Early detection of Coronary Heart Disease by using Naive Bayes Algorithm

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Abstract. In smart connected communities, Health monitoring devices are vital parts of smart health. The main goal of this project is to detect the mild abnormalities of the coronary heart disease in the initial stage by providing quality health care using Naive Bayes classifier. The Coronary heart disease is diagnosed by taking into consideration the parameters like age, gender, nature of chest pain, latent blood pressure, serum cholesterol level, fasting blood sugar level, resting ECG, maximum heart rate, exercise induced angina, ST depression induced, peak exercise ST, number of major vessels and thalassemia. These parameters are used in the classifier to examine whether the Coronary heart disease is present or absent along with its accurateness.

Keywords- ECG, SVM, ANN, Naive Bayes classifier.

1. Introduction
Cardiovascular infection (CVI) is one of the main demise roots on the planet that represents more than prescient demonstrating of irregular pulses has not been completely tended to yet. It has been demonstrated that specific highlights of ECG signs can reflect fundamental cardiovascular variations from the norm before the events of heart issue. Our current study confirms this perception and irregularities. A few Personal Computer based computerized apparatuses have been produced for progressively exact finding by reducing human damages, not very many investigations have been given to prescient examination of ECG signals.

The normal soul of existing techniques is handling a huge dataset of commented ECG flags and developing reference models that encourage assessing test recommends that a added in depth examination of ECG waveform can uncover minor irregularities in the sign morphology that implies about the up and coming serious variations from the norm. This idea is where beat 2 has mellow mutilation that can be an indicator of an increasingly serious mutilation of a similar sort in beat 10.

Regularly, these minor variations from the norm have been considered inside the ordinary range due to between understanding inconstancy of ECG signals; subsequently avoid the worldwide classification phase of regular strategies. The primary objective of this paper is to distinguish and utilize such gentle but then educational sign contortions to tell the client of raised danger of forthcoming heart variations from the norm. We call this component as prescient investigation. Until ongoing years, just a couple of papers have been centered around 30% of worldwide demise. Early identification of irregular cardiovascular issues through consistent checking of electrocardiogram (ECG) signs can forestall unexpected heart demise (SVM) by encouraging patients to take preventive activities before extreme heart conditions. These realities request more consideration from the exploration network to create strategies for early identification of heart checking dependent on ECG signs to help doctors also, patients with signals. Nonetheless, the creating prescient examination of ECG signals. Maybe, the best strategy is that utilizes a neural system classifier for prescient examination of pulses. Be that as it may, they just considered the expectation results as long as 3 seconds prior the events of variations from the norm. The second downside of existing ECG classifiers
is their ineptitude of giving customized classification results what's more, overlooking the characteristic inconstancy of ECG waveform morphology among various people because of sexual orientation, age, weight record, hereditary varieties, and so on.

To tackle this issue, a few inventive patient-intended classifiers are expected in the ongoing years. Individual master help is generally used to make the models patient specific. Through altering models for every patient, the exactness of recognizing ventricular beats from different beats is brought to 98.1%. Be that as it may, these strategies' dependence on master comment at any rank, confines their pertinence to new patients for whom master comment is not accessible. To deal with this issue and dispense with the need for human intercession in the examination stage, ongoing works planned utilizing singular ECG accounts to refrain parameters of the prepared neural system. The classification precision is raised to 98.9% for ventricular beats without trading off the affectability and specificity of the calculations.

Be that as it may, the classification execution significantly drops for some rarer variation from the norm classes. For model, the genuine positive rate is 64.6% for perceiving supraventricular beat, which is beneath an adequate level. Notwithstanding acknowledging prescient investigation of ECG signals, another objective of the proposed approach is empowering understanding adjustment without master intercession, while not settling the discovery execution for uncommon variation from the norm classes contrasted with the cutting edge techniques.

Our methodology depends on building up a patient-specific benchmark required for the proposed deviation examination to catch minor deviation of sign morphology from its typical pattern towards any of the irregularity classes. The instinct behind our technique is that the agent signal highlights for various abnor- break down the created edge based deviation investigation To tackle this issue, we propose a novel controlled nonlinear change to reshape the sign geometry into symmetric portrayal in the component space.

2. Related Works
Mechanical finding & categorization of cardiac arrhythmias is essential for analysis of cardiac abnormalities. These methods precisely categorize ECG arrhythmias through an arrangement of wavelets and artificial neural networks (ANN). The accurate feature extraction detection is achieved by decomposing wavelet transform signal from non-stationary signals like ECG. A set of discrete wavelet transform PWT coefficients, which contain the maximum information about the arrhythmia, is selected from the wavelet decomposition. The existing articles describe the skilled structure for reliable heartbeat identification. The recognition system uses the Support Vector Machine (SVM) working in the categorization mode. Two different preprocessing techniques namely higher order statistics (HOS) and Hermite characterization of QRS complex of the registered electrocardiogram (ECG) waveform are applied for production of features. Combining these preprocessing methods with SVM network gives in two neural classifiers that have been collective into one final expert system. The grouping of two classifiers employs the LMS method to optimize the weights of the weighted voting integrating design.

3. Framework methodology
In proposed system a naïve Bayesian algorithm is used to detect the coronary heart disease, the parameters such as age, sex, resting blood pressure, chest pain type, serum cholesterol, fasting blood sugar, resting ECG, Max heart rate, exercise induced angina, ST depression induced, peak exercise, ST, number of major vessels, thalassemia are considered to detect the coronary heart disease. The proposed methodology allows the patient to adapt without expert intrusion, while not compromising the detection performance for rare abnormality classes compared to the state of the art methods. At the outset, it presents an approach to be familiar with the patterns of parameters.
effectively. The readers can promptly discriminate the patterns between different parameters prior to incidence of ventricular arrhythmias.

Later, it offers a discussion on process to identify the anomalous ranges of the parameters. The age and sex are features to influence abnormal ranges of some parameters. Lastly, the article portrays the advances to improve detection rate of the parameters, as presented. The approaches include averaging, outliers handling and application of morphology detection algorithms.

4. Working Principle

The block diagram of the proposed system consists of user which is used to collect the dataset and the system is used to create a dataset which is also known as pre processing and the classifier is used to predict whether the disease is present or not.

A. User:
   The user is used as the input to collect the dataset.

B. System:
   The dataset is collected from the user and it is given to the system where the dataset is created.

C. Classifier:
   The classifier along with its parameters such as age, gender, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting ECG, max heart rate, exercise induced angina, ST depression induced, peak exercise ST, number of major vessels, thalassemia is used to predict whether the coronary heart disease is present or absent along with its accuracy.

D. Age wise Analysis:
   The patient ages are noted and according to the age wise the disease is analysed and detected.

E. Patient wise Analysis:
   Particular dataset is analysed and it is given to the server and the result is predicted according to the patient.

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**Fig. 1 Block Diagram of Proposed System**

- User: Load time patient history, Get factor associated with disease
- System: Start patient in big data, Classifier
- Dataset: 1. Age, 2. Sex, 3. Chest pain type, 4. Resting blood pressure, 5. Serum cholesterol, 6. Fasting blood sugar, 7. Resting ECG, 8. Max heart rate, 9. Exercise induced angina, 10. ST depression induced, 11. Peak exercise ST, 12. No. of major vessels, 13. Thalassemia
- Display Data on server, Age wise Analysis, Patient wise Analysis
F. Analysis on Data Server:
The result on the server is compared with the system and the disease is identified with its accuracy.

5. Result
The dataset is collected from the user and various parameters are considered for the patient and the Naive Bayes classifier is functioned which is used to detect the occurrence or absence of coronary heart disease for the patient along with the accuracy.

SVM CLASSIFIER:

![SVM Classifier Image]

Fig.2 This figure shows the SVM classifier with coronary heart disease present and Accuracy = 82.943

NB CLASSIFIER:

![NB Classifier Image]

Fig.3 This figure shows the NB classifier with coronary heart disease present and Accuracy = 84.0714
NN CASSIFIER:

![Image]

Fig.4 This figure shows the NN classifier with Coronary heart disease present and Accuracy = 80.1567

6. Conclusion
As acknowledged by several previous studies and established by our study of dataset, the heart aberrations grow over instance and hence some concealed signs may subsist in the patient’s ECG signal morphology. These signs are normally serene and patient definite, and so they are not confined by normal classifiers due to the inter-patient inconsistency of ECG samples, at the same time they are commendable of attention. Raising the sensitivity of existing classifiers is not a genuine option, as it creates undesired aggravating fake alarms. This Naive Bayes algorithm is used to detect the Coronary heart disease for the patient and preventive measures are taken according to the physician orders without any high risk.

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