HEART DISEASE PREDICTION USING MACHINE LEARNING

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***Abstract*— Day by day the cases of heart diseases are increasing at a rapid rate and it’s very Important and concerning to predict any such diseases beforehand. This diagnosis is a difficult task i.e. it should be performed precisely and efficiently. The research paper mainly focuses on which patient is more likely to have a heart disease based on various medical attributes. We prepared a heart disease prediction system to predict whether the patient is likely to be diagnosed with a heart disease or not using the medical history of the patient. We used different algorithms of machine learning such as logistic regression and KNN to predict and classify the patient with heart disease. A quite Helpful approach was used to regulate how the model can be used to improve the accuracy of prediction of Heart Attack in any individual. The strength of the proposed model was quiet satisfying and was able to predict evidence of having a heart disease in a particular individual by using KNN and Logistic Regression which showed a good accuracy in comparison to the previously used classifier such as naive bayes etc. So a quiet significant amount of pressure has been lift off by using the given model in finding the probability of the classifier to correctly and accurately identify the heart disease. The Given heart disease prediction system enhances medical care and reduces the cost. This project gives us significant knowledge that can help us predict the patients with heart disease It is implemented on the .pynb format.**

**Keywords: Machine Learning Techniques, Prediction, Health Analysis Applications.**

1. INTRODUCTION

“Machine Learning is a way of Manipulating and extraction of implicit, previously unknown/known and potential useful information about data” [1]. Machine Learning is a very vast and diverse field and its scope and implementation is increasing day by day. Machine learning Incorporates various classifiers of Supervised, Unsupervised and Ensemble Learning which are used to predict and Find the Accuracy of the given dataset. We can use that knowledge in our project of HDPS as it will help a lot of people.

Cardiovascular diseases are very common these days, they describe a range of conditions that could affect your heart. World health organization estimates that 17.9 million global deaths from (Cardiovascular diseases) CVDs [2]. It is the primary reason of deaths in adults. Our project can help predict the people who are likely to diagnose with a heart disease by help of their medical history [6]. It recognizes who all are having any symptoms of heart disease such as chest pain or high blood pressure and can help in diagnosing disease with less medical tests and effective treatments, so that they can be cured accordingly. This project focuses on mainly three data mining techniques namely: (1) Logistic regression, (2) KNN and (3) Random Forest Classifier. The accuracy of our project is 87.5% for which is better than previous system where only one data mining technique is used. So, using more data mining techniques increased the HDPS accuracy and efficiency. Logistic regression falls under the category of supervised learning. Only discrete values are used in logistic regression. The objective of this project is to check whether the patient is likely to be diagnosed with any cardiovascular heart diseases based on their medical attributes such as gender, age, chest pain, fasting sugar level, etc. A dataset is selected from the UCI repository with patient’s medical history and attributes. By using this dataset, we predict whether the patient can have a heart disease or not. To predict this, we use 14 medical attributes of a patient and classify him if the patient is likely to have a heart disease. These medical attributes are trained under three algorithms: Logistic regression, KNN and Random Forest Classifier. Most efficient of these algorithms is KNN which gives us the accuracy of 88.52%. And, finally we classify patients that are at risk of getting a heart disease or not and also this method is totally cost efficient.

1. LITERATUREREVIEW

A quiet Significant amount of work related to the diagnosis of Cardiovascular Heart disease using Machine Learning algorithms has motivated this work. This paper contains a brief literature survey. An efficient Cardiovascular disease prediction has been made by using various algorithms some of them include Logistic Regression, KNN, Random Forest Classifier Etc. It can be seen in Results that each algorithm has its strength to register the defined objectives [7]. The model incorporating IHDPS had the ability to calculate the decision boundary using the previous and new model of machine learning and deep learning. It facilitated the important and the most basic factors/knowledge such as family history connected with any heart disease. But the accuracy that was obtained in such IHDPS model was far more less than the new upcoming model such as detecting coronary heart disease using artificial neural network and other algorithms of machine and deep learning. The risk factors of coronary heart disease or atherosclerosis is identified by McPherson et al.,[8] using the inbuilt implementation algorithm using uses some techniques of Neural Network and were just accurately able to predict whether the test patient is suffering from the given disease or not. Diagnosis and prediction of Heart Disease and Blood Pressure along with other attributes using the aid of neural networks was introduced by R. Subramanian et al.,[24]. A deep Neural Network was Built incorporating the given attributes related to the disease which were able to produce a output which was carried out by the output perceptron and almost included 120 hidden layers which is the basic and most relevant technique of ensuring a accurate result of having heart disease if we use the model for Test Dataset. The supervised network has been advised for diagnosis of heart diseases [16]. When the testing of the model was done by a doctor using an unfamiliar data, the model used and trained from the previous learned data and predicted the result thereby calculating the accuracy of the given model.

Heart rate variability (HRV) has emerged as a reliable predictor for congestive heart failure (CHF). However, challenges remain in effectively extracting temporal features and efficiently classifying high-dimensional HRV representations. To address these challenges, this study proposes an ensemble method that utilizes short-term HRV data and deep neural networks for CHF detection. The research incorporates five publicly available databases: BIDMC CHF database (BIDMC-CHF), CHF RR interval database (CHF-RR), MIT-BIH normal sinus rhythm (NSR) database, fantasia database (FD), and NSR RR interval database (NSR-RR). Three different lengths of RR segments (N = 500, 1000, and 2000) are employed to evaluate the proposed method. Initially, expert features are extracted from the RR intervals (RRIs). Subsequently, a network based on long short-term memory-convolutional neural networks is constructed to automatically extract deep-learning (DL) features. Finally, an ensemble classifier is used to detect CHF using the aforementioned features. Blindfold validation is conducted on three CHF subjects and three normal subjects, resulting in accuracies of 99.85%, 99.41%, and 99.17% for N = 500, 1000, and 2000 length RRIs, respectively, utilizing the BIDMC-CHF, NSR, and FD databases[[15](https://www.nature.com/articles/s41598-023-40717-1#ref-CR15)]. In this publication, there is a summary of past studies and an analysis of how well the algorithm works. Before training and testing different algorithms, the suggested architecture processes the data that comes in first. The author suggests using Adaboost because it makes every ML method look better. Also, the author agreed that settings could be fine-tuned to improve accuracy. Researchers came up with a deep learning strategy for analysing and spotting cardiac conditions by using the UCI dataset. They went on to say that deep neural networks could help improve the analysis and diagnosis of cardiovascular disease as a whole. Compared to other ways to improve model performance, they found that the Talos Hyper process worked the best[[16](https://www.nature.com/articles/s41598-023-40717-1#ref-CR16)]. The KNN, RF, SVM, and DT algorithms were studied as ML models for predicting heart disease with high accuracy, high recall, and high precision. As shown in their estimation method for cardiac disorders, which is hosted on the UCI ML library, SVM-based categorization was the most accurate. We looked at the results of four machine learning techniques and one neural network (NN) for spotting heart disease. This study compared algorithms for predicting cardiac dose based on things like reliability, recall, accuracy, and F1. The Deep NN algorithm was able to spot heart problems 98% of the time. In order to show that the algorithm is useful for predicting illness, they focused on how it could be used with a medical dataset. The researchers came to the conclusion that boosting and bagging are good ways to improve the performance of classifiers that aren't very good at predicting the risk of heart disease. The results showed that the accuracy of predictions went up a lot after feature selection was used, which improved the procedure[[17](https://www.nature.com/articles/s41598-023-40717-1#ref-CR17)]. Ensemble approaches were used to improve the accuracy of bad classifiers by no more than 7%. In recent years, ML algorithms have gotten a lot of praise for how accurate and useful they have become at making predictions. It is critical to be able to create and recommend models with the greatest accuracy and efficiency possible[[18](https://www.nature.com/articles/s41598-023-40717-1#ref-CR18)]. Since hybrid models use many ML techniques and data systems, they may be able to accurately predict health problems. Weedy classifiers worked better when they used bagging and boosting, and their ability to predict cardiovascular disease risk was rated well when they worked together. They made the hybrid model by using majority voting with the Bayes Net, NB, C4.5, MLP, and RF classifiers[[19](https://www.nature.com/articles/s41598-023-40717-1#ref-CR19)]. With 85.48 percent of the time, the model that was made is right. In addition to learning models, the UCI cardiovascular disease dataset has recently been used with ML methods like RF and SVM. Accuracy went up when a lot of classifiers were added to the voting-based model[[20](https://www.nature.com/articles/s41598-023-40717-1#ref-CR20)]. Based on the data, using the weak classifiers led to an increase of 2.1% in accuracy. We used ML classification methods to figure out how people with long-term conditions would do. They found that the Hoeffding classifier can predict coronary disease with an accuracy of 88.56 percent. Overall, they found that when the hybrid model was used with the desired features, it was 87.41% accurate. We used an SVM model and the Fisher score method to choose features based on the mean[[21](https://www.nature.com/articles/s41598-023-40717-1#ref-CR21)].

We used a lot of different classification methods and feature sets to make this one-of-a-kind prediction model. The proposed HRFLM used an ANN with a deep network and 13 clinical features as inputs. Data mining techniques like DT, SVM, NN, and KNN were also looked into. Researchers have found that it's helpful to use SVM to predict who will get sick. There was a new method called "vote," and a hybrid method that combines LR and NB was talked about. The HRFLM strategy worked out to be 88.7% effective[[22](https://www.nature.com/articles/s41598-023-40717-1#ref-CR22)]. We were able to make a model to predict death from cardiac failure that takes into account a wider range of risk factors by improving the random survival forest[[23](https://www.nature.com/articles/s41598-023-40717-1#ref-CR23)]. The IRSF used a split criterion and a stop criterion that were new to the field to tell the difference between survivors and people who didn't make it. Data mining has also been used to find out if someone has a cardiovascular disease[[24](https://www.nature.com/articles/s41598-023-40717-1#ref-CR24)]. Heart diseases are still diagnosed using Bayesian, DT classifiers, NN, association law, KNN, SVM, and ML algorithms. SVM was right 99.3% of the time. Several classifiers based on machine learning have been made to predict how long a patient will live. Characteristics that were linked to the most important risk factors were rated, and the results were compared to traditional bio statistical testing. Researchers came to the conclusion that serum creatinine levels and ejection fraction are the two most important things to look at when trying to make accurate predictions. The ML algorithm was used to make a model for finding CVD. In this study, we cleaned and looked at the data in four different ways. The DT and RF methods got an accuracy rate of 99.83%, while the SVM and KNN methods only got accuracy rates of 85.32% and 84.49%, respectively. Using the ensemble method, another study predicted CHF by looking at HRV and using deep neural networks to fill in knowledge gaps in unrelated areas. Overall, the method suggested was 99.85% right. In a recent publication, different types of data were used to make an intelligence framework. These were principal component analyses and RF-based MLA. The FAMD was applied to RF in order to value the relevant properties and predict illness. The suggested method is correct 93.44% of the time, sensitive 89.28% of the time, and specific 96.74% of the time. In order to test their theory, the authors used a set of 303 cases that were made by adding to the Cleveland dataset. In tests, the suggested DT algorithm did 75.5% better than the baseline algorithm. Heart disease is often referred to as "cardiovascular disease". Several researchers are trying to make it easier to tell if someone has heart disease. Their research on heart disease covers a lot of ground. The author used data from the Hungarian and Statlog sets to classify CVD using the reduced error pruning tree (REP tree), R tree, M5P tree, logistic regression (LR), J48, naive bayes (NB), and JRIP. People use random forest (RF), decision tree (DT), and linear regression (LR). Support vector machine (SVM), CART, linear discriminant analysis (LDA), gradient boosting (XGB), and random forest (RF) are all used. The goal of this study is to find a way to figure out how likely someone is to get heart disease. The results show that SVM does better than LR because it gets 96% accuracy while LR only gets 92% accuracy. The author says that the DT model always does better than the NB model and the SVM model. SVM has been shown to be 87% accurate, DT to be 90% accurate, and LR to be the most accurate at predicting when heart disease will happen, compared to DT, SVM, NB, and k-nearest neighbour (KNN).

1. OVERVIEW OF SENTIMENTAL ANALYSIS

To overcome the problem of imbalanced datasets, ML prediction applications employ the strong Synthetic Minority Oversampling Technique (SMOTE). This technique plays an important role in various applications.

1. **Balancing class distribution**: In many prediction tasks, such as medical diagnosis and prediction, the dataset is often imbalanced. This implies that a particular class, typically the one of interest, has a lower representation than the other class. SMOTE interpolates minority class examples to create synthetic minority class samples. This balanced class distribution ensures the prediction model gets enough minority class examples to learn from.
2. **Improving predictive accuracy**: In predictive modeling, an imbalanced dataset can cause the model to be biased towards the majority class, leading to poor performance in predicting the minority class. Accurate prediction of the minority class poses a significant challenge. Applying SMOTE trains the model on a more balanced dataset, improving accuracy and predictive performance, particularly for the minority class. This is critical in applications where missing the minority class (e.g., disease cases) can have significant consequences.
3. **Enhancing recall and precision**: Predictive models trained on imbalanced datasets often exhibit high precision for the majority class but low recall for the minority class. This means they miss a large portion of the minority class instances, even if the ones they do identify are accurate. SMOTE helps improve recall without sacrificing precision, leading to a more balanced and effective model. In practical terms, this means the model is better at identifying all relevant cases, not just a select few.
4. **Reducing model bias**: In prediction applications, a biased model can result in unfair outcomes, especially when the minority class is underrepresented. By exposing the model to a sufficient number of minority class examples during training, SMOTE mitigates this bias. This helps create a more equitable model that makes fairer predictions across all classes.
5. **Improving generalization**: Models trained on imbalanced data may perform well on the majority class during training, but they fail to generalize well to new, unseen data, particularly for the minority class. By using SMOTE to create a balanced training set, the model is better equipped to generalize its predictions to new data, leading to more reliable and consistent performance in real-world applications.
6. **Enhancing robustness in deployment**: In deployed machine learning applications, robustness is key. Predictive models often face real-world data that is skewed or imbalanced. SMOTE helps create a more robust model that can handle such data more effectively, reducing the risk of failure in production environments. This is crucial for applications like predictive maintenance, where identifying rare but critical failures can prevent costly downtime.
7. METHODOLOGY

With the utilization of the heart dataset, we employed ML classifiers to predict the presence of coronary heart disease. The dataset was obtained from the UCI repository, and feature engineering was applied for data pre-processing before selecting the features. Subsequently, we divided it into training and test datasets, using around 70% of the total data for training and the remaining portion for testing. The training dataset is used to create a model that predicts heart disease, while the test dataset is utilized to evaluate the classifiers. Prior to transforming categorical variables into numerical values for classification, a thorough dataset analysis was conducted. The dataset was labelled as "normal" and "diseased" in Step 1. The "diseased" label indicates the presence of heart disease, while the "normal" label indicates the absence of heart disease. In Step 2, data cleaning was performed during the training phase. Data pre-processing involved handling missing values by calculating the mean due to the presence of partial and missing values. Step 3 involved data visualization using Exploratory Data Analysis (EDA) to examine relationships between various attributes. Notably, we identified that the correlation for FBS is relatively low. Moving to Step 4, ML classifiers were applied to the pre-processed dataset, and the classifiers' performance was evaluated using a variety of parameters. As previously mentioned, the dataset was split into test and training sets to respectively assess the classifiers and develop the model. The employed classifiers demonstrated varying levels of accuracy in detecting the presence of heart disease. Figure [1](https://www.nature.com/articles/s41598-023-40717-1#Fig1) illustrates the stages of our proposed working approach.

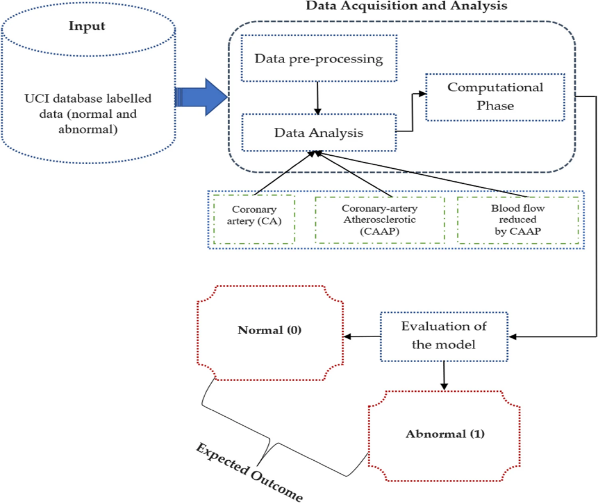


Figure 1: Proposed System

Using the heart dataset and ML classifiers, we were able to make accurate predictions on the presence of coronary heart disease. The dataset was obtained from the UCI-repository, and material that was previously carried out was carried out prior to feature engineering being used to pick the features. We then split it up into two portions, one for training and one for testing, with the former containing typically 75% of the total data and the latter the remainder. The training dataset is used to make predictions about cardiovascular illness, while the test information is used to evaluate classifiers. Before transforming categorical variables to quantitative data for classification, we first analyse the dataset.

Phase 1: The dataset was annotated with "normal" and "abnormal" labels. Both the "healthy" and "sick" labels indicate that the respective individuals are free of any heart-related issues. Phase 2: There was some tidying up of the data that we did. Due to the partial and missing data in the dataset, we averaged the remaining values to complete the phase. Phase 3: We used exploratory data analysis to visualise the data and look for patterns in the relationships between variables. Our research showed that the association between FBS and anything else was quite modest. Phase 4: We next examined the performance of the ML classifiers on the pre-processed dataset using a variety of metrics. As was previously said, the dataset is often divided into testing and training sets, the former of which is used to assess the efficacy of the classifiers and the latter to educate the model. Classifiers used to make predictions about cardiac health have varying degrees of success. Figure [1](https://www.nature.com/articles/s41598-023-40717-1#Fig1) depicts the stages of our suggested working method.

**Learning vector quantization: cardiovascular classification**

Learning vector quantization is a network that is based on competition and uses supervised learning. We could say that it is a method of organizing patterns into groups, in which each transfer function is a group. Since it uses a learning algorithm, the system will be given a collection of learning patterns with recognised classifications and a preliminary allocation of the output variable. After the training is done, LVQ would then categorise an input vector by placing it in the same class as the output channel.

1. EXPEEIMENTAL RESULTS AND DISCUSSION:

In this chapter, the results of ML classifiers on various evaluation requirements, such as accuracy, recall, and F-measure, are addressed. Examples of these evaluation constraints include: In addition to this, the performance of machine learning classification models is assessed using the dataset, which includes information on heart disease. k-NN did not do very well, although RBF, NB, and LVQ fared better than the other classifiers when compared to their overall performance. As can be seen in Table , the most important assessment criteria that were taken into consideration in this study to evaluate the performance of the ML classifier are the sensitivity, accuracy, specificity, recall, precision, and F-measure ratings. As a consequence of this, the specificity and sensitivity of the targeted class are calculated in order to evaluate the accuracy with which the given method is projected to perform. The "TP" (true positive), "TN" (true negative), "FN" (false negative), and "FP" (false positive) rates are used to compute the accuracy, precision, recall, and F measure in ML. These measures are determined by the quality of the data. Each correct positive and correct negative prediction is further subdivided into correct positive and correct negative forecasts. Every model correctly predicted the TP, TN, FP, and FN outcomes. The letters TP stand for diseased, which means infected. FN is an illness that is not believed to be related to cardiovascular disease. The FP illness is one that has been predicted but has never been seen in humans. In the actual world, TN does not exist as a disease, and this is not anticipated to change in the foreseeable future. The performance of ML approaches in terms of accuracy is listed in Tables. By associating the performances of these classifiers, we observed that radial basis functions, naive bayes, and learning vector quantization, as well as their relatedness to other ML classifiers, led these models to achieve almost 90.06%, 94.16%, and 98.07% accuracy, respectively.

| **Classification techniques** | **Performance metric parameters** | | | | | |
| --- | --- | --- | --- | --- | --- | --- |
| **Precision** | **Accuracy** | **Sensitivity** | **Specificity** | **Recall** | **F-measure** |
| Random forest | 88.07 | 88.78 | 87.91 | 87.1 | 85.31 | 87.89 |
| **Proposed learning vector quantization** | **98.07** | **98.78** | **97.91** | **97.1** | **95.31** | **97.89** |

1. CONCLUSION:

In this study, machine learning classifiers are utilised to determine whether or not a patient has heart problems. The dataset was taken from the repository at UCI. Following data collection, they will go through cleaning and pre-processing steps. Following this step, machine learning models are used for predictive analysis. We investigated the potential of these eight applied machine learning methods for making accurate predictions about cardiac disease. The inclusion criteria for these algorithms are that they be mature, representative, and at the state of the art in their respective fields. We have previously used the Naive Bayes and RBF neural networks, but other scholars have not used them on the UCI cardiovascular disease dataset. As a result, we have achieved a higher level of accuracy than they have, as shown in the table titled "state of the art," which compares our results to those of other researchers. The final findings demonstrate that when the learning machine classifiers were put to use, the Naive Bayes and RBF neural networks achieved an accuracy of 94.78% when attempting to forecast the presence of coronary cardiovascular disease. However, the Learning Vector Quantization method achieved the highest categorization accuracy of 98.78%, with a specificity of 97.1% and sensitivity of 97.91%, a precision of 98.07% and 95.31%, and 97.89% F1score and F-measure values, respectively.

1. FUTURE SCOPE:

In the future, our research aims to further enhance the reliability of our conclusions by incorporating additional datasets. We will explore the use of metaheuristic techniques and nature-inspired algorithms to optimize the parameters of machine learning classifiers and deep learning methods. This optimization process will enable us to more effectively evaluate the presence of heart disease across various heart disease-related datasets. Additionally, we will focus on improving the accuracy of existing algorithms to enhance their performance in detecting heart disease. By leveraging these advancements, we aim to provide more robust and accurate methods for the diagnosis and evaluation of heart disease.

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