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Identification of Significant Clinical Attributes for Developing Heart Disease Prediction System

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Abstract: The doctor uses a variety of laboratory testing, physical exams, and occasionally even invasive tests to identify diseases. To identify the disease in its early stages, a physician with exceptional training, experience, and domain expertise is required. Medical professionals may benefit from using diagnostic tools based on machine learning. Medical tests, both invasive and non-invasive, are required for the diagnosis of heart disorders. For the Indian population, prediction models for heart disease based on non-invasive clinical features will be very helpful. Affordable, accessible, and high-quality healthcare is still out of reach for a large portion of the population in India. The lack of infrastructure in rural locations makes it difficult to provide early disease diagnosis and treatment, which delays care, increases morbidity, and increases mortality. In India during the past two decades, the mortality rate from non-communicable diseases has increased alarmingly. These forecasting models were developed using four distinct machine learning procedures: logistic regression, k-NN, Support vector machine, and Random Forest. Numerous combinations of clinical indicators were thought of. The most crucial features were those that boosted performance in tandem. Important clinical factors were identified in this study to include gender, age, BMI, hypertension, diabetes, alcohol use, smoking, family history, total cholesterol, inactivity, healthy eating habits, stress, and anxiety. A random forest-based system achieved 91.2 percent accuracy, 93.5 percent specificity, and 92.5 percent sensitivity. The primary clinical characteristics utilised in creating a low-cost and easily accessible CVD prediction system. It has been suggested that similar research be conducted on large datasets obtained from other universities. This could help researchers find even more potentially important clinical traits.

Keywords*: *Invasive medical tests, Non-invasive medical tests, diagnostic tools, CVD.

1. Introduction

In India, epidemiology has undergone a significant transformation over the past 20 years. Two decades ago, undernutrition, maternal and childhood illnesses, and infectious diseases were the main causes of mortality in India. Non communicable diseases (NCDs) are becoming the greatest cause of concern for the Indian healthcare system, it has been noted over the past 20 years [1]. The most significant cause for concern for developing nations like India is this trend because such diseases are expensive to treat and manage. Because there is a lack of early access to high-quality, inexpensive medical care, many consequences from these diseases manifest at comparably younger ages. The labor force in low- and middle-income nations like India becomes less productive as a result [2].

An Illness might cause one in four Indians to pass away before they turn 70, according to a report [3]. The program intends to reduce NCD-related mortality during the next ten years. The Indian government has been implementing a number of significant healthcare reforms, including the transformation of Health and Wellness Centres and the construction of district hospitals that can provide long-term care for non-communicable diseases. To achieve these goals, though, much more work must be done [4].

Compared to individuals who belong to high-income groups, members of low-income groups have the issue of excessive out-of-pocket expenses and higher rates of catastrophic health expenditures [5]. Low-income families impacted by CVD are therefore more likely to experience financial hardship or catastrophic medical costs. According to a survey, families in rural India spend

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an average of 27% of their income on medical care for heart-related illnesses. As a result, the poor and marginalized populations are forced even deeper into the CVD and poverty nexus [6].

Risk factors for cardiovascular disease (CVD) include smoking, an unhealthy diet, inactivity, obesity (which can be brought on by a combination of an unhealthy diet, inactivity, and other factors), high blood pressure (hypertension), abnormal blood lipids (dyslipidemia), and high blood sugar (diabetes mellitus). As atherosclerosis progresses as a result of continued exposure to these risk factors, clinical symptoms of these diseases, such as angina pectoris, myocardial infarction, heart failure, and stroke, occur [7]. The entire risk-factor profile of the individual determines their overall CVD risk. In India, CVDs are a cause for concern for a number of reasons. They include the rapid build-up, the population's early onset, and the high fatality rate. Over the past 20 years, villages have seen a sharp increase in the mortality rate from CVDs. This problem requires rapid attention. It is important to note that while the mortality rate from CVDs has significantly decreased in the US, it grew by about 34% in India during the same time period [8]. The death rate from CVD decreased in the US as a result of early diagnosis and advice for lifestyle modifications. India's healthcare systems are facing a significant challenge as a result of the CVD epidemic there. It will be challenging to accomplish the NPCDCS goal of reducing non-communicable diseases by 2030 unless India focuses on the early identification of CVDs [9].

In patients with a high overall risk of CVD, timely, cost-effective, and sustained healthy lifestyle interventions and, when necessary, medication treatment will lower the risk of heart attack and stroke, and hence lower premature morbidity, mortality, and disability [10]. Those who receive treatment for either high blood pressure or high cholesterol can reduce their risk by more than 25% to a third and by 50% if both conditions are addressed. We have had low-cost treatments for hypertension for a long time (HTN). Generic statins have lately become more widely accessible and have been included on the WHO list of Essential Medicines. Despite the greater accessibility of medications, less than 10% of people worldwide have their blood pressure under control. Lack of awareness among people of their risk status contributes to poor control of risk variables [11]. Hence, determining risk levels by healthcare professionals is an effective way to spot those at high risk for CVD and identify those who could benefit from therapy for high blood pressure, abnormal blood lipids, and raised blood sugar [12].

What follows is the outline for the rest of the paper. The related work is briefly described in part 2, and the methodology and the theoretical foundations of the methods used are described in section 3. The simulation results and analysis are presented in section 4. For the chapter’s final section, “key findings” we summarize the most important results.

2. Previously Done Related Work

Many epidemiologic studies have been conducted throughout the world to look into the causes of heart disease. One of the most significant studies to date, which identified the numerous risk variables associated with the risk of CVDs, was a cardiac study conducted by one of the scientists. Moreover, the lifetime risk of CVDs is assessed. Age, gender, increased lipid profiles, obesity, and smoking behaviours are significant factors associated with a greater risk of developing heart disease [13-14]. In this study, roughly 15 million participants between the ages of 25 and 64 from various nations took part. This study relied on data including cardiac enzyme measures, angina symptoms, and aberrant ECGs in addition to blood pressure, body mass index (BMI), cholesterol, other lipids and lipoproteins, and cigarette use [15].

Another researcher's study evaluates the contribution of variances in traditional risk variables to changes in CVDs among project participants. One more important study deserves special attention. This study focused on Japanese men between the ages of 45 and 69. This study came to the conclusion that sedentary lifestyles increase death rates and cholesterol levels. A study that was conducted in several nations throughout Europe, Australia, South America, North America, Asia, and the Middle East revealed additional insights [16]. This study discovered significant risk variables linked to acute myocardial infarction. They include unhealthy levels of obesity, diabetes, hypertension, apo lipoprotein I, smoking, apo lipoprotein B, the psychosocial index, inactivity, and binge drinking. Psychosocial stress is also believed to raise the risk of acute myocardial infarction [17]. A few researchers in another study talked about the extent to which society influences cardiovascular risk factors and other chronic non-communicable diseases. Age, diabetes, hypertension, obesity, cholesterol levels, lack of exercise, smoking habits, and binge drinking are some of the major risk factors for CVDs as shown in all of this research [18].

The total predictive potential of machine learning algorithms to foresee cardiovascular illness was evaluated by researchers. It was discovered that certain conditions, such as coronary artery disease, cardiac arrhythmias, heart failure, and stroke, might be forecasted. The area under the curve was used as the metric in the study that made the predictions. However, because there is such a wide variety of machine learning algorithms, it is still difficult to determine which one is the most effective for diagnosing cardiovascular disease. Another group of researchers investigated the link between the quantities of heavy metals in the blood and urine and the risk of dying from cardiovascular disease and cancer [19]. During the course of the investigation, data sets from the National Health and Nutrition Examination Survey were utilised. Poisson's regression was carried out so that we could evaluate both single and multiple metal exposure. There was a wide range of ages represented in this study, from twenty-five to eighty-five years old. Age, gender, degree of education, body mass index (BMI), serum cotinine, and medical comorbidities were all taken into consideration in this study. According to the findings of the study, an increased presence of metal mixers in both the blood and the urine is linked to an increased chance of dying from cancer. However, the authors do point out that the necessity of conducting further research on cardiovascular sickness was the driving force behind this particular study [20].

A strategy for instance-based learning is the Relief algorithm. A few scientists employed it when doing binary classification jobs. This technique is a particular assessment filter method that is effective at locating relationships between different features [21]. The nearest neighbor concept is used in this approach to create attribute statistics that are indirectly responsible for interactions between distinct characteristics. This method's flaw is that it does not take into account the dataset's missing values. Moreover, multi-class data cannot be handled by this approach. In one of the research, the authors made the argument that continuing physical activity is essential to prevent harmful cardiovascular effects [22]. Both cardiovascular and non-cardiovascular patients' fecal ribosomal RNA 16S were examined. There are five primary classifications of machine learning strategies that were utilised in the process of training decision trees, random forests, neural networks, elastic nets, and support vector machines. There were found to be many distinct bacterial taxa in their various forms. The random forest led to the production of an improved characteristics curve with a value of 0.70. [23].

A study by a few authors focuses on methods for predicting chronic disease by employing Naive Bayes, Decision trees, Support Vector Machines (SVM), and Artificial Neural Networks to mine the data from past health records (ANN). To assess classifier performance more accurately, comparative research is conducted. In this experiment, SVM has the best accuracy rate, whereas Naive Bayes has the highest accuracy for diabetes [24].

3. The Objective of the Work

1) To create a cardiac disease prediction system with high performance, cost-effectiveness, and ease of access employing substantial non-invasive clinical features, especially suitable for the Indian population.

4. The Proposed Work:

Figure I depicts the procedure that was followed during the experiment. Pre-processing the data was the first order of business. Incomplete data were omitted from the analysis. It was decided to normalise the data. After data was pre-processed, feature engineering was used to select appropriate feature sets. After combining the input features, standard machine learning methods such as logistic regression were used to create models of prediction. The feature-selection and classification-modelling tasks were run multiple times with different input features. The process was repeated until just one of the input attributes (out of a possible twenty-five) remained. Different prediction models were developed in each iteration based on the features used and the ML method used. The efficiency of individually model was determined by calculating assessment criteria.

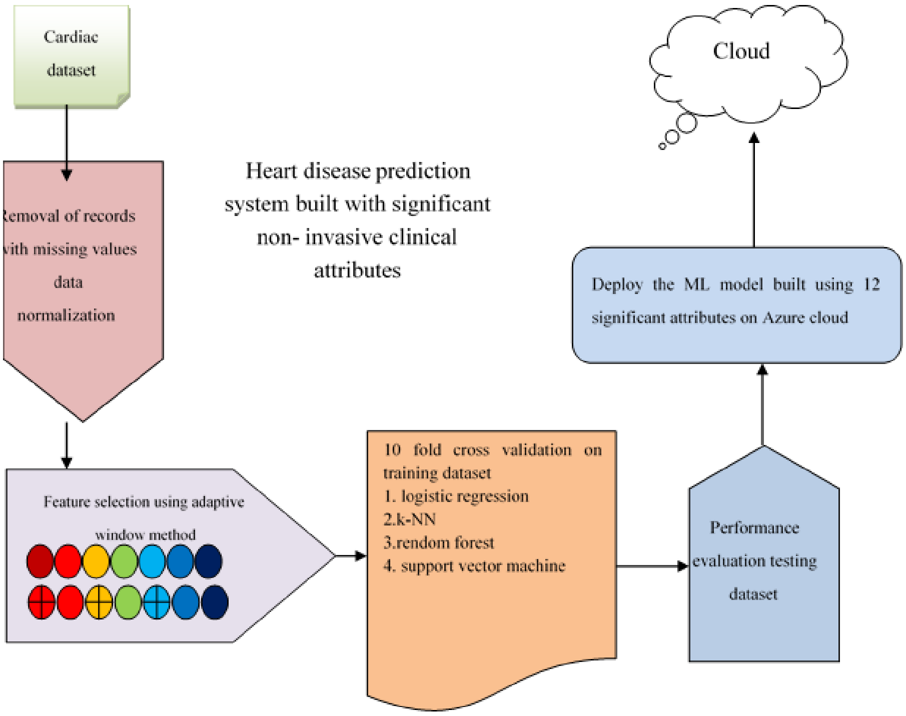

Fig I: The Projected Model Work Flow Diagram.

4.1. Data Pre-processing:

In order to construct a reliable ML prediction system, data pre-processing is a crucial step. The dataset was looked out for any missing values and outliers. None of the records had any missing values or outliers in the data. The nominal values were encoded from the nominal categories. The attributes' varying scales necessitated the application of z-score normalisation.

4.2. Classification and Analysis:

About 70% of the data records were utilised to train the ML module, while the other 30% were used to assess the effectiveness of the system. Logistic regression, k-NN, support vector machine (SVM), and Random Forest were employed on different attribute subsets and combination attributes to determine which ones were most important. It was determined to evaluate the efficacy of every possible combination of clinical variables and each of four machine learning algorithms in order to identify the most important features. Figure II depicts the scheme that has been developed.

Each of the four machine learning methods benefits from the feature selection module's exhaustive exploration of all potential combinations of clinical attributes. The feature selection module actively monitors the input attribute vector with an adaptive window frame. The window frame magnitude starts at 1 and is placed at the leftmost side of the input feature vector (n=25). The feature subset excludes the window/frame attribute. Machine learning algorithms develop the prediction system using the left-over (n-1) attributes. This subset's prediction algorithm was tested on a dataset. Shifting the window right followed. The window frame feature was removed. The remaining (n-1) attributes train prediction models. Evaluated again.

The window frame was shifted and the feature eliminated till the nth characteristic. First feature selection cycle completed. First-cycle feature subset size was n-1. Figure II shows the floating window frame method for identifying significant features. While training the models, the red characteristic is eliminated. Second round: window frame size raised to 2. The window frame drifted from left to right side of attribute vector eliminated two attributes each time. Train machine learning models with the left-out $n - 2$ attributes. Each ML method was assessed. The experiment's outcomes were compared to the best subgroup attribute performance. The best performance and optimal subset of attributes were updated when performance improved. Repeated until the window frame reached the feature vector's extreme right. Third round: frame size raised to 3. The technique was repeated until the frame size was increased to n-1. Performance improvements updated the optimal selection of features.

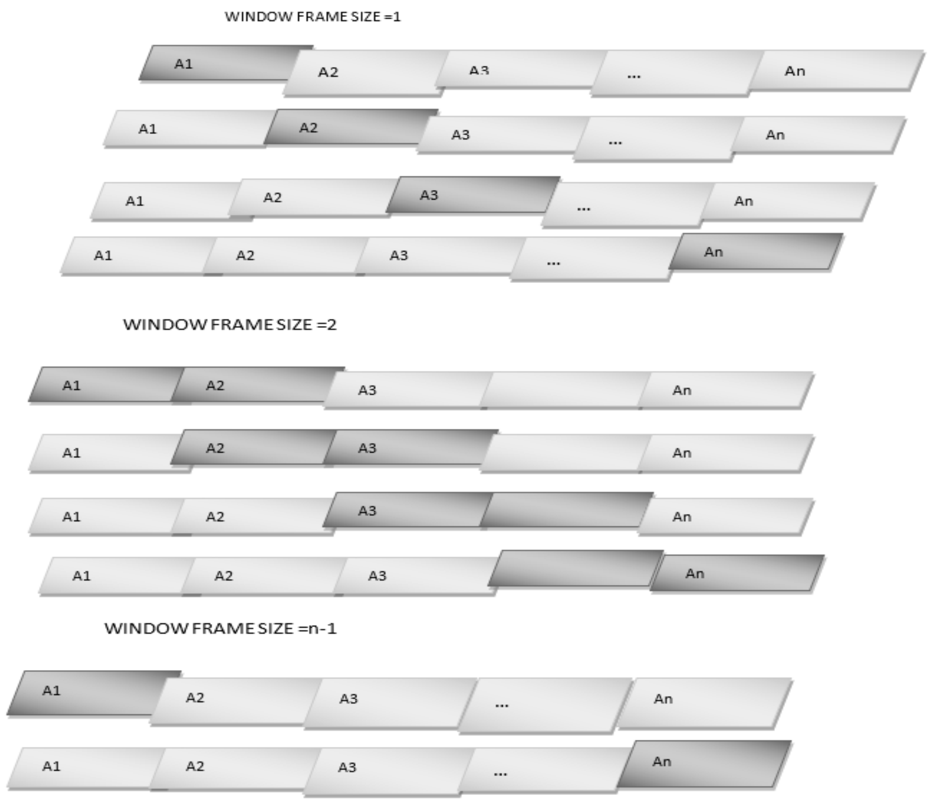

Fig II: Various Stages of Proposed Algorithm.

4.3. Methods for making forecasts with machine learning models

Four different machine learning techniques were used to create the prediction models after each round of feature selection. k-NN, Logistic regression, Random Forest, and support vector machine are all examples of such algorithms. Ten-fold cross validation was used to verify the accuracy of the models.

5. Result and Analysis:

Accuracy, specificity, and sensitivity were used to evaluate the prediction system's effectiveness. The effectiveness of a method for predicting cardiovascular disease was evaluated by use of a confusion matrix. True positives, false positives, true negatives, and false negatives are the four primary components of a confusion matrix.

5.1. Accuracy:

It is a typical metric for classifying test results numerically. Increased precision indicates a more efficient system.

$$\text{Accuracy} = \frac{TN+TP}{Total\ data\ Sample} X100 \qquad (1)$$

5.2. Recall:

Specificity was defined as the absence of incorrect data classification. True Negative Rate is another name for it (TNR). Figure IV displays the recall of the current method in comparison to commonly utilized methods.

$$\text{Specificity} = \frac{TN}{TN+FP} X100 \qquad (2)$$

5.3. Precision:

The present work is believed to have the precision to provide useful outcomes. The value of precision indicates what fraction of valid affirmative identifications were made. Figure III displays the results of a comparison between the current model and the commonly used techniques in terms of accuracy. The present system's accuracy was determined by

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

5.4. Sensitivity:

The accuracy with which the model places the test data into one of its classes constitutes the present method's sensitivity. How many true positives were successfully detected was the question it addressed. True Positive Rate is another name for it.

$$Senstivity = \frac{TP}{TP+FN} X100 \qquad (4)$$

The effectiveness of four different machine-learning approaches was evaluated one at a time, using each combination of clinical attributes that could be found. Tables I contain a tabulation of the performance indicators that were collected.

Table I: Different Machine Learning methods evaluation based on various parameters.

S. No.	Machine Learning Methods	Accuracy (%)	Precision (%)	Sensitivity (%)
1	Logistic Regression	86.5	88.4	88.3
2	k-NN	87.2	87.9	86.7
3	Support Vector Machine	86.8	87.2	84.6
4	Random Forest	91.2	93.5	92.5

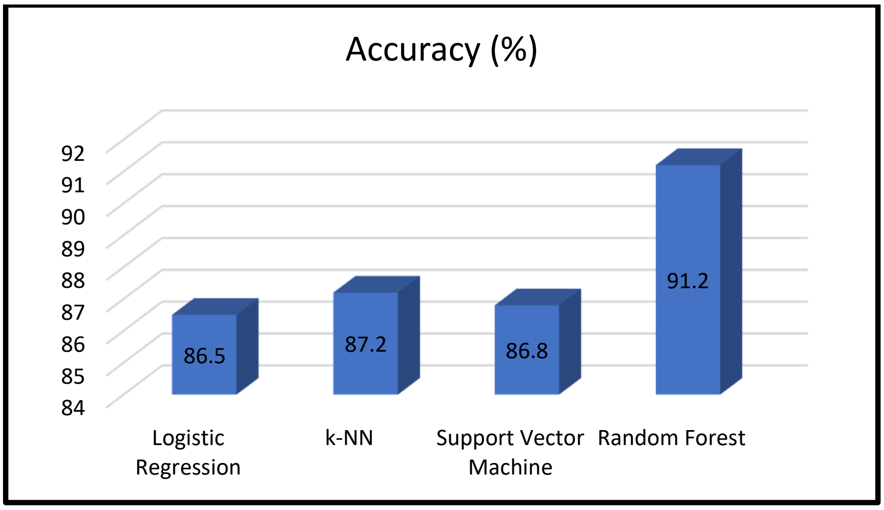

Fig III: Accuracy (%) Comparison of Different Machine Learning Methods.

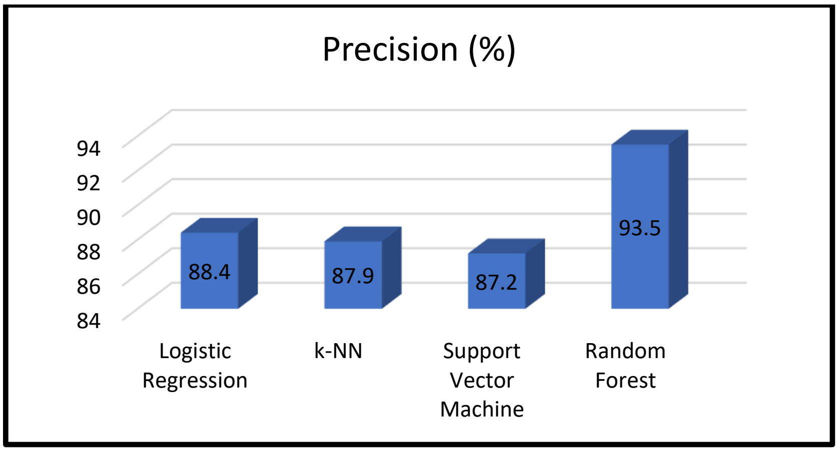

Fig IV: Precision (%) Comparison of Different Machine Learning Methods.

Input variables such as age, diabetes, total cholesterol, HDL, Exercise, family history, hypertension, heart rate, alcohol, smoking, gender, and waist circumference were used to train a Random Forest based system that achieved a maximum accuracy of. When Random Forest was fed the input features of age, gender, HbA1c, hypertension, exercise, alcohol, smoking, body mass index (BMI), high density lipoprotein (HDL), heart rate, and serum creatinine, the highest sensitivity achieved was 92.5%. Moreover, Specificity for Random forest was also scored highest as 93.5% in comparison to other ML methods.

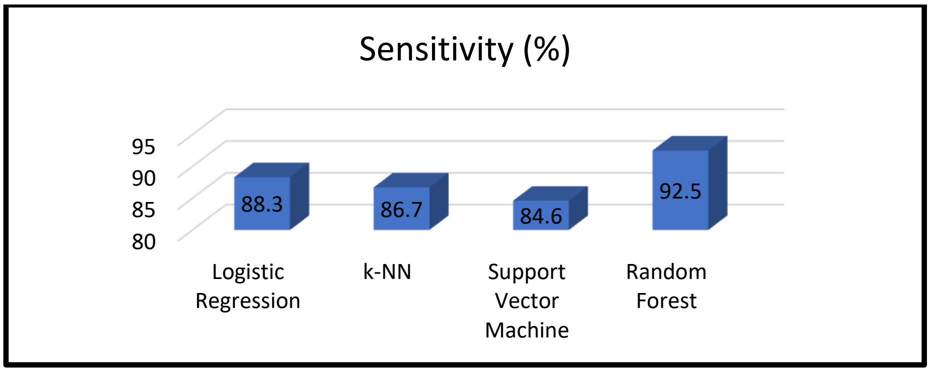

Fig V: Sensitivity (%) Comparison of Different Machine Learning Methods**.**

Logistic regression, k-NN, Support vector machine, and Random Forest are the four distinct approaches to machine learning that were applied in the process of developing these forecasting models. It was thought that each and every possible combination of clinical features. The traits that contributed most to an increase in performance were the ones that interacted with one another. According to the findings of this study, key clinical factors include gender, age, body mass index, hypertension, diabetes, alcohol use, smoking, tobacco use, family history, total cholesterol, inactivity, healthy eating habits, stress, and anxiety. A prediction system based on a random forest was able to achieve an accuracy of 91.2 percent, a specificity of 93.5 percent, and a sensitivity of 92.5 percent. The most important clinical characteristics considered throughout the design process of a cardiovascular disease prediction system that is both inexpensive and easily accessible. It has been suggested that similar research be carried out on vast datasets that have been generated from a variety of other institutions in order to find additional possibly significant clinical characteristics.

6. Conclusion:

Heart disease is responsible for millions of annual deaths. Many countries, including India, lack easy access to and affordability for diagnostic tests for cardiovascular disease. The purpose of this research was to create a non-invasive, meaningful, routine clinical attribute based, cost effective, and easily accessible heart disease prediction system utilising machine learning. An Indian medical centre provided the data for a dataset with 25 attributes. A drifting frame of varying size was utilised for feature selection. There were four different machine learning techniques utilised to create these forecasting models: logistic regression, k-NN, Support vector machine, and Random Forest. Countless permutations of clinical characteristics were considered. The most important characteristics were those that worked together to improve performance. In this analysis, we found that gender, age, body mass index, hypertension, diabetes, alcohol use, smoking, family history, total cholesterol, inactivity, good eating habits, and stress and anxiety are all important clinical characteristics. Accuracy of 91.2 percent, specificity of 93.5 percent, and sensitivity of 92.5 percent were all reached using a prediction system based on a random forest. The major clinical features used in the development of an affordable and accessible CVD prediction system. It is proposed to do similar studies on massive datasets compiled from other institutions in order to identify additional potentially significant clinical features.

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