handling various information qualities, scale and standardization. This covers managing large, disjointed, small databases, classification variance, name archives and preventing over fitting. This study integrates the recommended outlier detection strategy of an ensemble learning technique to improve the model's precision and durability. Learning may be hampered by data points known as outliers that significantly deviate from the rest of the sample, especially when collaborative techniques are being employed. We lessen the influence of noise and potentially deceptive data on model predictions by first using an outlier identification technique to increase the accuracy of the information sent to the composition. More specifically, our outlier detection method finds and eliminates abnormal data points that may otherwise distort the learning process in ensemble methods like boosting or bagging, where little variations in the data frequently affect the results. This technique enhances the predictive power of ensemble models by reducing the distortion that exceptions may introduce and increasing the model's ability to extrapolate to fresh data. Additionally, it reduces noise sensitivity and increases ensemble model stability, which is very useful when utilizing high-variance systems like Random Forests' decision trees or other enhanced algorithms. Outlier identification and ensemble learning are combined to provide a more refined dataset that conforms to the underlying structure of the ensemble. This, in turn, leads to increased predictive accuracy and reliability across a variety of cases in the diagnosis of cardiovascular disease and related applications. This investigation suggests pre-processing techniques including removing oddities (outliers) and running the first set of data through a conventional scalar to show how well the model works and provides a sufficient level of performance for disease forecasts. We also made the following modifications to the collected data in order to concentrate on the traits that influence heart diseases (cardiovascular disease).

A) Characteristics are changed while keeping the data in order to make the collection of knowledge easier to comprehend. The sex property was converted to a single value and the age band in the information set was changed from days to years.
B) Take the date of birth, age, gender and ID out of the data collection.
C) To find anomalies and eliminate those rows containing them, analyse the largest and weakest intervals.
D) Based on the patient's interaction with the doctor, analyse the four CP types.

Algorithm Classification

To enhance our clustering performance, we suggest a stacking paradigm based on ML and DL models. Four machine learning approaches XGB, RF, DT approach and KNN as well as two deep learning techniques FNN and RNN were employed in this study. The section that follows demonstrates how to identify heart illness utilizing the DL approach with machine learned category classification in order to assess the efficacy of our strategy.

Mixture Classification for ML

An ensemble-based mixture classification approach was adopted to enhance classification accuracy and generalization performance, as different machine learning models exhibit complementary strengths when applied to clinical datasets (25, 26). In this framework, multiple classifiers independently generate predictions for each data instance and the final class label is obtained by aggregating these predictions using suitable voting strategies (27).

Four machine learning classifiers RF, XGB, DT and KNN were employed as base learners. The KNN classifier assigns class labels based on neighbourhood similarity measures (28), whereas XGBoost improves predictive performance through gradient-based optimization and boosted decision trees (29). Decision Tree models were included due to their simplicity, interpretability and effectiveness in handling structured medical data (30).

Among the evaluated models, Random Forest demonstrated superior individual performance and robustness, owing to its ability to reduce variance and capture complex nonlinear feature interactions. Consequently, RF was considered a key contributor within the ensemble framework.

The final ensemble decision was obtained by selecting the class label corresponding to the maximum aggregated prediction score, expressed as in equation [1]:

$$arg\, arg\, Max\, f(i), \quad i \in Z \qquad [1]$$

Where, (i) represents the aggregated score associated with class i. This mixture classification strategy improves predictive reliability and reduces overfitting compared to conventional single-model learning approaches.

Weighted Majority Voting

To improve cardiovascular disease prediction, ensemble learning combines a variety of models from machine learning. The procedure entails building an ensemble classifier that combines predictions from several classifiers, such as XGB, KNN, DT and RF. Each predictor votes on the prediction's outcome and the sorting procedure with the most results is chosen as the output. The final ensemble categorization choice is based on this weighted majority vote approach (31). Weighted majority vote is subject to the following conditions.

A) Each of the models in the ensemble is assigned a weight, which is often based on metrics such as reliability and F1 score on the data set.

B) Each simulator in the ensemble predicts the same given item. These projections are then pooled.
C) The vote of every prototype is weighted in accordance with the weight assigned to each possible class label.
D) All models' votes are added together for each class label. The ultimate forecast is made by the group having the highest total weighted vote.

Classifier with Deep Learning

Deep learning models were employed to capture complex nonlinear relationships within the cardiovascular disease dataset. Two architectures FNN and RNN were implemented and evaluated for classification performance.

The models were designed with optimized network architectures, including multiple hidden layers and appropriate activation functions. Training was performed using the Adam optimizer with binary cross-entropy as the loss function to ensure stable convergence and effective learning. Hyper parameters such as learning rate, number of layers and neuron configuration were selected experimentally to achieve optimal performance. The deep learning models were trained and validated on the pre-processed dataset and their performance was evaluated using standard metrics, including accuracy, precision, recall, F1-score and ROC-AUC (32-34).

A stacking-based ensemble framework combining ML and DL classifiers was developed to improve the accuracy and reliability of cardiovascular disease prediction. By integrating the complementary strengths of ML and DL models, the proposed ensemble achieves better classification performance compared to using individual models alone.

The ensemble consists of four ML classifiers DT, XGB, RF and KNN and two DL models FNN and RNN. All base learners were trained independently on the same cardiology dataset to capture diverse patterns and feature representations.

The stacking mechanism operates in two stages. In the first stage, both ML and DL base learners generate independent predictions for each data instance. In the second stage, these predictions are aggregated using a weighted majority voting strategy, where higher-performing classifiers contribute more significantly to the final decision. This approach effectively balances the strengths and limitations of individual models and enhances overall prediction robustness.

The performance of the proposed ML-DL stacking ensemble was evaluated using standard metrics, including accuracy, precision, recall and ROC-AUC.

Results and Discussion

The performance results of the machine learning classifiers are presented in Table 1. RF, XGB, KNN, and DT were detected coronary sickness in a sample of cardiac diseases. When matched to various other techniques for estimation, the RF classification strategy achieved the greatest efficiency rate of 90.65%, as Table 1 illustrates the matching recall, F1, AUC and accuracy for RF were 90.33%, 90.22%, 94.14% and 92.13%. Compared to FNN, we achieved 88.55% efficiency, 89.54% specificity and an F1 score of 88.27%. Additionally, the RF functioned remarkably well on the heart disease information, as evidenced by the curve seen in the ROC imaging in Figure 2 (which likewise has a ROC grade of 94.14%).

Table 1: Performance of ML Algorithms

Algorithm	Accuracy	Precision	Recall	F1 Score	ROC-AUC
RF	90.65	92.13	90.33	90.22	94.14
KNN	88.55	89.54	88.24	88.27	92.25
SVM	88.39	88.43	88.25	88.52	90.65
XGB	90.49	90.45	90.81	90.01	95.25

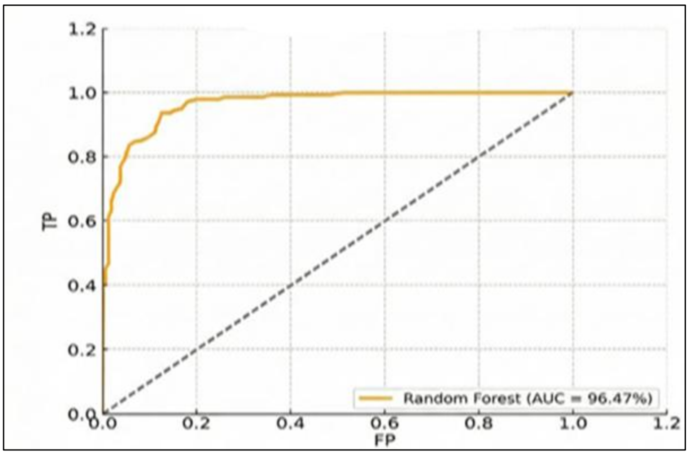

Figure 2: Random Forest ROC Curve

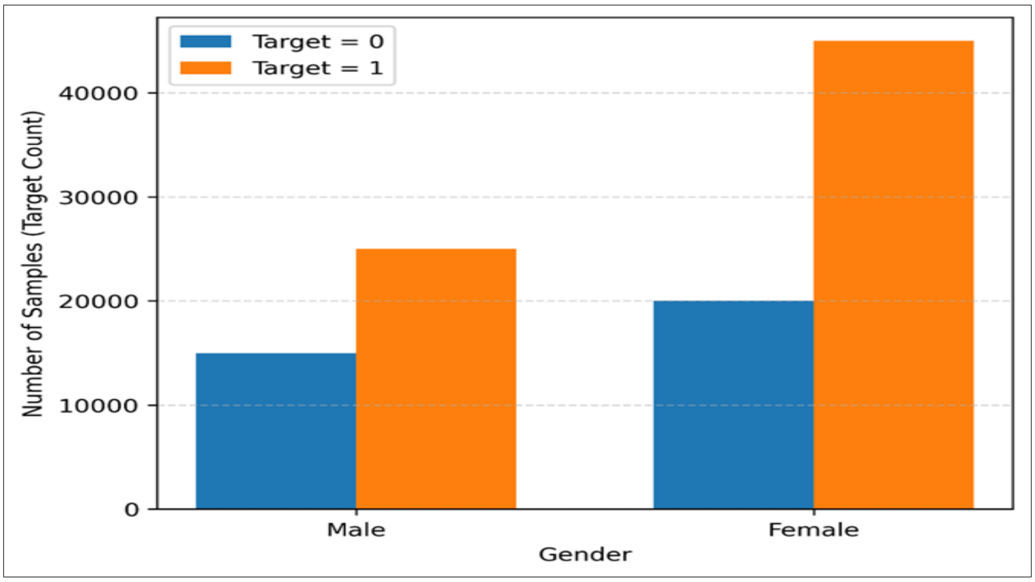

Figure 3: Distribution of Target Classes Across Gender Categories in the Dataset

The paired plot calculated around the aim element is shown in Figure 3. The figures of men and women with heart disease and those in good health are depicted in this plot using a bar chart. The next stage of the investigation shows the outcomes of the deep learning-developed model. Table 2 displays the deep learning technique's outcomes. The DNN evaluations have a recall rating of 79.87%, a certainty rate of 91.35%, an F1 score of 69.06% and a ROC AUC of 95.08%, according to Table 2.

Table 2: Deep Learning Performance

Algorithm	Accuracy	Precision	Recall	F1 Score	ROC Curve
RNN	91.04	97.45	79.07	69.04	94.22
FNN	91.35	98.48	79.87	69.06	95.08

The deep learning algorithms all did well. The exactness scores of the two approaches are nearly identical since when dealing with a lot of data, a deep learning algorithm fares better. The FNN-generated model has the highest level of efficacy when compared to the RNN technique. The efficiency, precision, recall, F1 score and ROC AUC of the RNN model are as follows: 91.04%, 97.45%, 79.07%, 69.04 and 94.42%. Figure 4 (A) illustrates the model's performance in forecasting accuracy across 400 learning and testing stages, while Figure 4 (B) displays the FNN approach's beginning point and validates loss. Figure 4(C) displays a ROC curve demonstration. Yet, the multilayer categorizing was inefficient due to the absence of data.

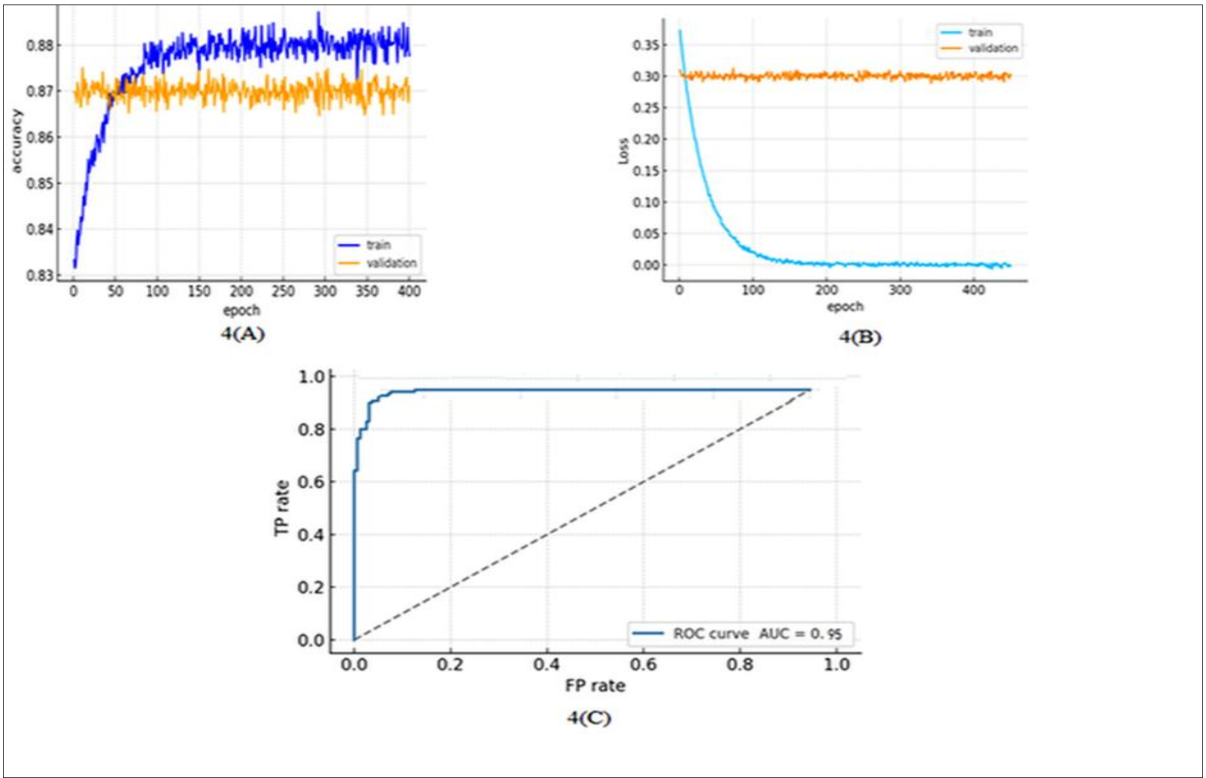

Figure 4: (A) Model Accuracy for Training and Validation, **(B)** Model's Validating and Training Losses, **(C)** FNN Model ROC AUC Curve

Table 3: Evaluation of ML-DL Ensemble

Model Curve	Accuracy	Precision	Recall	F1 Score	ROC Curve
ML- DL Ensemble	94.22	92.5	92.69	92.82	95.72

Table 3 displays the results of the group's predicting model, which detects cardiovascular disease using ML-DL stacked classifiers gives 92.5% precision, 94.22% accuracy, 92.69% recall, 95.72% ROC-AUC and 92.80% . F1 scores were the results of the ML-DL hybrid model.

Table 4: Evaluation of the Suggested System using the Baseline Approach

Method References	Model	Accuracy
	LR	85.54%
	RF	86.03%
(17)	DT	85.93%
	KNN	84.56%
	MLP	87.23%
	Method of GA-ANN	73.43%
	Method of ANN	68.35%
(16)	Method of LR	72.35%
	DT	61.72%
	RF	68.94%
(18)	ML Ensemble	88.70%
Our Proposed Methodology	ML-DL Ensemble	94.22%

The results of this investigation are contrasted with our baseline methodology in Table 4. Two machine learning models, RF and MLP, which produced positive outcomes with effectiveness ratings of 86.03% and 87.23%, respectively (17). Two newly developed neural networks and three computational models were employed (16). Using the GA-ANN model, this particular study had the greatest degree of accuracy (73.43%). Four machine learning models and two models for deep learning are used in their ML ensemble learning approach (18). For the ML ensemble, the researcher obtained an accuracy of 88.70%. As an ML-DL collaborative model was created using a full survey technique, the suggested approach performed more accurately than the initial results. Although the individual deep learning models achieved high accuracy and precision, their recall and F1-scores were comparatively lower due to class imbalance and conservative decision thresholds. In medical diagnosis, this may lead to increased false negatives. The proposed ML–DL ensemble mitigates this limitation by improving recall and F1-score, thereby enhancing sensitivity to positive cardiovascular disease cases

Conclusion

This work offers a multi-layered mixed model that enhances the accuracy and resilience of the heart failure forecast method by combining ML and DL approaches. Using a two-layer stacking method, a meta-learner in the second layer integrates the individual predictions made by the base learners in the first layer to improve the final choice. This method's use of a weighted majority voting technique is one noteworthy innovation. Each model's impact is scaled according to how well it performs.

The accuracy of the suggested approach was 94.22%. The ensemble model showed its effectiveness in predicting cardiovascular illness and exceeded every single one of the classifiers. Additionally, it offers a strong framework for combining DL and ML models. Although the proposed ML–DL ensemble demonstrates improved performance compared to individual classifiers, statistical significance testing such as confidence intervals or hypothesis testing was not conducted in this study. The results are based on comparative evaluation using standard performance metrics. Incorporating statistical validation methods will be considered in future work to further strengthen the reliability of the observed improvements.

Abbreviations

AUC: Area Under the Curve, ROC: Receiver Operating Characteristic.

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Author Contributions

Prashant M Goad: conceptualization, developed the theory, worked on the computations, Kiran H Sonawane: conceptualization, developed the theory, worked on the computations, validation of analytical method, Vipul D Punjabi: conceptualization, developed the theory, worked on the computations, validation of analytical method, Shailendra M Pardeshi: conceptualization, developed the theory, worked on the computations, validation of analytical method, Pramod J Deore: conceptualization, developed the theory, worked on the computations, validation of analytical method, supervision, Smital D Patil: conceptualization, developed the theory, worked on the computations validation of analytical method, Pramod J Deore advised Prashant M Goad, Kiran H Sonawane, Vipul D Punjabi, Vijay S Patil: study every algorithm and feature selection technique. He also oversaw the work's outcome. Every author discussed the results and added to the finished manuscript.

Conflict of Interest

None.

Declaration of Artificial Intelligence (AI) Assistance

The authors declare that no generative AI or AI-assisted technologies were used in the writing or preparation of this manuscript.

Ethics Approval

This study utilized a publicly available, anonymised dataset obtained from an open-access repository. The data contain no personally identifiable information and no human participants were directly involved in the study. Therefore, ethical approval and informed consent were not required for this research.

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