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Article

Intelligent System for Early Detection of Heart Disease Using XGBoost Machine Learning Algorithm on Web Application

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Abstract: Heart disease remains a major contributor to global mortality, highlighting the importance of effective early detection systems that can assist both clinicians and general users. This study develops a heart disease prediction model based on the XGBoost algorithm and deploys it within a web-based application to enhance accessibility and practical usability. The research uses a dataset of 918 instances containing 12 demographic and clinical features commonly associated with cardiovascular risk. Pearson correlation analysis was performed to assess feature relevance, revealing that ExerciseAngina, Oldpeak, ST_Slope, Age, and MaxHR exhibit the strongest correlations with the HeartDisease outcome. These findings align with established clinical evidence on exercise-induced angina, ST-segment depression, and cardiac functional capacity. Following preprocessing and feature encoding, the XGBoost model was trained and evaluated. The model achieved strong predictive performance, with 88.26% accuracy, 88.32% precision, 91.66% recall, an F1-score of 89.96%, and an ROC-AUC of 0.93. The results demonstrate that XGBoost effectively discriminates between positive and negative cases and provides a good balance between sensitivity and precision. To enable real-world applicability, the final model was deployed on a Flask backend and integrated into a web application that allows users to input clinical parameters and receive real-time predictions. System testing confirmed that the application accurately delivers outputs and functions reliably across different input conditions. Overall, this study shows the feasibility of combining machine learning with web technologies to support early, accessible heart disease screening. Future work will involve usability testing and validation using real patient data to further strengthen the system's clinical relevance.

Keywords: *Early Detection, Heart Disease Detection, Machine Learning, Web-based Application, XGBoost Algorithm*

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1. Introduction

Heart disease remains one of the leading causes of death globally, accounting for approximately 17.9 million deaths each year, or 32% of all global mortality [1]. In Indonesia, coronary heart disease has also become a major health concern, with prevalence rising from 0.5% in 2013 to 1.5% in 2018 [2]. These trends demonstrate an urgent need for early detection, as timely diagnosis and treatment are known to improve patient outcomes and reduce life-threatening complications [3], [4] However, limited access to medical specialists, high diagnostic costs, and the complexity of conventional clinical assessments continue to hinder early detection efforts, particularly in developing countries.

In recent years, machine learning (ML) has emerged as a promising solution for supporting early diagnosis by enabling fast, data-driven predictions of heart disease risk

[5], [6]. Given its rising global prevalence and severe impact, including economic losses from reduced productivity, accurate and timely diagnosis is vital [7], [8]. Early treatment not only improves recovery and life expectancy but also prevents life-threatening complications [9]. To address these challenges, recent studies have explored the use of algorithms to analyze patient data and symptoms for more effective detection [10].

Recent research shows that XGBoost offers superior performance compared to Naïve Bayes, SVM, and Random Forest, achieving accuracy levels of 82-89% in heart disease prediction [11],[12],[13]. Its advantages such as handling missing values, regularization, and efficient tree boosting make it highly suitable for medical tabular data [14], [15]. Nevertheless, most existing studies primarily emphasize offline performance evaluation using publicly available datasets with standard clinical attributes, while limited attention is given to system-level implementation and real-time usability. As a result, the translation of high-performing models into practical, user-oriented screening tools remains insufficiently explored.

To address these gaps, this study develops an XGBoost-based machine learning model that integrates clinical, physical, and symptom-related features for more comprehensive early heart disease prediction. The model is embedded into a user-friendly web application designed to provide accessible, fast, and accurate preliminary risk assessment. This system aims not only to enhance prediction performance but also to increase public awareness and promote early heart health monitoring.

The objectives of this study are: (1) to evaluate the performance of the XGBoost algorithm in predicting heart disease using an enhanced feature set, and (2) to implement the trained model in a web-based application that enables real-time preliminary screening. The findings are expected to contribute to the development of more accessible diagnostic support tools and guide future research in applying machine learning for cardiovascular risk detection.

2. Materials and Methods

This study employs an experimental approach to develop and evaluate a heart disease prediction model using the XGBoost algorithm and to integrate the resulting model into a web-based application for early screening. The methods used in this research consist of dataset preparation, data preprocessing, model development, model evaluation, and system implementation.

2.1. Dataset

The primary dataset used in this study is the Heart Disease Dataset obtained from the Kaggle open-data platform. The dataset contains 918 records and 12 attributes, divided into 11 input features and 1 output label (*heartdisease*). The attributes used are:

1. age
2. sex
3. chest pain type
4. resting bp (resting blood pressure)
5. cholesterol
6. fasting bsm (fasting blood sugar measurement)
7. resting ecg
8. max hr (maximum heart rate achieved)
9. exercise angina
10. oldpeak (ST depression induced by exercise)
11. st_slope
12. heartdisease (binary output: 0 = Normal, 1 = Heart Disease)

These features include demographic information, clinical measurements, and physiological indicators commonly used in cardiovascular assessment. The dataset is

publicly available, free of copyright restrictions, and appropriate for supervised classification.

2.2. Data Processing

To ensure the dataset met the requirements for machine learning modeling, several preprocessing steps were conducted.

2.2.1. Handling Missing Values

The dataset was examined for incomplete or inconsistent records. Missing values in numerical features were resolved using median imputation, while categorical features were treated using mode imputation to maintain the statistical distribution of each attribute.

2.2.2. Encoding Categorical Features

Categorical attributes such as *sex*, *chest pain type*, *resting ecg*, *exerciseangina*, and *st_slope* were transformed using one-hot encoding. This approach avoids introducing unintended ordinal relationships and enables the model to learn patterns effectively.

2.2.3. Dataset Splitting

The dataset was divided into training and testing subsets using an 80:20 stratified split. Stratification was used to maintain balanced proportions between the two output classes, minimizing bias and improving evaluation reliability.

2.3. Model Development Using XGBoost

The XGBoost (Extreme Gradient Boosting) algorithm was selected due to its superior performance in classification tasks, efficient gradient boosting framework, regularization capability, and robustness on tabular medical data. Model development included hyperparameter optimization through Grid Search, aiming to identify the best configuration to maximize predictive accuracy. The optimized XGBoost model parameters are as follows: number of estimators ($n_estimators = 200$), maximum tree depth ($max_depth = 6$), learning rate ($learning_rate = 0.1$), subsample ratio ($subsample = 0.8$), column sampling by tree ($colsample_bytree = 0.8$), and regularization parameter ($\gamma = 0$). These values were selected based on the highest average cross-validation accuracy during the K-fold evaluation. Reporting these hyperparameters allows other researchers to replicate the experiments and validate the model's performance under the same conditions.

2.4. Model Evaluation

The performance of XGBoost was assessed through four evaluation metrics: accuracy, precision, recall, and F1-score. These metrics were chosen to provide well-rounded insights, especially in a medical context where false negatives must be minimized. A confusion matrix was also generated to observe the distribution of true and false predictions. All evaluation procedures were implemented using Python libraries including *scikit-learn*, *pandas*, and *xgboost*.

2.5. System Implementation

After obtaining the best-performing model, it was integrated into a web-based application designed to provide real-time heart disease risk predictions. The development followed the waterfall methodology, consisting of requirements analysis, system design, implementation, testing, and deployment phases.

The system adopts the Model–View–Controller (MVC) architecture. The frontend was developed using Flutter with BLoC state management, while the backend utilized Flask to handle API requests. The trained XGBoost model was exported in .json format and deployed on a server, allowing the application to send input data and receive predictions via REST API. Key features include user authentication, clinical data input, prediction results display, and profile management. Compatibility and usability tests were conducted to ensure smooth system performance across devices.

3. Results

The development of the machine learning model was conducted using the Python programming language within the Visual Studio Code IDE environment. Prior to model training, feature correlation analysis was performed using the Pearson correlation coefficient to identify the strength of relationships among variables. The analysis began with an exploratory assessment of feature relationships using the Pearson correlation coefficient (Figure 2). The correlation heatmap revealed that ExerciseAngina exhibited the strongest positive correlation with the target variable HeartDisease (0.49). Other clinically relevant features—including Oldpeak (0.41), ST_Slope (0.38), Age (0.28), and MaxHR (−0.40)—also demonstrated meaningful correlations. These results indicate that both demographic and physiological factors contribute to the likelihood of heart disease, consistent with established clinical knowledge regarding exercise-induced angina, ST-segment depression, and functional cardiac capacity.

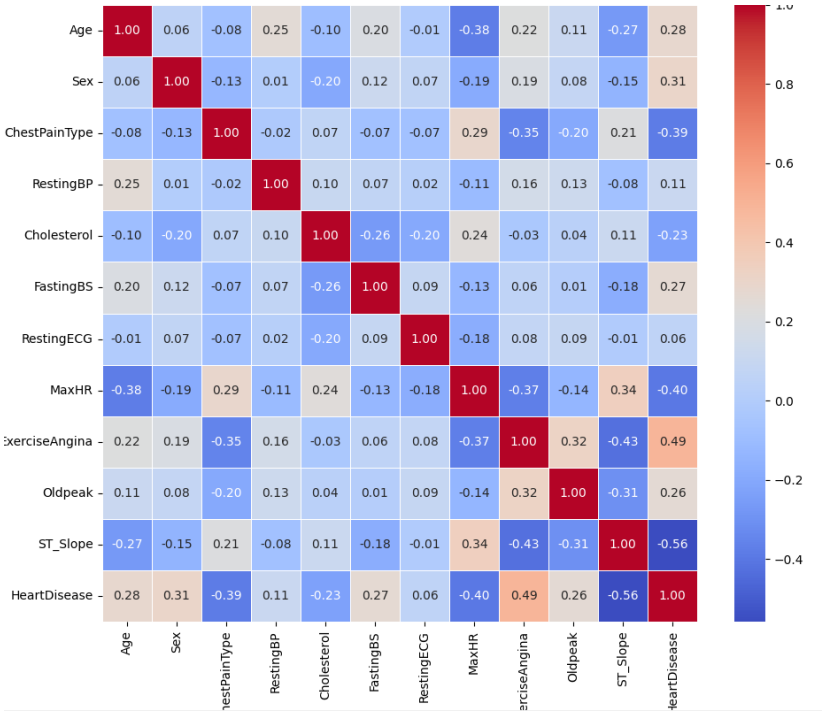


Figure 1. Correlation Matrix

The predictive model was developed using the XGBoost algorithm, which was trained on the processed dataset. XGBoost optimizes an objective function that combines a loss function measuring the difference between predicted and actual values, and a regularization term to control model complexity. The general objective function can be expressed as:

$$Obj(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (1)$$

Where l represents the loss function (e.g., logistic loss for classification), $\hat{y}_i$ is the prediction for the i instance, and Ω(fk) is the regularization term for the k tree. The regularization function is defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda||\omega||^2 \quad (2)$$

with T denoting the number of leaves in the tree, ω the leaf weights, and γ,λ, hyperparameters controlling model complexity. This formulation allows XGBoost to achieve both high predictive accuracy and good generalization. The performance of the final XGBoost model on the test set is summarized in Table 1.

Table 1. Model Performance Evaluation

Metric	**Score**
Accuracy	88.26%
Precision	88.32%
Recall	91.66%
F1-Score	89.96%
ROC-AUC	0.93

The performance evaluation showed on Table 1. that XGBoost achieved an accuracy of 88.26%, precision of 88.32%, recall of 91.66%, and an F1-score of 89.96%. To contextualize the performance of the proposed XGBoost model, a comparative analysis was conducted using other commonly applied machine learning algorithms on the same heart disease dataset. Naïve Bayes achieved an accuracy of 82%, Random Forest reached 86%, and SVM obtained 89%. In comparison, the proposed XGBoost model demonstrated an accuracy of 88.26%, indicating competitive performance relative to these standard approaches. This comparison highlights the robustness and reliability of the proposed model while providing a benchmark for future research on similar datasets.

Following the training and evaluation phase, the final XGBoost model was integrated into a web-based application to provide a practical tool for early detection. The integration was carried out by deploying the model on a Flask server and connecting it with the application's backend and frontend components. The user interface of the application (Figure 3) presents a heart disease prediction page, where users are required to input clinical and demographic data such as age, gender, chest pain type, blood pressure, cholesterol levels, blood sugar, resting ECG results, maximum heart rate, exercise-induced angina, ST segment changes, and ST slope. Upon submission, the application generates an immediate prediction result, enabling users to conduct independent early screening of heart disease risk. This integration demonstrates the feasibility of combining machine learning models with web technologies to create an accessible, user-friendly decision-support system, particularly valuable in preventive healthcare contexts.

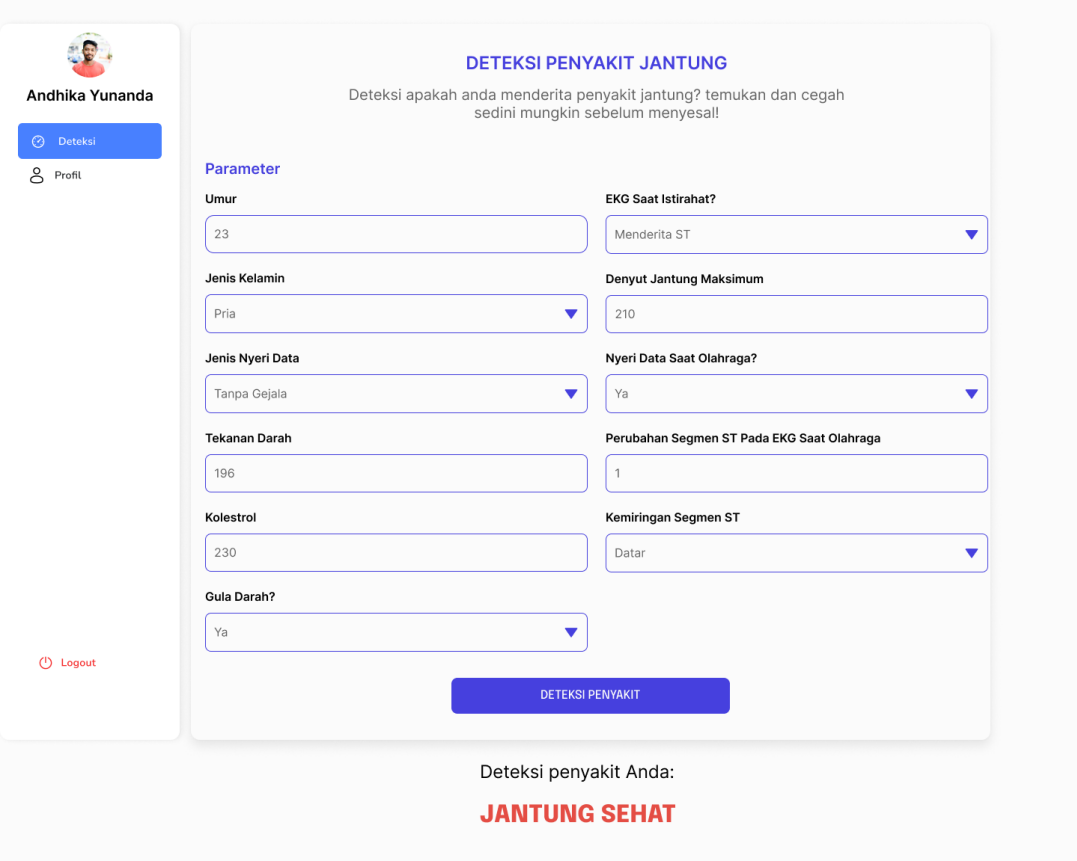


Figure 2. User Interface of Heartache Detection Web Application

The results of the integration demonstrate that the web application is capable of correctly displaying prediction outputs based on the data entered by users. Once the input form is completed and submitted, the system utilizes XGBoost as the primary prediction model. This choice was based on preliminary experiments, which showed that XGBoost outperformed other algorithms, achieving higher accuracy than Naïve Bayes (82%) and Random Forest (86%) on the same dataset, thereby confirming its robustness and suitability for early heart disease detection. These results indicate that the integration between the machine learning model and the web system functions as intended, enabling end-users to perform independent, accurate, and real-time early screening of heart disease risk. This capability underscores the practicality of the system and its potential contribution to preventive healthcare.

4. Discussion

The findings of this study demonstrate that the application of the XGBoost algorithm provides strong predictive capability for early detection of heart disease, supported by statistically meaningful relationships among key clinical features. The Pearson correlation analysis conducted prior to model development revealed that ExerciseAngina exhibited the strongest positive correlation with HeartDisease (0.49), indicating that patients experiencing exercise-induced angina have a significantly increased likelihood of cardiovascular abnormalities. Other highly relevant features—such as Oldpeak (0.41), ST_Slope (0.38), Age (0.28), and MaxHR (–0.40)—also showed substantial associations with the target variable. These findings are consistent with established cardiology literature, where ST-segment depression, abnormal ST slope, reduced heart rate capacity, and advanced age are well-known markers of cardiac dysfunction.

The correlation patterns further support the clinical interpretability of the model by confirming that the features contributing to XGBoost's predictions align with real-world

physiological mechanisms. Notably, the negative correlation of MaxHR with heart disease reflects the reduced exercise tolerance typically observed in individuals with compromised cardiac output. This concordance between correlation insights and clinical expectations strengthens the reliability of the model's predictive behavior.

The XGBoost model achieved an accuracy of 88.26%, precision of 88.32%, recall of 91.66%, F1-score of 89.96%, and an ROC-AUC of 0.93, indicating a strong balance between sensitivity and specificity. The high recall demonstrates the model's ability to correctly identify patients with heart disease, minimizing false negatives critical for early medical screening. Slightly lower accuracy and precision can be attributed to borderline or atypical patient profiles that inherently challenge classification, as reflected in the approximately 12% misclassified cases. Analysis of these errors revealed that most misclassifications occurred in patients with intermediate ST_Slope values or minor deviations in ExerciseAngina and Oldpeak, highlighting ambiguous cases where feature patterns resemble both positive and negative classes. This examination provides insight into the model's limitations and suggests potential improvements, such as incorporating additional clinical indicators or refining preprocessing. Compared to previous studies on similar heart disease datasets, where accuracy typically ranges from 82% to 89%, the proposed XGBoost model demonstrates competitive performance, particularly in terms of recall and F1-score, confirming its robustness and suitability for practical early screening in clinical settings.

The successful integration of the trained model into a Flask-based web application further underscores the practicality and translational potential of the system. The application allows users to input demographic and clinical variables such as age, sex, chest pain type, resting blood pressure, cholesterol level, fasting blood sugar, resting ECG results, maximum heart rate, exercise-induced angina, oldpeak, ST slope and instantly obtain predictive results. This seamless pipeline from data entry to model inference confirms the reliability of the deployment process and validates that the backend–frontend integration functions effectively.

Moreover, the web interface's ability to deliver real-time, user-friendly screening results highlights the system's relevance for preventive healthcare. By enabling independent early detection outside of clinical settings, the application may assist individuals in recognizing potential cardiac risks earlier and seeking timely medical consultation. This is particularly valuable in regions where access to healthcare services is limited or where routine cardiovascular screening is uncommon.

Overall, the combination of robust model performance, clinically meaningful feature relationships, and successful web-based deployment demonstrates that the proposed system is both technically sound and practically applicable. The results reinforce the feasibility of integrating machine learning–based decision-support tools into accessible digital platforms, contributing to early detection strategies that may ultimately improve cardiovascular health outcomes.

5. Conclusions

This study demonstrates that the XGBoost algorithm provides an effective approach for the early detection of heart disease, as evidenced by both strong predictive performance and clinically meaningful feature relationships. Correlation analysis indicates that key attributes—such as ExerciseAngina, Oldpeak, ST_Slope, Age, and MaxHR—have substantial influence on heart disease risk, which is consistent with established cardiovascular clinical knowledge. The proposed model achieved an accuracy of 88.26%, indicating that the majority of patient cases were correctly classified. A precision of 88.32% reflects a low false-positive rate, which is particularly important to avoid unnecessary clinical follow-up. Furthermore, the recall of 91.66% demonstrates the model's strong ability to correctly identify patients at risk, a critical requirement for early screening applications. The resulting F1-score of 89.96% highlights a well-balanced trade-off between precision and recall. In addition, an ROC-AUC value of 0.93 indicates

excellent discriminative capability, confirming that the model can reliably distinguish between patients with and without heart disease across different decision thresholds.

The successful deployment of the trained model into a Flask-based web application further highlights the system's practical utility. The application allows users to input demographic and clinical attributes and instantly receive prediction outcomes, enabling accessible, real-time, and independent preliminary screening. This integration demonstrates the feasibility of combining machine learning techniques with web technologies to support early identification of heart disease, particularly in preventive healthcare contexts.

While the present study focuses on model development and system integration, future research may include usability testing, validation with real clinical patient data, and broader system evaluation in operational healthcare environments. Such extensions will strengthen the system's reliability and its potential adoption as a decision-support tool in real-world medical practice.

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