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Heart Disease Diagnosis and Prediction Using Naïve Bayes and Gradient Boosting Machine Learning Models

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ABSTRACT
This paper discusses the design and development of machine learning models using extreme gradient boosting and Naïve Bayes Algorithms for heart disease diagnosis and prediction. The system leverages patient medical records and other demographic information to deliver personalized health assessments. The heart disease dataset comprises 1,025 records with 18 clinical variables sourced from the UCI Machine Learning Repository. Disease prediction was performed using Naïve Bayes and Gradient Boosting Machine Learning Models, chosen for their effectiveness and good classification performance. Model training involved preprocessing the data to address issues related to noise and missing values, and normalization to reduce redundancy and improve prediction accuracy. Results of the implementation of the heart disease prediction systems show that the XGBoost model achieved superior results, with an accuracy of 89.3%, precision of 87.5%, recall of 90.1%, and F1-score of 88.8%, outperforming the Naïve Bayes classifier, which obtained higher rates of false predictions. The system operates in near real-time, providing timely alerts to users, which supports continuous health monitoring and enables proactive medical intervention.

Keywords: Heart Disease Prediction; Mobile Health Monitoring; Machine Learning; fusion models; Real-Time Health System

1. INTRODUCTION

To meet the demands of a growing human population and the increasing financial challenges in healthcare, cost-effective and intelligent healthcare has become more widespread [1]. The use of technology to enhance patient quality of life and care has yielded promising results in recent advances in personal and mobile healthcare [2],[3]. The technology-driven mechanisms of the 21st century make it easier to achieve optimal efficiency in healthcare service delivery. Internet of Things (IoT)-based wearable devices, such as smartwatches, smartphones, and smart glasses embedded with sensors like Electrocardiographs (ECG), gyroscopes, and accelerometers, have demonstrated important technological solutions to address health-related issues for people in both rural and urban areas [4]. These sensors are used to collect physiological signals and biodata for healthcare data analysis. As a result, the biomedical community is increasingly interested in personalized and mobile healthcare [5]. The intention behind these approaches is to provide individuals with health advice and diagnoses tailored to their specific needs. This can be achieved through continuous monitoring of patients' physiological processes using various sensors, including ECG, pulse rate, gyroscopes, and others [6].

Hence, health monitoring is best described as the periodic observation of changes that provide information on an individual's welfare. Health monitoring at work can be summed up as keeping an eye on someone to see whether their health condition changes as a result of exposure to specific health risks associated with running a business or project [7]. Accordingly, mobile health (m-Health) is the act of deployment of a portable technological mechanism such as smartphones, wearable, handheld devices, and other automated-based sensors for mobile health monitoring, care systems, and to support public health in telemedicine practice [8],[9]. Additionally, the phenomenon known as the Internet of Things (IoT) is when a network of physical objects, devices, vehicles, buildings, and other items is embedded with electronics, software, sensors, and network connectivity, allowing these objects to gather and share information [10]. The Internet of Things (IoT) can also be defined as an integrated communication environment of interconnected devices and platforms that engages both the virtual and physical worlds [11], [12].

The evolution of wireless sensor networks (WSNs) and mobile apps has given rise to parameters for health monitoring systems. These mobile-based apps track the patient's heart rate in real time and alert the user when a health problem manifests itself. The doctors and family members may then receive information on the patient's health status from the mobile app [13], [14]. This inspired the concept of creating a mobile app-based integrated health monitoring system based on the IoT [15]. Access to, delivery of, and management of health information in our settings are being transformed by the rise of mobile IoT and applications. IoT computing has many advantages for the healthcare sector, care facilities, emergency response, and other healthcare providers in terms of the dissemination and expediting of healthcare services. Hence, mobile-based health monitoring offers health awareness, health applications and services, low maintenance costs, preventive care, self-monitoring, real-time, remote monitoring, and information on personal hygiene [16], [17]. Mobile apps can also help with self-management tasks, including offering instructional materials and aiding in problem-solving and self-regulation [18].

Even though lots of mobile apps such as health and fitness trackers with calorie counters, health mate, total health tracking, instant heart rate monitor and pulse checker, and cardiograph, heart rate has been developed for monitoring various health-related issues and physiological signals, deployment of these data for heart disease diagnosis and prediction through machine learning is still at its developmental stage.

Heart disease is a category of cardiovascular diseases that involves the structure and functioning of the heart. It has been identified as one of the most frequent causes of morbidity and mortality globally, causing the death of millions of people every year [19]. Heart disease is caused by several risk factors, among them being genetic predisposition, lifestyle habits, metabolic disorders, and environmental factors. Its main causes include atherosclerosis (deposition of plaque in the arteries), high blood pressure, high levels of cholesterol, smoking, obesity, inactivity, and excessive consumption of alcohol [20]. Also, cardiovascular disorders are caused or enhanced by underlying diseases, including diabetes mellitus and chronic kidney disease [21].

Furthermore, heart disease has been classified into different categories depending on physiological features and clinical implications [22], [23]. These classifications include coronary artery disease (CAD), Heart Arrhythmias, heart failure, pericardial disease, cardiomyopathy (heart muscle disease), and congenital heart disease. These categories of heart disease are caused by narrowing or blockage of the coronary arteries, electrical conduction system disorders of the heart, inflammation of the pericardial sac, and structural abnormalities of the heart [24]. These categories of heart disease present different symptoms that manifest in different forms such as chest pain, shortness of breath, fatigue, dizziness, irregular heartbeat patterns, swelling in the legs and ankles, rapid weight gain, and persistent coughing. Others include sharp chest pain, fever, cyanosis, poor weight gain in infants, and developmental delay [25], [26], [27].

For instance, utilizing a pilot telemedicine project in Southern Italy as a case study, Marino et al. [28] established mobile screening units for the early diagnosis of breast cancer and cardiovascular disease.

In this paper, Extreme Gradient Boosting (Boost) and Naïve Bayes (NB) algorithms are implemented to predict heart disease using patients' clinical information. The contributions of the study to the current body of knowledge are:

- To investigate an existing mobile-based health monitoring system to achieve an efficient heart disease prediction system;
- Develop a machine learning algorithm-based framework to predict heart disease in patients using clinical information;
- Extensive evaluation of the machine learning models using various evaluation metrics;
- The machine learning models utilized seventeen (17) health information and clinical features.

The remainder of the paper is organized as follows: Section 2 presents the methodology, including the dataset, preprocessing, feature extraction, machine learning models, and implementation procedure. Section three discusses the results obtained, while section 4 concludes the paper.

2. METHODOLOGY

This section explains the methodological procedures adopted to develop the machine learning models as depicted in Figure 1. These procedures include data collection, feature descriptions, data preparation, and model descriptions. Other procedures are algorithm description and machine learning evaluation using different performance evaluation metrics.

2.1 Data Collection

The dataset obtained from the UCI (University of California, Irvine) [29] machine learning repository was used for the heart disease diagnosis and prediction system using machine learning models. The data were collected from both male and female patients between the ages of 40 and 75 years. These are the age ranges with the highest number of cardiovascular disease patients. The data contains 1025 instances with 18 attributes/features and two target classes. The target classes show the presence or absence of heart disease in the patients. Table 1 shows the features of the collected data.

2.2 Feature Description

Feature analysis is the process of identifying important and discriminant attributes that would predict the outcome of heart disease in elderly patients who visit the hospital. To ensure a comprehensive analysis of factors that contribute to heart disease, different patient information was collected and analysed for its discriminative factors. Age, sex, chest pain, cholesterol level, resting blood pressure, fasting blood sugar level, resting electrocardiography, physical activity levels as measured using an accelerometer, gyroscope, and magnetometer, measured in tri-axial data, are some of the characteristics that are crucial for the detection of patients with heart disease. The maximal heart rate, angina brought on by exercise, depression brought on by exercise, the slope of the peak by exercise segment, blood vessel blockage, and the diagnosis of heart disease, angiographic disease status are some additional factors. These features were integrated with patients' demographic information and formed the dataset for heart disease prediction.

Table 1: Attributes/features of the dataset used for disease prediction

Attributes	Description	Types	Values
Age	Age of the patient	integer	[40-77]
sex	Gender of the patient	Integer	Male =1; female = 0
Cp	Chest pain type	Integer	Angina =1; abnanr=2; notang=3, asympt=4
Trestbps	Resting Blood pressure value	integer	[94-200]
Chol	Cholesterol	Integer	[126-564]
Fbs	Fasting blood sugar	Integer	True=1; false=0
Restecg	Resting electrocardiographic results	Integer	[0-2]
Avacc	Average accelerometer value	Float	[0.0-3.0]
Avgyro	Average gyroscope value	Float	[0.0-2.0]
Avmag	Average magnetometer	Float	[0.0-250.0]
Thalach	Maximum heart rate	Integer	[71-202]
Exang	Angina-induced exercise	Integer	[1-4]=yes; 0=no
Avg_glucose	Average glucose level	Float	[50-250]
Oldpeak	Depression induced by exercise	Float	[0-4]
Slope	The slope of the peak exercise	Integer	Upsloping=1; flat=2; downsloping=3
Ca	Number of major blood vessels	Integer	[0-3]
thal	Blood vessel status	Integer	Normal=3; fixed defect=7; reversible defect=7
Target class	Coronary heart disease diagnosed	Integer	Present=1; absent=0

2.3 Data Preparation

In most cases, the collected patients' information is affected by noise, anomalies, missing values, and data duplication. Consequently, data preprocessing is an essential method to remove duplicate data and anomalies in patient data. In addition, inputting missing values using an average of each column is also an important method to ensure improved performance of the disease prediction system. Here, the data's mean was used to fill in the gaps left by the missing values. Duplicate values in the data were eliminated, and noise and errors were located and eliminated. For feature analysis, the pre-processed data was saved in a comma-separated values (CSV) file format.

2.4. XGBoost and Naïve Bayes Classifier for Heart Disease Prediction

2.4.1 Naïve Bayes Classifier

The Naive Bayes algorithm is a probabilistic classifier that is applied to the Bayes theorem and makes use of the independence of predictors. Although it is a simple test, it has been successively used in predicting heart diseases because of its capability to address the categorical and continuous variables. As an example, it has been demonstrated that Naive Bayes is capable of categorizing patient data, such as age, cholesterol, or blood pressure, to identify the existence of coronary heart disease with moderate to high probability [30]. Its benefits are that it is computationally efficient, interpretable, and strong for small-scale data sets, so it can be used as a baseline model in medical diagnosis.

2.4.2 Extreme Gradient Boosting (XGBoost)

XGBoost is an improved ensemble methodology of gradient boosting, which is characterised by high predictive capability and the ability to work with large and complicated data. XGBoost has been used in the prediction of heart diseases using structured clinical data, and it has always done better than its predecessors in that it can capture the non-linear interactions between the variables. It can prioritize the features (cholesterol, blood pressure, glucose levels) and give correct classification results. Studies have shown that XGBoost can be more accurate, precise, and recall than Naïve Bayes, Decision Trees, and even traditional regression models when it comes to the prediction of such conditions as coronary artery disease and heart failure [31].

2.5. Algorithm Descriptions

Algorithm 1: Pseudocode of Naïve Bayes Algorithm for Heart Disease Prediction System

Input:

- D ← Dataset with labelled instances (features and target)
- x ← New input instance (unlabelled)

Output:

- Prediction: Heart Disease Present (1) or Absent (0)

Begin:

1. *Preprocess the dataset D:*
   a. Handle missing values using column-wise mean imputation
   b. Remove duplicates and noisy data
   c. Normalize categorical and continuous features
2. *Calculate prior probabilities* for each class label (heart disease = 1, No Heart Disease = 0).
3. For each feature f in x:
   a. Compute the likelihood of observing f given each class using a Gaussian distribution (for continuous features) or frequency counts (for categorical features).
4. *Apply Bayes' theorem* to compute posterior probability for each class:
   $$P(Class|x) \propto P(Class) \times \Pi P(f|Class)$$
5. Select the class label with the maximum posterior probability.
6. Return the predicted class label (0 or 1).

End

Algorithm 2: Pseudocode of XGBoost Algorithm for Heart Disease Prediction System
Input:

- D ← Dataset with labeled instances (features and target)
- x ← New input instance (unlabeled)
- M ← Maximum number of boosting rounds

Output:

- Prediction: Heart Disease Present (1) or Absent (0)

Begin:

1. *Preprocess the dataset D:*
   a. Handle missing values using imputation
   b. Remove duplicates and noisy data
   c. Normalize features if required
2. *Initialize the model* with a base prediction (e.g., mean of the target variable).
3. For each boosting round m=1m = 1m=1 to M:
   a. Compute the *gradient (g)* and *hessian (h)* of the loss function for each instance.
   b. Train a regression tree using *ggg* and *hhh* to fit the residuals.
   c. Compute optimal leaf weights to minimize the loss function with regularization.
   d. Update the model by adding the new tree multiplied by a learning rate.
4. For the new instance x:
   a. Pass x through all trees in the ensemble.
   b. Aggregate the predictions to compute the final score.
   c. Apply a threshold (e.g., 0.5) to classify as heart disease (1) or No Heart Disease (0).
5. Return the predicted class label (0 or 1).

End

2.6. Performance Evaluation Metrics

In order to assess the performance of the proposed heart disease prediction system, several standard evaluation metrics were employed. These metrics considered in the study provide both general and detailed insights into the accuracy, reliability, and robustness of the machine learning models, and the evaluation metrics used for the context of this study are accuracy, precision, recall, F-score, and the confusion matrix.

- *Accuracy:*

Accuracy measures the proportion of correctly classified instances (both positive and negative) among all cases. It is defined as:

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

Where TP (True Positives) are correctly predicted disease cases, TN (True Negatives) are correctly predicted healthy cases, FP (False Positives) are healthy patients incorrectly classified as diseased, and FN (False Negatives) are diseased patients incorrectly classified as healthy.

- *Precision:*

Precision evaluates the correctness of positive predictions, i.e., the proportion of patients predicted as having heart disease who actually have the condition. It is given as:

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

A high precision value implies fewer false alarms and that the system rarely misclassifies healthy individuals as diseased.

- *Recall (Sensitivity):*

Recall measures the model's ability to correctly identify patients with heart disease. It is particularly important in medical applications where missed cases (false negatives) can have severe consequences. It is defined as:

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

High recall means the model is sensitive to detecting true cases of heart disease.

- *F-Score (F1-Score):*

The F-score is the harmonic mean of precision and recall. It provides a single measure that balances both metrics, making it especially useful when there is a trade-off between precision and recall. It is calculated as:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

This metric ensures that both false positives and false negatives are considered in evaluating performance.

- *Confusion Matrix:*

The confusion matrix provides a detailed representation of classification results by showing the number of correctly and incorrectly classified instances across different categories, as shown in Table 2. It is structured as follows:

Table 2: Confusion Metrix

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

This breakdown helps identify whether the system tends to over-predict or under-predict heart disease cases.

3. RESULTS AND DISCUSSIONS

To assess how well the heart disease prediction system performed, developers carried out a series of real-world tests using actual patient data and readings from phone sensors. These evaluations were designed to assess the system's accuracy, responsiveness, and dependability when used in a non-laboratory setting. The system processed the data using the Naïve Bayes and XGBoost models, comparing user health profiles with existing cases to detect potential heart risks. Key performance indicators, including accuracy, precision, recall, and F1-score, were analysed to determine how effectively the system could identify health issues.

To determine the usefulness of the mobile-based heart disease prediction system, a detailed analysis was conducted using a set of patient records totalling 1,025. These data were 18 different attributes that comprised age, gender, chest pain, blood pressure, cholesterol, glucose, and real-time sensor values of mobile phones, like the accelerometer, gyroscopes, and magnetometer. The data were processed and normalized, and then the Naive Bayes and XGBoost models were applied to analyze the data. The test was conducted on an 80/20 train-test split, and the findings indicated that XGBoost was better than Naive Bayes. In particular, the XGBoost model demonstrated an accuracy of 89.3%, a precision of 87.5%, a recall of 90.1%, and an F1-score of 88.8%, which is a strong and balanced predictor. In contrast, the Naive Bayes model achieved the accuracy of 84.7%, the precision of 81.2%, the recall of 85.4%, and the F1 score of 83.2%, which is reasonable but with greater misclassifications than XGBoost. The overall findings of the two models are shown in Figure 2.

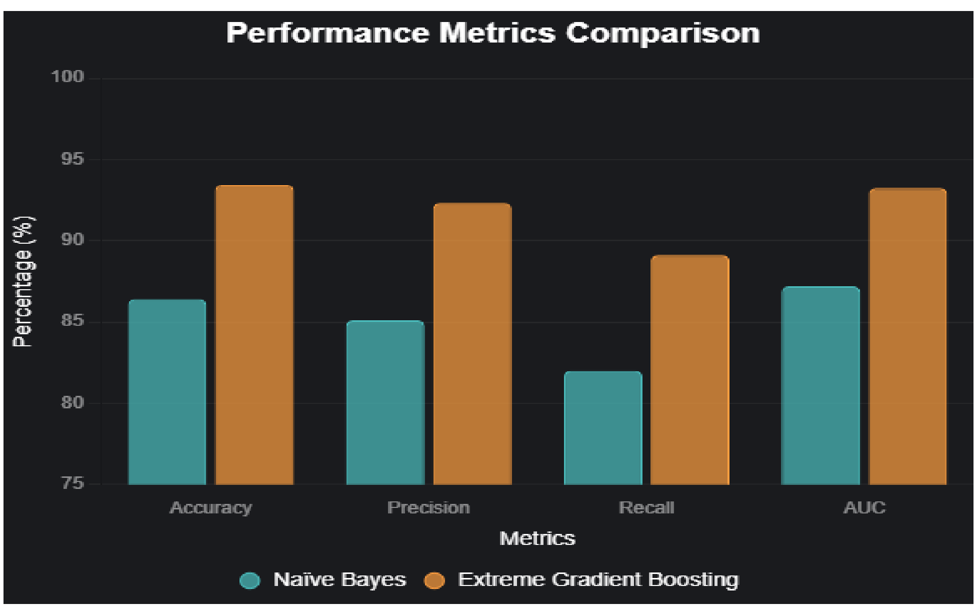

Figure 2: Results of the proposed Naïve Bayes and XGBoost models

The system also proved to be highly responsive, with the Android application delivering prediction results in under 2 seconds on average after users entered their data, ensuring a smooth, near real-time experience. Usability testing revealed that users found the app interface intuitive and easy to

navigate. They especially appreciated the clear presentation of health status
messages and the built-in alert feature for potential heart risk. These outcomes highlight the system's practical effectiveness and show that it is well-suited for real-world use in continuous health monitoring scenarios. The confusion matrix result of the classification models is presented in Figures 3 and 4.

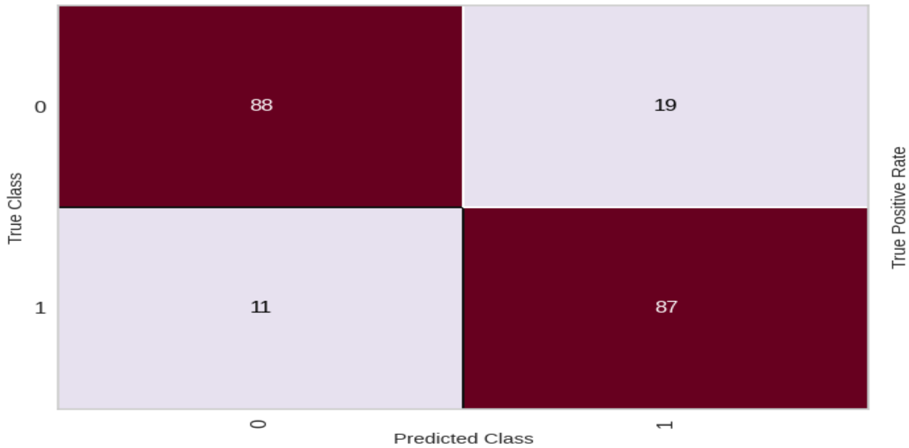

Figure 3: Confusion Matrix Result for XGBoost

The confusion matrix in Figure 3 gives an accurate overview of the performance of the binary classification model, and it shows both the strong and weak sides of the model. The model had a high predictive ability with 88 true negatives and 87 true positive outcomes, indicating it was able to predict the majority of the situations. Nonetheless, the false positives and false negatives that stand at 19 and 11, respectively, mean that there is still space to improve, particularly in reducing misclassifications.

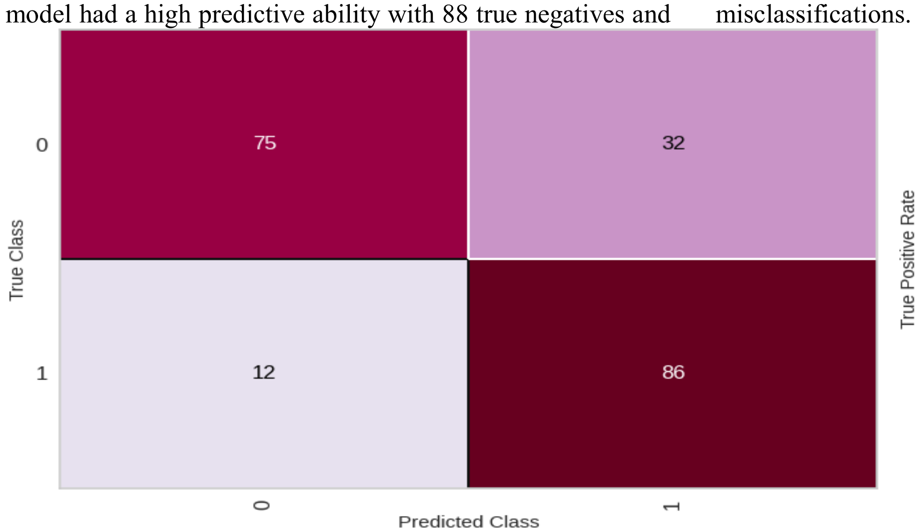

Figure 4: Confusion Matrix Result for Naïve Bayes Model

The confusion disorder outcome in Figure 4 indicates the existence of a classification model that is reasonably effective but exhibits the presence of an imbalance in its forecasts. In all cases, 75 were correctly classified as class 0 (true negatives) and 86 as class 1 (true positives), which points to the fact that the model has a good understanding of both classes. The 32 false positives (where the model falsely indicated that the data belongs to class 1) and 12 false negatives indicate, however, that this model is biased towards the positive class.
The findings of this paper show that the developed system of prediction of heart disease via mobile devices is accurate and applicable in the real world. Among the two evaluated models, XGBoost outperformed Naïve Bayes across all evaluation metrics, achieving an accuracy of 89.3%, precision of 87.5%, recall of 90.1%, and F1-score of 88.8%. These results indicate that XGBoost is highly effective in correctly identifying patients with heart disease while minimizing false predictions. The Naive Bayes classifier was found to have more false positives and false negatives; thus, it is not as reliable as a standalone model since it is computationally efficient. The obtained results of the confusion matrix only supported the effectiveness of XGBoost, where most cases were rightly identified, and Naïve Bayes demonstrated the relative imbalances. Also, the system can make predictions

within less than 2 seconds, and its positive feedback with usability makes it suitable to be used to monitor the patient regularly and identify cardiovascular risks early. On the whole, the results reveal that the use of machine learning models, specifically XGBoost, and mobile sensor data can be used to support predictive healthcare apps to a great extent.

4. CONCLUSION

This study presents the design and implementation of a mobile-based system to predict heart disease through machine learning with specific reference to Naive Bayes and XGBoost algorithms. The patient demographic and clinical data were utilized and then pre-processed, including the removal of noise, the normalization of data, and the imputation of missing values. The processed data was used as input in the machine learning models for heart disease diagnosis and prediction. The models were assessed using the performance evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix.

The results showed that the system achieved strong predictive performance, confirming its feasibility for real-world applications. The implementation shows that XGBoost was the most accurate and reliable in its predictions.

Future studies will be aimed at working with increased and more heterogeneous populations, incorporating physiological sensors, and deep learning models that will further enhance prediction accuracy and generalization.

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