

# Prediction and Classification of Binary and Multi-class Heart disease with Artificial Intelligence

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**Abstract**—Heart disease poses a significant threat to human existence because of its high mortality and morbidity rates. For early treatment, localization, and countermeasure, precise anticipation and conclusion are becoming increasingly important. The Internet of Things and artificial intelligence make it easier for doctors to find, evaluate, and diagnose cardiac disease. However, the majority of prediction models only assess the severity of an individual's illness and only predict whether they are ill. In this study, we present a hypothesis model for simultaneous assumption for both matched and distinct request coronary illness that is based on machine learning (ML). We first develop a fuzzy-GBDT strategy that combines fuzzy reasoning with gradient boosting decision tree (GBDT) to advance the matched portrayal assumption and reduce data complexity. To avoid over fitting, the pressing is completed with fleecy GBDT. Theseverityofcardiacdiseaseisalsoincludedinthemulticlassificati on assumption based on Bagging-Fuzzy-GBDT. The assessment shows that the Packing Fluffy GBDT is incre dibly dependable and exact for both twofold and different get-together presumptions.

**Keywords** :Fuzzy logic, gradient boosting decision tree, the Internet of Medical Things cardiac disease prediction and diagnosis, and machine learning

## I. INTRODUCTION

One of the most difficult and life-threatening diseases affecting humans, heart disease has a high mortality and morbidity rate [1]. People's quality of life suffers as a result, and treatment and monitoring incurs significant costs. It is possible to anticipate, recognize, and diagnose health conditions with artificial intelligence (AI) [2]. By making it possible for patients to receive the appropriate medical information, treatment, and intervention, it may lessen the devastation caused by heart disease. Continuous cardiac illness prediction and suggestive out comes may be possible for e-medical care frameworks that heavily rely on Internet of Medical Things (IoMT) data using AI learning algorithms [3]-[6]. In addition, it alleviates the financial and administrative challenges associated with intelligent systems for the treatment, monitoring, and prevention of chronic diseases. However, how to guarantee the strength, generalizability, and high accuracy of ML-based expectation models and computations must be addressed.

In today's society, the idea of anticipating cardiac disease is a significant one that is altering people's perceptions of health. The basic concept is to use the Random forest algorithm to figure out the age group and heart rate. Based on user-supplied inputs like blood pressure and other variables, our study shows how a system analyzes heart rate and condition. Compared to other algorithms, RFA produces

results that are more accurate and offers a better user experience. The assessment of a person's heart rate in relation to their overall health is just one of the many uses for this. Additionally, it aids in the early detection of disease.

The bootstrap totalling (bagging) method is added to the learning model to increase the area under the curve (AUC) while decreasing change. However, the accuracy of any prognosis has not been established because previous studies on the prediction of heart disease have heavily relied on complex data. The initial multi-category method for diagnosing various risk groups for heart disease still has room for improvement in terms of accuracy.

For both binary and multiple-order heart disease expectations, we present a stable and precise expectation method in this work. By simplifying the input, fuzzy logic, on the other hand, encourages model generalization and reduces model deviation. By reducing the change and deviation of the assumption model, the unrivaled Bagging-Fuzzy-GBDT enhances estimate exactness and adequacy. Early detection of heart disease in high-risk, upgraded symptomatic individuals using an expectation model has been widely proposed to cut down on deaths and further advance treatment and prevention options. In CDSS, a forecast model is made and used to help doctors figure out why people are so likely to get heart disease and give them the right drug to lower that risk. In addition, a number of studies have demonstrated that utilizing CDSS may enhance the quality of decisions, clinical navigation, and deterrent consideration. Coronary artery disease (CAD), also known as ischemic heart disease (IHD), is the most common cause of death among people over the age of 35 in some nations. It also rose to become the most common cause of death in China over the same time period. IHD occurs when coronary artery stenosis reduces blood flow to the heart. Myocardial damage can result in a potentially fatal myocardial infarction, which can either result in ventricular arrhythmia or sudden cardiac death.

## II. LITERATURE SURVEY

[1] The authors in this paper explored the use of trend analysis in telemonitoring data to predict decompensation events in heart failure patients. Decompensation events are acute worsening of heart failure symptoms that often lead to hospitalization, reduced quality of life, and increased healthcare costs. Early prediction and intervention are crucial to prevent these events and improve patient outcomes.

[2] The authors explore the concept of home care robotic systems offering a vision for the future of health care and

discussing the enabling technologies that can facilitate the development and deployment of these systems. Home care robotic systems have the potential to revolutionize health care by providing personalized, convenient, and efficient care in patients' homes, which is particularly relevant given the aging global population and increasing demand for healthcare services.

[5] The authors combined deep Long Short-Term Memory (LSTM) recurrent neural networks with adaptive kernel spectral clustering to provide a novel method for monitoring health with AI. The primary goal of this research is to enhance the effectiveness of machine health monitoring systems, which are essential for preventing failures, reducing maintenance costs, and ensuring the safe operation of machinery. The authors employ deep LSTM recurrent neural networks to model the temporal dependencies within the extracted features. This approach is particularly effective in handling time series data, as LSTM networks can capture long-term dependencies and learn complex patterns. The deep LSTM is built and trained to predict the machine's health state, enabling early identification of potential failures or deteriorating conditions.

[6] This study gives a novel approach to the detection and localization of ischemic heart disease (IHD) using magnetocardiography (MCG) and machine learning techniques. Reduced blood flow to the heart muscle is the primary cause of ischemic heart disease, which is also a leading cause of death globally. The authors' work is significant as it offers a promising alternative to traditional diagnostic methods and demonstrates the potential of machine learning in improving the accuracy and efficiency of IHD detection.

[9] The authors investigate the potential of Graphics Processing Units (GPUs) for improving the efficiency of Gradient Boosting Decision Tree (GBDT) training. Because of its excellent accuracy and capacity for handling big data sets, GBDT is a potent machine learning method that is frequently used for a variety of tasks, including classification and regression. However, the training process for GBDT can be computationally intensive and time-consuming, especially when dealing with large-scale data. This research is significant because it addresses the challenge of GBDT training efficiency by leveraging the parallel processing capabilities of GPUs, which can lead to faster and more efficient model training.

[14] This study investigated the prediction of prefix availability in the Internet. Prefix availability refers to the reachability of a specific IP prefix, which can impact the stability and performance of Internet communication. The authors used a variety of machine learning approaches, including decision trees, logistic regression, and support vector machines, to develop models for predicting prefix availability. Many metrics, such as precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve, were used to assess the models' performance.

[15] This study proposes a method that combines traditional classification algorithms to enhance accuracy and efficiency of diagnosis. Heart disease is a major global health concern, and early detection is crucial for successful treatment and management. The authors' work is significant because it presents a novel approach to heart disease prediction, leveraging the strengths of both associative classification and genetic algorithms to improve the performance of traditional prediction methods. A genetic algorithm is used to optimize the rule set generated in the first phase. The genetic algorithm searches for the best combination of rules that maximizes prediction accuracy while minimizing the complexity of the rule set. This optimization process results in a more efficient and accurate prediction model compared to using associative classification alone.

### III. METHODOLOGY

As previously demonstrated, most current assumption models and calculations only address the matched portrayal issue of heart disease speculation without taking into account the actual severity of the condition. Based on angiographic data, the level severity of the disease is divided into five classes, ranging from mild disease to level four. In any case, the primary multiclassification method's accuracy in requesting various heart disease bet classes needs to be improved. Reducing fluctuation and deviation is frequently used in machine learning to improve computation accuracy. The learning model accomplishes a bigger region under the bend (AUC) and confines change by including the bootstrap collecting (packing) technique. However, the exactness of each type of coronary disease prediction has not been provided in previous studies on cardiac illness forecasting due to key information complexities. In fact, there's still a chance to increase the accuracy in multiclassification problem. Although it does not cover every kind of heart disease anticipation, previous research on the prediction of heart disease contains a significant amount of information complexity.

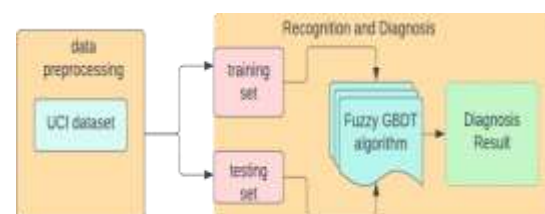
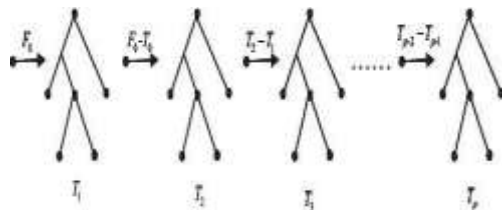


Fig 1 System Architecture

Thomas et al. forecasted each player's wager. In any case, the primary multiclassification method's accuracy in requesting various heart disease bet classes needs to be improved. From one point of view, by making information simpler, fuzzy logic makes model speculation better and reduces model deviation. To improve accuracy, we incorporate fluffy logic into the GBDT computation. In contrast, the sacking method reduces model change by repeating erroneous inspections. Accordingly, we incorporate the putting away strategy to



build the model's solidarity. When contrasted with the band flow estimations, our proposed reciprocal can foresee whether people are debilitated as well as the seriousness of heartsickness.

Fig2 Schematic diagram of GBDT Algorithm

The benefit of a Fuzzy-GBDT-based twofold characterization expectation technique for heart disease conclusion are presented. These advantages include an increase in the GBDT's speculation limit and a reduction in the complexity of the information regarding heart disease.

The superior Bagging-Fuzzy-GBDT manages strength and accuracy of figures. By minimizing the change and deviation in the assumption model, we present in this article a consistent and high-precision supposition method for both twofold and numerous heart diseases solicitations.

### Modules

The below modules were developed by us for the notion in our project.

- Data investigation: We will enter data into the system with this module.
- Treatment: We will read data for processing using this module.
- Separating train and test data: Train and test data will be separated by this module.
- Models that can be generated include SVM, RF, DT, LR, KNN, XGBoost, Gaussian Naive Bayes, Voting Classifier, GBDT, Bagging+GBDT, Fuzzy+GBDT, and Bagging+Fuzzy+GBDT.
- Login and registration for users: Sign Up and authentication are required in order to access this module.
- User-provided prediction information: Prediction input will result from using this module.
- Prognosis: The final predicted value is shown.

## IV. IMPLEMENTATION

### 1. Data Pre-processing

We make use of the heart disease open-sourced dataset from the University of California, Irvine (UCI) [25]. Four distinct medical databases, including those in Cleveland, Hungary, Switzerland, and VA Long Beach, provide the information. There are 836 data in total and 14 significant attributes in this database. Most of the datasets Switzerland and VA Long Beach require the completion of missing values. The average values from other complete datasets are used to fill

in the blank fields.

The dataset in this study is split into a training set and a test set in the ratio of 7 to 3.

### 2. Bagging Fuzzy GBDT Algorithm

There are six parameters for the Bagging-Fuzzy-GBDT algorithm that must be determined. They are depicted as follows. The values of these parameters have an impact on the predictability and precision of the suggested model. Hence, one of the main issues is how to determine the ideal values.

- M decision trees are present. Each iteration of the Bagging-Fuzzy-GBDT growth process results in the creation of a decision tree.
- Each decision tree can have a maximum depth of MD. MD cannot have an excessively high or low value. The algorithm takes too long to run if MD is too large since each tree's training period is prolonged.
- To separate an internal node, MS samples are needed as a bare minimum. Two circumstances define the value of MS.
- A leaf node requires ML samples to be present as a minimum. A splitting point of any depth will only be taken into consideration if both of its left and right branches still contain at least ML training samples.
- There will be m samples collected for bagging. To create m sub-datasets, mis the number of samples from the original set that must be replaced.
- My rate of learning. By regulating the contribution of a single decision tree in the model using the regularization technique known as learning rate, an overfitting of the Bagging-Fuzzy-GBDT can be prevented.

## V. PERFORMANCE EVALUATION

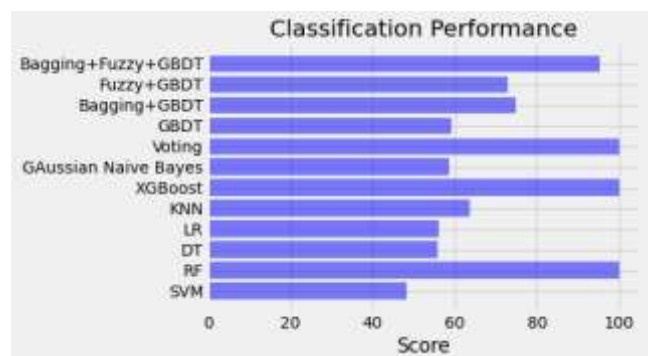
### GBDT

```
*Classification Report for GBDT:
              precision    recall  f1-score   support

     0       0.73         0.82         0.77         287
     1       0.51         0.55         0.53         161
     2       0.47         0.42         0.44          71
     3       0.39         0.24         0.30          71
     4       0.53         0.48         0.50          21

 accuracy          0.59         531
 macro avg         0.52         0.50         0.51         531
 weighted avg      0.57         0.59         0.58         531
```

Fig5 Precision and Recall



The Bagging-Fuzzy-GBDT approach provides a significant improvement in precision and accuracy. First, GBDT performs better at predicting heart disease than traditional decision tree prediction models. Second, using the comparison results between Bagging-GBDT and Fuzzy-GBDT with GBDT

```
*Classification Report for Bagging + Fuzzy + GBDT:
precision recall f1-score support
0 0.94 0.98 0.96 207
1 0.96 0.93 0.94 161
2 0.94 0.94 0.94 71
3 0.99 0.94 0.96 71
4 1.00 1.00 1.00 21

accuracy 0.95 531
macro avg 0.97 0.96 0.96 531
weighted avg 0.95 0.95 0.95 531
```

Fig 3 Precision and recall Naive Bayes

```
*Classification Report for NB:
precision recall f1-score support
0 0.62 0.91 0.74 207
1 0.63 0.65 0.64 161
2 0.74 0.39 0.51 71
3 0.65 0.21 0.32 71
4 1.00 0.18 0.17 21

accuracy 0.64 531
macro avg 0.73 0.45 0.48 531
weighted avg 0.66 0.64 0.60 531
```

Fig 4 Precision and Recall

In the experiment, the predicted accuracy for each category ranges from 80 to 95%, showing that the Bagging-Fuzzy-GBDT algorithm performs exceptionally well when multiclassification is being used. With an average accuracy of 93%, type 2 had the best prediction effect of the bunch. The 85% accuracy rate for type 1 and type 3 predictions is the same. Each type's predictive performance is essentially the same, which speeds up and improves diagnosis while providing patients with various therapies based on their individual types. Therefore, comparing the precision of each individual categorization for multiclassification is unrealistic.

## VI. CONCLUSION

For the cardiac disease prediction and detection, we proposed a consistent and precise Bagging-Fuzzy-GBDT method in this study. In both parallel and distinct configurations, the proposed Bagging-Fuzzy-GBDT method predicted cardiac disease. To reduce information complexity and prevent overfitting, we integrated fluffy logic and packing calculations into the GBDT method. The model's security was significantly improved when the borders were expanded using lattice search. In terms of performance and accuracy, AUC, and other metrics, the evaluation revealed that the proposed model performs better than conventional computations currently in use. In addition to accurately predicting illness, the Bagging-Fuzzy-GBDT computation also distinguishes the type of infection. In the field of e-medical services, it could be

used to better understand the conclusion and the board. We intend to refine the proposed model in the future and produce and test its presentation with authentic and open data in collaboration with other nearby institutions.

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