

# Cardiovascular Disease Long-Term Care Risk Prediction by Claims Data Analysis Using Machine Learning

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## ARTICLE INFO

### Article History:

Accepted: 20 March 2024

Published: 06 April 2024

### Publication Issue :

Volume 11, Issue 2

March-April-2024

### Page Number :

166-171

## ABSTRACT

Heart complaint is a major global health concern, especially in prognosticating cardiovascular issues. Machine literacy (ML) and the Internet of effects (IoT) offer new ways to dissect healthcare data. still, current exploration lacks depth in using ML for heart complaint vaticination. To fill this gap, we propose a unique system that uses ML to identify crucial features for better heart complaint vaticination delicacy. Our model combines colorful features and bracket ways to achieve an delicacy of 88.7 in prognosticating heart complaint, with the cold-blooded arbitrary timber and direct model (HRFLM) proving particularly effective. This study advances heart complaint discovery by integrating ML and IoT technologies.

**Keywords :** Cardiovascular Disease Prediction, Healthcare, Machine Learning, Artificial Intelligence

## I. INTRODUCTION

Coronary complaint is a significant global health issue affecting millions worldwide annually. Beforehand discovery and timely intervention are vital for perfecting survival rates and reducing complications. The emulsion of Artificial Intelligence (AI) and the Internet of effects (IoT) holds pledge in transubstantiating healthcare by enabling more precise and prompt opinion of coronary complaint. Through data analysis and real- time monitoring, this combined approach empowers healthcare providers with precious perceptivity into patient health, easing informed decision- timber and substantiated care. Our

design aims to develop a system that uses AI algorithms and IoT technology to descry coronary complaint, with the primary ideal of enhancing patient issues. The healthcare sector is decreasingly interested in using AI and IoT technologies, particularly for early discovery and forestallment of habitual conditions like coronary illness. By employing advanced analytics and the vast data from IoT bias, we can produce prophetic models that identify heart complaint beforehand, enabling timely intervention and treatment. Recent advancements in patient monitoring systems have been substantial. Our system utilizes colorful detector data to cipher essential parameters similar as ECG, temperature, heart rate, palpitation, and blood

pressure. Research underscores a rising mortality rate due to heart complaint, emphasizing the need for an intelligent vaticination system to address this trend. Heart complaint can have different origins, including life factors and environmental influences. While data mining ways have been employed to prognosticate heart- complaint grounded on parameters like blood pressure, heart rate, and ECG, rooting meaningful perceptivity from expansive clinical data remains a challenge. The heart is abecedarian to mortal life, and maintaining good health relies on its proper function. Our primary end is to produce a comprehensive system for prognosticating and covering coronary complaint to support healthcare professionals in delivering timely interventions, eventually leading to bettered health issues and enhanced quality of life for cases.

## II. LITERATURE SURVEY

In Senthilkumar Mohan et. al. [1] introduced a machine learning approach for accurate heart disease prediction. Their innovative method identifies key features to enhance the precision of cardiovascular prediction through the application of various machine learning techniques. The prediction model incorporates diverse feature combinations and established classification methods, utilizing machine learning to analyze raw data and offer fresh insights into heart disease.

In Amin Ul Haq et. al. [2] utilized seven established machine learning algorithms, a cross-validation technique, three feature selection algorithms, and various evaluation metrics to assess the performance of classifiers in terms of accuracy, sensitivity, specificity, execution time, and Matthews' correlation coefficient. They evaluated all classifiers based on accuracy and execution time using all available features. The performance of these classifiers was further assessed using feature selection algorithms like LASSO with k-fold cross- validation, mRMR, and Relief on selected features.

In P. Suresh et al. [3] has implemented and developed an enhanced prediction model using genetic algorithms and examined different prediction models and key feature selection techniques. Their model outperformed traditional prediction models. They reevaluated various prediction models using heart disease datasets and validated them with real-time data. The K-Cross validation method was utilized to create balanced training and testing datasets.

In Li Yang et. al. [4] Li Yang and team employed a variety of strategies to create a prediction model. They ensured ongoing monitoring using an electronic health record system. Their study resulted in the development of a three-year risk assessment prediction model for Cardiovascular Disease (CVD) based on a substantial high-risk population in eastern China.

In Youness Khourdifi et. al. [5] The researchers enhanced the heart disease classifier by eliminating unnecessary features through Fast Correlation-Based Feature Selection (FCBF). Subsequently, they conducted classification using various classification algorithms.

## III. PROPOSED SYSTEM DESIGN

The proposed framework is organized into two key stages:

Planning and testing, with the objective of fulfilling correct ailment estimate through AI procedures.

The accuracy of the classification process significantly hinges on the dataset employed throughout the procedure. Two datasets were defined for this think about: one sourced from IoT gadgets for heart infection forecast and another determined from an IoT setting. To capture real-time user body data, a variety of sensors were deployed and connected to a microcontroller, which stored the acquired data in a database.

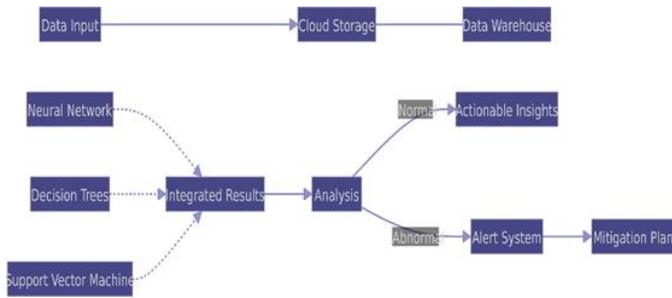


Fig. 1 Flow of Design

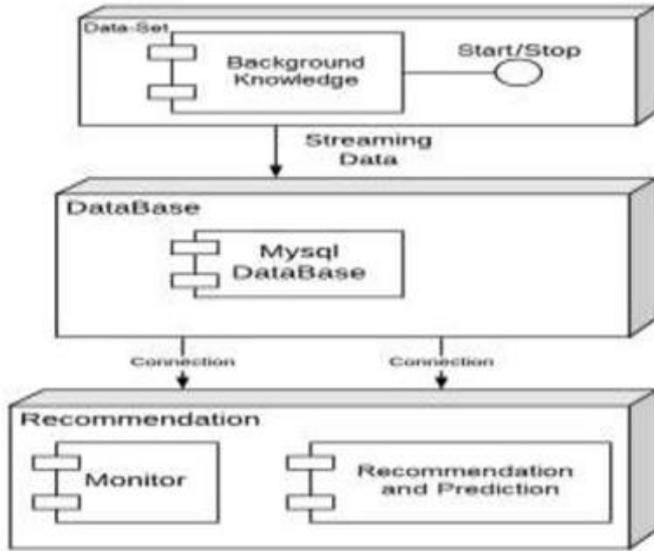


Fig. 2 Block Representation

To address these limitations, a modern Body Sensor Network has been deployed to enable fully automated and wireless monitoring of patients' bodies. The system is structured into two distinct phases: training and testing. This study proposes an efficient disease prediction method using deep learning techniques. The accuracy of classification is heavily dependent on the dataset used throughout the process. Data was sourced from two different environments: the first dataset was acquired from Kaggle, specifically the heart disease prediction dataset, while the second dataset was generated from an Internet of Things (IoT) setting. Various sensors were installed and linked to a microcontroller to capture real-time bodily data from users, which was then stored in a cloud database.

The recommended framework comprises distinctive components counting IoT modules, database modules,

and GUI modules. Within the taking after segment, each module will be explained upon in detail.

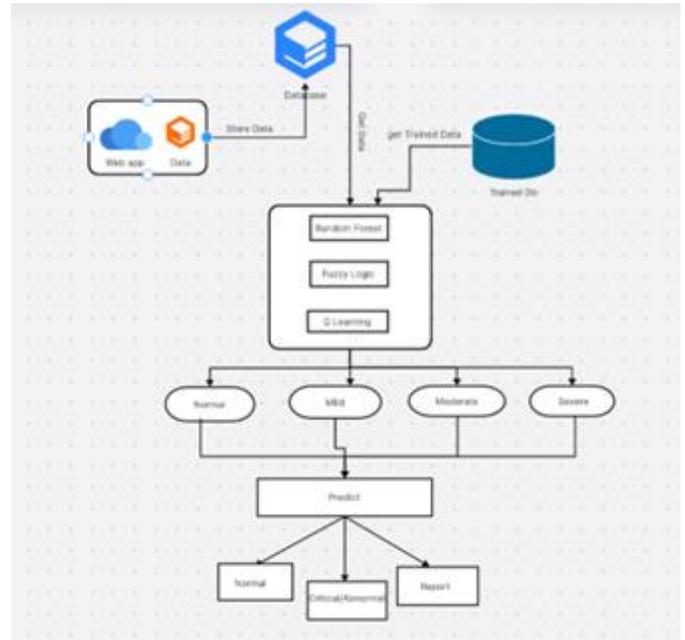


Fig. 3 Proposed System Design

### I. Training:

- Acquire data.
- Employ data mining techniques.
- Save the data in a database known as background knowledge, which is utilized during the testing phase.

### II. Testing:

- The system operates with both synthetic and real-time patient input data via the internet to predict the likelihood of disease based on the trained module.
- Employing a link-oriented architecture, all gathered data is stored in a central database.
- During testing, both testing and training data are accessed concurrently.
- Implement machine classification for prediction and anticipate the future use of decision-making techniques.

- Ultimately, assess the study's reliability through the system's true (positive) and false (negative) outcomes.

#### IV. ALGORITHM DESIGN

##### Q- Learning Algorithm

**Input:** Input [1.....n] all input parameters which is created by sensors, Edge bunch TMin[1...n] and TMax[1...n] for all sensor, Wanted Limit Th. **Yield:** Trigger executed for yield gadget as label. **Step 1:** Perused all records from database (R into DB)

**Output:** Trigger executed for output device as label.

**Step 1:** all records from database (R into DB), at that point check the database for records in case included or not in it.

**Step 2:** given Parts [] Split(R)

**Step 3:** 
$$CVal = \sum_{k=0}^n \text{Parts}[k]$$

**Step 4:** Check (Ceval with Respective threshold of TMin [1...n] and TMax [1...n])

**Step 5:** if (Ceval > Threshold)  
Review all metrics related to penalty TP (True Positive) and reward FN (False Negative) Else Continue

**Step 6:** Now calculating the penalty score = (True Positive \*100 / Tot)

**Step 7:** if (score >= Th)  
Generate event! End for

##### Fuzzy Logic Algorithm

**Input:** The user input file comprises data records containing sensor values for all body parameters, along with the patient ID (Pid) and timestamp (T).

**Output:** Classified label

**Step 1:** Read R {All attributes} from current parameters.

**Step 2:** Map it with train feature with each one of the samples.

**Step 3:** Compute of the mean weight of the training database using identical evidence.

$$AvgTScore = \sum_{k=0}^n (Sc)$$

**Step 4:**

**Step 5:** evaluate AvgTScore > threshold

**Step 6:** Return AvgTScore

##### Random Forest

**Input:** Selected feature of all test instances D[i...n], Training database policies {T[1]... ..... T[n]}

**Output:** No. of probable classified trees with weight and label.

**Step 1:** Read (D into D[i]) and V Extract features (D)

**Step 2:** N []CountFeatures(D)

**Step 3:** for eachone (c into TrainDB)

**Step 4:** Nc[i] []ExtFeatures(c)

**Step 5:** Select relevant features of w= {Nc[i], N}

**Step 6:** Statement (w>t)

**Step 9:** Return Tree Insatnce { Nc[i], N, w, label}

#### V. RESULTS AND DISCUSSION

Results and Discussions

The implementation was finalized within a Java open-source environment. The system runs on the Java 3-tier analytics platform, utilizing a distributed INTEL 3.0 GHz i5 CPU and 2 GB RAM. The classification of emails as spam or non-spam was based on the Email Spam dataset. An experimental analysis

was conducted on ensemble machine learning techniques to validate the results.



Figure 4: Accuracy of system analysis



Figure 5: Results of Patients



- prediction model based on random forest in eastern China “ Scientific Reports (2020) 10:5245
- [5]. S. Mohan, C. Thirumalai and G. Srivastava, have further studied "Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques," in IEEE Access, vol. 7, pp. 81542-81554, 2019, doi: 10.1109/ACCESS.2019.2923707

**Cite this article as :**

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