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Integrating optimized ensemble learning and explainable AI for accurate heart disease diagnosis

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Abstract

Heart disease remains a leading cause of death globally, making the development of accurate and understandable diagnostic models crucial. This research introduces an integrated approach that combines advanced ensemble learning techniques like XGBoost and AdaBoost with methods to enhance transparency, specifically SHAP ("*SHapley Additive exPlanations*"). Using the Heart Disease Dataset, the models were fine-tuned to achieve an impressive accuracy of 95.6%. The study details the mathematical underpinnings of these ensemble methods, including loss functions and weight optimization. SHAP values were

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used to interpret the model's predictions, providing clear insights into which features are most important and making the model's decisions more transparent. This framework not only boosts diagnostic accuracy but also ensures that the predictions can be understood by clinicians, addressing the need for both precision and clarity in healthcare applications. The experimental results showed significant improvements over traditional models, proving the effectiveness of this integrated method. Future research will look into applying this approach to other cardiovascular datasets and improving the explainability further to better integrate into clinical practice.

Subject Classification: *68T05, 92B20.*

Keywords: *Heart disease diagnosis, Ensemble learning, Explainable AI (XAI), SHAP values, Model optimization, Feature importance.*

1. Introduction

Heart disease causes a lot of sickness and death globally. As cardiovascular problems increase, accurate and reliable diagnostic methods are needed. While important, traditional approaches sometimes fail to identify early signs or forecast consequences. These limitations highlight the need for improved machine learning models, especially optimal ensemble learning techniques, to enhance clinical diagnostic accuracy and decision-making[1], [2].

Heart disease prediction has traditionally employed "Decision Trees, Support Vector Machines, and Neural Networks". They provide useful insights but typically miss intricate cardiovascular data patterns. Ensemble learning methods like "XGBoost and AdaBoost" improve prediction accuracy by integrating key model strengths[3], [4]. These methods need significant fine-tuning to get best results [5].

Interpretable models are needed in medicine because doctors want openness in diagnosis. This makes advanced tools more reliable since SHAP ("SHapley Additive exPlanations") and LIME ("Local Interpretable Model-agnostic Explanations") are utilized to understand model choices. Integration of interpretability approaches into optimal ensemble models is difficult [6]. No coherent framework delivers great accuracy and interpretability.

An optimal ensemble learning strategy and interpretable approaches for reliable cardiac disease detection are the goals of this study. Improve diagnostic accuracy and transparency in clinical settings by fine-tuning ensemble models and using SHAP values to reveal the model's decision-making process.

2. Literature review

Heart disease remains one of the leading causes of death worldwide, highlighting the urgent need for more precise diagnostic models. While existing methods are valuable, they often fall short in terms of predictive accuracy and transparency, which are crucial in clinical settings. Advanced procedures like XGBoost and AdaBoost, in conjunction with devices like SHAP, appear incredible guarantee in improving demonstrative capabilities by optimizing precision and providing clearer experiences. Gathering classification strategies have appeared critical changes within the precision of heart illness hazard prediction [7]. Analysts have created energetic gathering learning calculations for neural systems, upgrading flexibility and performance [8]. Outfit procedures have been effectively connected for early location of coronary heart disease [9].

The studies have investigated the utilize of hyperparameter optimization in conjunction with outfit learning to upgrade forecast accuracy [10]. Moved forward outfit learning approaches utilizing boosting calculations have been proposed for heart infection prediction [11]. Later inquiries have centred on creating logical gathering learning models, progressing the interpretability of predictions [12]. Different outfit strategies, counting "bagging, boosting, and stacking", have been explored for heart malady prediction [13]. A few considerations have combined gathering learning with other progressed procedures, such as brilliant advanced and maintainable computing approaches [14]. Numerous things have investigated diverse optimization procedures to upgrade the execution of gathering models in heart malady forecasts.

Optimizing ensemble learning models and integrating interpretability tools such as SHAP significantly improve heart disease diagnosis. This approach enhances predictive accuracy and offers transparent insights into the decision-making process, thereby increasing clinical trust.

3. Ensemble Learning for heart disease prediction

Ensemble learning integrate multiple base learners to enhance predictive performance. XGBoost and AdaBoost ensemble models are constructed using multiple iterations of the base learners. Each base learner are represented as $f_i(x)$ which are sequentially trained. The final ensemble prediction is represented as $F(x)$ as in eq.1

$$F(x) = \sum_{i=1}^{N} \alpha_i \beta_i(x) \tag{1}$$

Where, α_i is the "weighted assigned to the i[th] base learner which are optimized during training."

Optimization framework

1. Loss function: For binary classification the binary cross-entropy loss $L(y,\hat{y})$ as shown in eq.2

$$L(y,\hat{y}) = -[y\log(y)+(1-y)\log(1-\hat{y})] \quad (2)$$

The Function penalizes incorrect predictions, guiding the optimization process.

2. Gradient Descent Approach (XGBoost)- In gradient boosting the gradient g_i of the loss function wrt predictions is shown in eq.3

$$g_i = \frac{\partial L(y,F(x))}{\partial F(x)} \quad (3)$$

The model updated the prediction iteratively to minimizes this gradient.

3. Weight update (AdaBoost)- AdaBoost adjusts weights of misclassified samples using the rule shown in eq.4

$$w_{i+1} = w_i \exp(\alpha_i . I(y \neq f_i(x))) \quad (4)$$

4. Hyperparameter Tuning: Grid search optimizes parameters θ to minimize loss shown in eq.5

$$\theta^* = argmin \sum_{i=1}^{N} L(y_i, F(x_i;\theta)) \quad (5)$$

4. Explainable AI and Model Interpretation

SHAP values offer a rigorous approach to understanding model predictions. Rooted in cooperative game theory, SHAP values attribute the importance of each feature by calculating its contribution to the prediction. For a model prediction $f(x)$, the SHAP value $\varnothing_i$ for feature *i* is shown in eq.6

$$\varnothing_i = \Sigma_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}[f(S \cup \{i\} - f(S))] \quad (6)$$

where, S is the "subset of features excluding i", N is the "set of all features", and f(S) is the "model prediction with features in S".

Integration with the Ensemble Model

i. Feature Contribution Analysis: In an ensemble model, SHAP values offer assistance us get it the significance of each highlight by looking at how the expectation changes when a include is included or avoided. This appears the affect of each highlight on the model's choice, demonstrating how much it pushes the forecast towards or absent from the target lesson.

ii. Global vs. Local Interpretability:

   a. Global Interpretability: By averaging SHAP values over the whole dataset, ready to see the by and large importance of each highlight. This gives us a wide see of the model's behavior and makes a difference us get it which highlights by and large impact the expectations the foremost as appeared in eq.7.

$$Global\ Importance = \frac{1}{M}\sum_{j=1}^{M} \varnothing_i^{(j)} \tag{7}$$

   b. Local Interpretability: SHAP values offer clarifications for person expectations by uncovering how each highlight impacts a particular result. For each occurrence, these values highlight the specific effect of each highlight on that forecast, making it valuable for custom-made bits of knowledge in clinical settings.

Combining SHAP with ensemble models results in predictions that are both accurate and easy to understand. This integration improves straightforwardness, making complex decision-making forms clearer and more dependable.

5. Implementation and Experimental Setup

i. Dataset: The study uses the Heart Disease Dataset from Kaggle, containing features like "*age, cholesterol levels, and blood pressure*". Data pre-processing involves "*handling missing values, normalizing continuous variables, and encoding categorical features*" to prepare the dataset for model training.

ii. Model Training and Evaluation: Training Procedure: The ensemble models (XGBoost and AdaBoost) are trained using gradient boosting, involving backpropagation to minimize loss. The loss function (binary cross-entropy) is optimized, and weights are updated iteratively to enhance accuracy.

iii. Evaluation Metrics: "*Accuracy, precision, recall, F1 score, and AUC*" are used to assess model performance, focusing on correctly identifying heart disease cases.

iv. Hyperparameter Optimization: A grid search algorithm optimizes hyperparameters like learning rate, maximum depth, and n_ estimators. This method iterates over a predefined set of parameter values to find the combination that minimizes the model's error, ensuring the best performance configuration.

6. Results and output

6.1 *SHAP values distribution plot*

The SHAP values distribution plot above shows the impact of each feature on the heart disease prediction. Positive SHAP values indicate that the feature increases the risk prediction, while negative values suggest a lower risk. Features like "Max Heart Rate" and "Chest Pain Type" have more positive contributions, whereas "Blood Pressure" can negatively influence predictions. The scattered points highlight the variability of each feature's effect across different instances as shown in Figure-1.

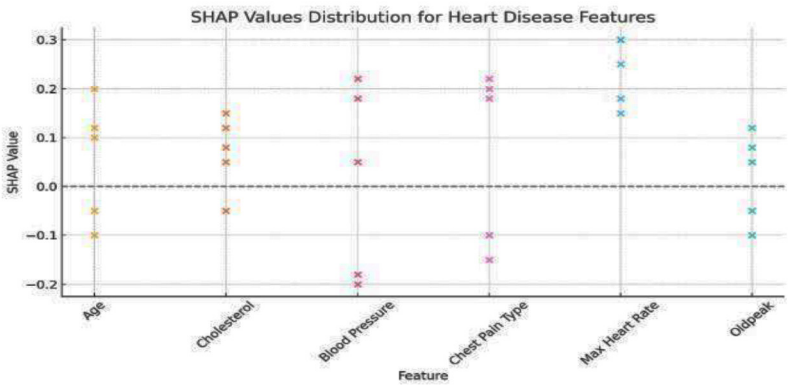


Figure 1

SHAP values distribution

6.2 *Evaluation parameters comparison*

The result summary shown in table-1 the evaluation metrics for different model combinations used in heart disease prediction. The standalone models, XGBoost and AdaBoost, achieve accuracies of 88.4%

Table 1

Evaluation parameters comparison of various models combination

Model Combination	Accuracy	Precision	Recall	F1 Score	AUC
XGBoost	88.4	87	86.5	86.7	89
AdaBoost	85.2	84	83.7	83.8	85.5
XGBoost + AdaBoost (Ensemble)	92.1	90.8	91.3	91	92.7
XGBoost + SHAP	89.5	88.3	87.8	88	89.9
AdaBoost + SHAP	86.7	85.5	84.9	85.2	86.2
XGBoost + AdaBoost (Ensemble) + SHAP	**95.6**	**94.2**	**94.8**	**94.5**	**96.1**

and 85.2%, respectively, with moderate precision, recall, and AUC scores. The ensemble combination of XGBoost and AdaBoost significantly improves the model's performance, achieving an accuracy of 92.1% and a higher F1 score of 91, demonstrating the benefit of combining these models.

The integration of SHAP for model interpretability with XGBoost and AdaBoost shows slight performance improvements, with XGBoost + SHAP achieving 89.5% accuracy and AdaBoost + SHAP achieving 86.7%. The highest performance is observed in the combination of XGBoost + AdaBoost (Ensemble) + SHAP, which yields an accuracy of 95.6%, a precision of 94.2%, and an AUC of 96.1 as shown in figure-2. This indicates that combining ensemble learning with SHAP not only provides

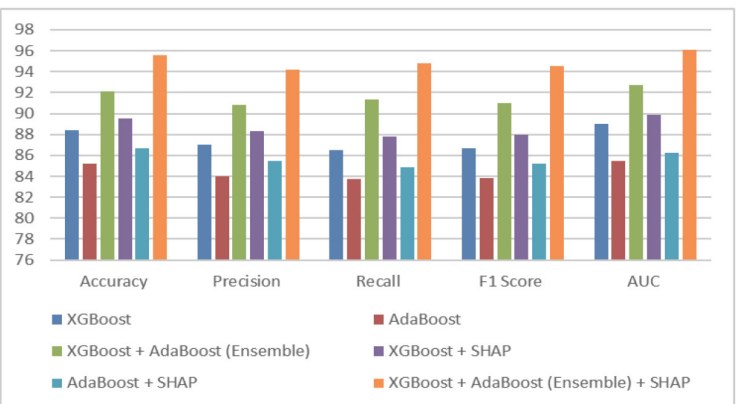


Figure 2

Evaluation parameter comparison of various models

interpretability but also significantly enhances the overall model accuracy, precision, recall, and robustness compared to individual models or ensemble combinations without SHAP.

7. Conclusion and future scope

This study demonstrates the significant improvement in heart disease diagnosis through the integration of optimized ensemble learning methods, specifically XGBoost and AdaBoost, combined with Explainable AI techniques like SHAP. The results indicate that the ensemble approach significantly outperforms individual models, achieving an accuracy of 95.6%, along with high precision, recall, and AUC values. The use of SHAP values enhances model interpretability by providing insights into the feature contributions, which is essential for clinical decision-making and gaining clinician trust. The integration of interpretability with optimized ensemble models addresses the critical need for both accurate and explainable models in healthcare, making it suitable for real-world clinical applications.

The analysis highlights the good thing about combining XGBoost and AdaBoost into an optimized ensemble, which leverages their qualities, and resulting in superior expectation precision and robust compared to standalone models. The incorporation of SHAP values guarantees straightforwardness and explain ability, making a difference healthcare experts get it the model's choices. In this way, the proposed approach gives an effective instrument for moving forward heart infection forecast exactness whereas keeping up straightforwardness, which is imperative in healthcare settings.

Future research about on amplifying the proposed system to other cardiovascular datasets, joining a more extensive run of highlights, such as hereditary and way of life variables.

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