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# Prediction of Cardiovascular Disease Using Machine Learning Technique—A Modern Approach

**Visvasam Devadoss Ambeth Kumar[1], Chetan Swarup[2], Indhumathi Murugan[1], Abhishek Kumar[3], Kamred Udham Singh[4], Teekam Singh[5] and Ramu Dubey[6,*]**

[1]Department of Computer Science & Engineering, Panimalar Engineering College, Anna University, Chennai, 600123, India
[2]Department of Basic Science, College of Science & Theoretical Studies, Saudi Electronic University, Riyadh-Male Campus 13316, Saudi Arabia
[3]Department of Computer Science & IT, JAIN (Deemed to be University), Bangalore, 560069, India
[4]Department of Computer Science and Information Engineering, National Cheng Kung University, Tainan 701, Taiwan
[5]Department of Mathematics, Graphic Era Hill University, Dehradun, 248002, India
[6]Department of Mathematics, J. C. Bose University of Science & Technology, YMCA, Faridabad, 121006, India
[*]Corresponding Author: Ramu Dubey. Email: rdubeyjiya@gmail.com
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**Abstract:** Cardio Vascular disease (CVD), involving the heart and blood vessels is one of the most leading causes of death throughout the world. There are several risk factors for causing heart diseases like sedentary lifestyle, unhealthy diet, obesity, diabetes, hypertension, smoking and consumption of alcohol, stress, hereditary factory etc. Predicting cardiovascular disease and improving and treating the risk factors at an early stage are of paramount importance to save the precious life of a human being. At present, the highly stressful life with bad lifestyle activities causes heart disease at a very young age. The main aim of this research is to predict the premature heart disease based on machine learning algorithms. This paper deals with a novel approach using the machine learning algorithm for predicting the cardiovascular disease at the premature stage itself. Support Vector Machine (SVM) is used for segregating the CVD patients based on their symptoms and medical observation. The experimentation results by using the proposed method will facilitate the medical practitioners to provide suitable treatment for the patients on time. A sophisticated model has been developed with the current approach to examine the various stages of CVD and the performance metrics used have given effective and fruitful results as compared to other machine learning techniques.

**Keywords:** Machine learning; support vector machine; classification; cardiovascular disease

## 1 Introduction

Based on the estimated facts, World Health Organization (WHO) had claimed that about 17.9 million men and women died from Cardio Vascular Disease (CVD) in year 2016, which

is nearly 31% of the deaths worldwide [1]. Globally, CVD is the major cause of death in men and women who die annually from CVD [2]. It is also reported that one third of the deaths for people aged below 70 years occur by stroke and heart attacks [3]. Though there are leaping advances in medical field, it is still challenging to predict the heart disease in an earlier stage. Antenatal practices help in identifying the risk factors and modern technology is used to overcome the risk [4]. Still, the morbidity rate is very high due to the unpredicted and unexpected reasons. Currently, there are no proven and concrete interventions that reduce the risk of cardiovascular disease [5,6].

In cardiovascular disease, the data provided to the medical field is vast, multi-dimensional and critical, which makes it challenging and cumbersome to understand such extensive data. It is quite difficult to predict whether the patient has heart disease symptoms or not based on the patient's records [7,8]. Some of the typical symptoms for patients having CVD are chest pain, shortness of breath, radiating pain in the arms, left shoulders and elbows, discomfort while walking, high blood pressure, dizziness, nausea, fatigue, etc. while the risk factors causing CVD are cholesterol, hypertension, genetic or heredity, obesity, diabetes, dietary habits, aging, [9–11], etc. Life Style modifications with regular cardio friendly exercises followed by a heart-healthy diet, quitting smoking and alcohol intake, usage of tobacco, salt, sugar and fat intake can prevent CVD. Based on the analysis of worldwide data on CVD patients, it is noted that CVD affects even young men and women and therefore, requires prediction and prevention at the incipient stage itself.

The key objective of this research is to predict cardiovascular disease at an earlier stage. To envisage the detection of CVD at the incipient stage and intervene appropriately, Support Vector Machine (SVM) is used for classifying the patients depending on their symptoms and risk factors. By using these machine learning algorithms, it becomes easy to understand the nature and type of heart disease in all aspects.

The important aspect of this method is to train the machine to analyze a massive set of data with the known inputs and outputs, i.e., Supervised machine learning is applied [12]. The main objective of the work is to improve the accuracy of prediction of cardiovascular disease [13,14], which can help for preventive treatments and reduce the cases having CVD.

The rest of the paper deals with various sections viz.., the related works are discussed in Section 2, while in Section 3, the various stages of CVD are elaborated and the techniques involved for the prediction of cardiovascular disease are explained thoroughly. Section 4 highlights the Experimental results, Comparison of results using multiple techniques, Summarization of the methods and percentage of CVD based on the collected datasets. Finally, in Section 5, the conclusion of research and the thrust for more related research work is highlighted.

## 2 Related Works

The clinical study was designed as a controlled clinical study, open-label [15]. To estimate the event-free rate, Kaplan-Meier has been used [16,17]. The logistic regression (LR) model reveals that a Coronary Artery Calcium (CAC) score of >=100 rather than a Cardio Ankle Vascular Index (CAVI) of >=9 had a higher predictive value for all cardiovascular events [18]. The absolute risk was calculated using charts and adjusted according to these notes. More than 20% chances of developing a cardiovascular event due to the prevalence of WHO/ISH of high CVD risk [19]. From the Receiver Operating Characteristic (ROC), a cross-sectional study was conducted. The risk of carotid arteriosclerosis was positively associated with CAVI [20].

The study includes neural networks, support vector machine, Decision Tree models, ID3 algorithm, and association rules [21]. To analyze the application of data mining algorithms, a study has been done [22]. Principal Component Analysis (PCA) is a method in which the large data set is reduced by PCA, wherein the original data is transformed into new dimensions. The bivariate model was used to find the relationship between two variables. In the future, the research can be extended by using different techniques like an outlier and link analysis used to associate rule mining on a large number of patients. Usage of various techniques and association of rule mining has been referred for many patients [23,24]. The methods used here are classification methods such as DT and SVM. The results present a better accuracy of 99.42% by using the decision tree, whereas the support vector machine gives an accuracy of 89% [25].

The KNN algorithm is based on the similarity measure and the distance has been evaluated [26]. To develop predictive models, machine learning techniques like SVM, DT and ANN are used. The main aim is to compare the three algorithms using the performance measure algorithms like sensitivity, accuracy, and specificity [27]. Nephritis of renal pelvis origin is a disease that affects the urinary system [28]. The machine learning algorithms used here are SVM, Naive Bayes, Logistic regression, J48, and one R. The highest accuracy is still unable to exceed the accuracy of 80% with the best performing algorithm [29]. The techniques used here are machine learning, such as logistic regression and classification trees [30].

Using ANN, the multi-layer feed-forward neural network with Levenberg-Marquardt learning algorithm was used on CVD and diabetes mellitus patients [31,32]. The proposed system's primary method was a neural network ensemble method.89.01% of classification accuracy has been taken from the Cleveland Heart Disease database [33]. Iris image was cropped from the region of interest, and the discrete wavelength transformation feature, statistical, texture is extracted from the area of interest [34].

In the proposed system, the main aim is to investigate the CAD system for breast cancer. The database used here was the Springer link (SL), inclusion and exclusion criteria [35]. Data mining methods, like feature extraction and selection, have been used. K means and SVM has been used for diagnosing tumors and extracting useful information [36]. Based on the classification technique, machine learning had been approached. For solving the classification of problems, the Genetically Optimized Neural Network (GONN) algorithm had been used [37]. In the proposed system, by using the data, the prediction of chronic disease has been done by using machine learning algorithms. MLT like KNN, SVM, decision tree and logistic regression has been used [38]. In the proposed research, the pre-processing techniques like removal of missing data, deletion of noisy data, if applicable, will fill the default values. The performance has been measured using methods like classification, sensitivity, accuracy and specificity analysis [39–41]. Advanced data mining techniques has been used to discover the relationship and hidden pattern. The dataset used here was the Iranian Center for Breast Cancer (ICBC) [42–44].

## 3 Proposed Work

In the past several years, Cardio vascular disease (CVD) is one of the main contributing factors that cause innumerable fatalities worldwide. The medical condition that affects the heart and blood vessels is called CVD. Risk assessment and risk predictions have become essential in preventing CVD. Even though risk prediction tools are recommended, they are not adequately implemented in clinical practice. If the CVD patient is not properly assessed and intervened on time, there is every chance of resulting in fatality. To reduce the mortality rate and improve the heart health conditions, a new method is proposed. This proposed method analyzes the

parameters (hypertension, diabetes, obesity, blood pressure, heredity), and also the typical and atypical symptoms associated with the heart patients. To identify and classify the stages of CVD affected patients, new classification methods are designed. The proposed classification methods have high accuracy in predicting CVD patients. It also has a fast-training process and therefore easy to indicate whether the patients are affected by CVD or not.

The various stages of CVD are shown in Fig. 1 constituting various stages as
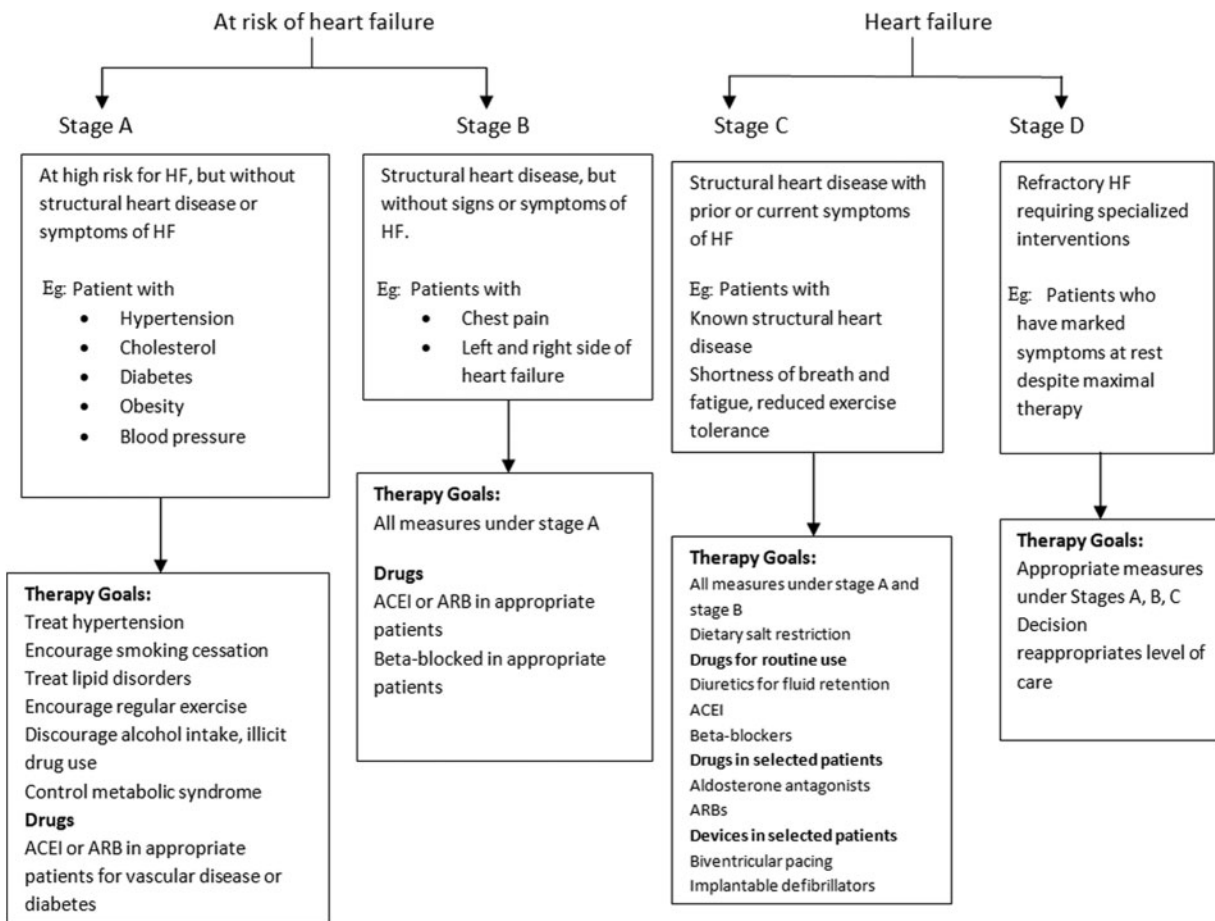


**Figure 1:** Stages of CVD

### 3.1 STAGE A: No Heart Disease and No Symptoms (High Risk)

Stage A is considered to be at high risk for heart failure but without structural heart disease or heart failure symptoms. The patient with symptoms of hypertension, cholesterol, diabetes, obesity, and blood pressure should have a standing goal therapy to self-care, carry out regular exercise and control metabolic syndrome and avoid alcohol intake. Drugs used for Stage A are ACEI or ARB in appropriate patients for vascular disease.

### 3.2 Stage B: Structural Heart Disease Without Symptoms

Stage B is considered to be a structural disease without symptoms, and there is also a risk of heart failure. The symptoms of Stage B are patients having chest pain and left and right-side heart failure. The goal therapy for Stage B is same as that of Stage A. The drugs used for Stage B is ACEI or ARB as well as beta-blockers for in appropriate patients.

### 3.3 Stage C: Structural Heart Disease with Symptoms

Stage C includes the problem of forming a structural heart disease with typical symptoms. There will be difficulty in breathing while doing exercises. Diuretics for fluid retention, ACEI and beta-blockers are the drugs used for daily routine.

### 3.4 Stage D: Refractory HF

Stage D is a refractory heart failure requiring specialized interventions for those patients having marked symptoms at rest despite maximal therapy. The goal therapy is the appropriate measures given for Stages A, B, C.

### 3.5 Predicting CVD Using SVM

SVM is a supervised machine learning algorithm, which is mainly used to classify the symptoms and common risk factors. Linearly separable data is used for data classification. The kernel function is used for nonlinear data. By using a "hyperplane," the variation between two data can be detected. To separate the given data into two classes, the hyperplane should have the largest margin in a large-dimensional space. The margin between the two categories is represented in the longest distance between the classes closest to data points, as shown in Fig. 2.
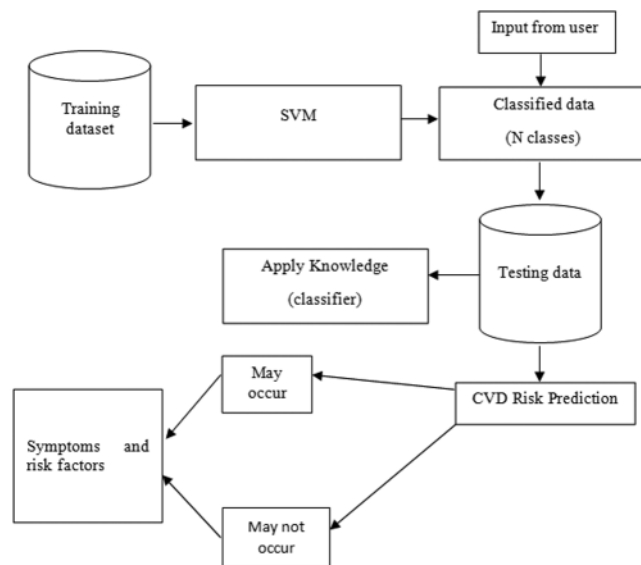


**Figure 2:** Predicting CVD using SVM

Various types of heart disease are shown in Tab. 1.

**Table 1:** Types of cardio vascular disease (CVD)

| Cardiovascular disease | Description | Risk factor | Symptoms | Treatment |
|---|---|---|---|---|
| Coronary heart disease | It includes diseased vessels, structural problem, and blood clots | Cholesterol, HBP, genetic, smoking, diabetes and Obesity | Chest pain, Nausea, sweating, Shortness of breath | Self-care, medications, medical procedure, and surgery |
| High blood pressure (HBP) | The force of blood against the artery wall is too high. | Diabetes, hypertension, unhealthy diet, Obesity, genetic and family history | HBP | Self-care, medications |
| Cardiac Arrest | There is a sudden, unexpected loss of heart function, consciousness, and breathing | Smoking, HBP, High Blood Cholesterol, Obesity, diabetes | Chest pain, lightheadedness, shortness of breath | Self-care, medications, medical procedure |
| Heart failure (HF) | The heart does not pump blood | High blood pressure (HBP) | Chest pain, dry cough, the inability to exercise, fast breathing, shortness of breathing, weight gain, swollen legs and feet | Treatment depends on the severity, self-care, medications, medical procedure, surgery |
| Arrhythmia | Improving the beating of the heart, whether irregular, too fast, or too slow | - | Chest pain, lightheadedness, slow heart rate, shortness of breath | Medication, medical procedures, devices, and supportive care. |
| Peripheral artery disease | Narrowed blood vessels reduce | HBP, High blood cholesterol, obesity, diabetes mellitus | Symptoms in leg pain, mainly when walking | Self-care, medications and, medical procedure |
| Stroke | Damage in the brain from interference of its blood supply | - | Trouble speaking, walking. | Medications, supportive care, Surgery, Therapies |

To find the optimal hyperplane, the separation of the symptoms of CVD has been done by using the vectors with one category as a target variable (risk factor) on one side of the plane with another class on the other side of the plane. Support vector is the vector near the hyperplane. In Fig 3, The SVM performs classification, regression and outline detection. The classification of linear SVM is done by drawing a straight line between the two classes. Consider a symptom or risk factor for the classification with T training data $\{x_\alpha, y_\beta\}$, where $\alpha = 1\ldots r$, for every input is considered as symptom $x\alpha$ has one attributes and in others of two classes as $y\beta \in \{-1, +1\}$. $-1$ denotes negative hyperplane, $+1$ denotes positive hyperplane.

The symptoms or risk factor (training data) in the form:

$$\{x_\alpha, y_\beta\} \text{ where } \alpha = 1\ldots r, \ y_\alpha \in \{-1, 1\}, \ x_\alpha \in R^D \tag{1}$$

The hyperplane has been described as

$$\langle w, x_\alpha \rangle + h = 0 \tag{2}$$

where w is the hyperplane and perpendicular distance from the hyperplane to the origin is $\frac{b}{||w||}$.
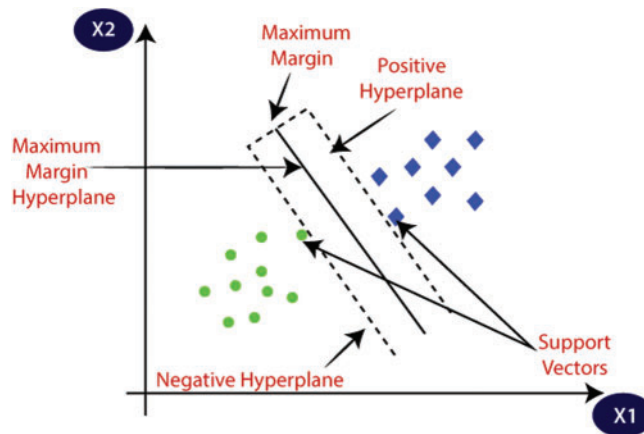
**Figure 3:** Structure of SVM

Solving the optimization problem is equal to finding the optimal hyperplane

$$\left\{ \frac{1}{2} w^t w y_\alpha (\langle w.x_\alpha \rangle + b) \geq 1 \right\}, \quad \alpha = 1, 2 \ldots N \tag{3}$$

The problem is in the quadratic form. For constraints minimization, longing to allocate Lagrange multipliers $\beta$ and conclude that in the dual form:

$$\left\{ \begin{array}{l} \sum\_(\alpha = 1)^\wedge N i\_\alpha - 1/2 \sum\_(\alpha, \beta) i\_\alpha, i\_\beta \times y\_\alpha y\_\beta \langle x\_\alpha, x\_\beta \rangle i\_\alpha \geq 0 \\ \sum\_(\alpha = 1)^\wedge N i\_\alpha y\_\alpha = 0 \end{array} \right\} \tag{4}$$

By evaluating Eq. (4), Lagrange multipliers $\alpha$ is found out, and the optimal hyperplane is given below:

$$\begin{array}{l} w^\wedge* = \sum\_(\alpha = 1)^\wedge N i\_\alpha y\_\alpha x\_\alpha \\ b^* = -\frac{1}{2} \langle w^*, x_r + x_s \rangle \\ f(x) = sign \langle w^*, x \rangle + b^* \end{array} \tag{5}$$

where xr and xs are any support vectors from each class satisfying:

$$\alpha_{r,} \alpha_{s.} > 0, \quad y_r = -1, \quad y_s = 1 \tag{6}$$

By use of optimization quadratic Algorithms 1 the optimization problem has been solved.

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**Algorithm 1:** Pseudo Code for the Prediction of CVD (SVM)

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BEGIN
  Input: Build the training dataset T
  Output: Prediction of CVD
for each input $x_\alpha$
  do
  $x_\alpha = \{x1, x2, x3, \ldots, xn\}$
  $y_\beta = \{-1, +1\}$

---

(Continued)

```
  −1⇒ Negative hyperplane
  +1⇒ Positive hyperplane
the hyperplane is described as ⟨w, x_α⟩ + h = 0
for each labeled instance (x_α, y_β)
    do
    if x_α an unknown data set then
        X is invalid
    else then
for each process in training data
    do
    calculating Lagrange multiplier
    if (x_α, y_β) = 1 then
        X may occur exit
    else then
        X is may do not occur
END
```

## 4 Results and Discussions

In this, SVM classification algorithm are used to analyze the health data for cardiovascular disease. For each attribute in SVM, the optimal hyperplane has been predicted. The performance metrics such as Accuracy, Specificity and Sensitivity were used to prove the efficacy of this modern approach. Tab. 2 gives the baseline clinical characteristics of patients.

**Table 2:** Baseline clinical characteristics of patients

| Variable | Men | Women | Probability |
|---|---|---|---|
| Age, Years | $50.02 \pm 4.33$ | $58.40 \pm 4.10$ | <0.001 |
| Height, m | $1.88 \pm 0.10$ | $1.71 \pm 0.07$ | <0.001 |
| Weight, Kg | $102.25 \pm 17.01$ | $86.20 \pm 14.26$ | <0.001 |
| BMI, kg/m$^2$ | $33.08 \pm 5.36$ | $33.39 \pm 6.20$ | 0.285 |
| Total cholesterol | $7.76 \pm 2.72$ | $8.12 \pm 2.40$ | <0.001 |
| Oral glucose tolerance test, mol/L | $6.96 \pm 3.06$ | $8.12 \pm 3.60$ | <0.001 |
| Right CAVI | $8.96 \pm 1.76$ | $9.00 \pm 1.51$ | 0.530 |
| Left CAVI | $8.86 \pm 2.82$ | $8.92 \pm 2.40$ | 0.030 |
| Mean CAVI | $7.95 \pm 1.56$ | $8.96 \pm 2.35$ | 0.098 |
| Heart rate, bpm | $65.83 \pm 10.51$ | $66.34 \pm 10.16$ | 0.009 |
| Smoking, n (%) | 330(45) | 190(15) | <0.001 |
| Family history of CLDN (%) | 295(37) | 450(35) | 0.921 |
| Diabetes, n (%) | 150(20) | 250(20) | 0.962 |
| Hypertension | $109.01 \pm 13.06$ | $107.08 \pm 15.23$ | 0.045 |

### 4.1 Confusion Matrix

Confusion matrix is defined to showcase the performance of an algorithm through visualization or to describe the performance of a classification model on a set of test data for which the true values are known. A confusion matrix is also called an error matrix shown in Fig. 4 that depicts the time taken for the completion of the training dataset. After the construction of confusion matrix, the sensitivity, specificity, and accuracy are calculated as,

$$Sensitivity = \frac{TP}{(TP + FN)} \tag{7}$$

$$Specificity = \frac{TN}{(TN + FP)} \tag{8}$$

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{9}$$

where, TP-True positive; FP-False positive; TN-True negative; FN-False-negative.
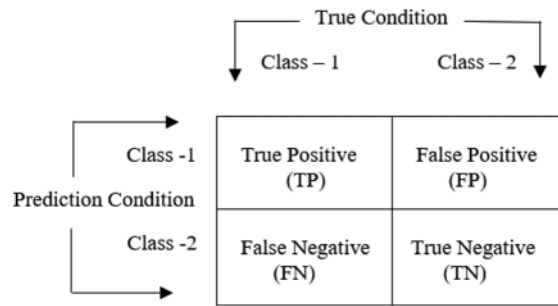


TP – True Positively predicted instances is called TP.

FP – False Positively predicted instances is called FP.

TN – True Negatively predicted instances is called TN.

FN – False Negatively predicted instances is called FN.

**Figure 4:** Confusion Matrix

### 4.2 Kappa Statistic

Kappa Statistics is the measure of how closely the instances have been classified. The kappa coefficient is represented as follows

$$k = \frac{p_0 - p_e}{1 - p_e} \tag{10}$$

where k is kappa value, p0 denotes the probability of observed agreement and pe denotes the probability of hypothetical agreement. With the help of confusion matrix, p0 and pe is computed followed by $p_{class1}$ and $p_{class2}$.

$$p_0 = \frac{TP + TN}{TP + FP + TN + FN} \tag{11}$$

p0=pclass1 + pclass2,

where pclass1 and pclass2 is computed as follows

$$p_{class1} = \frac{TP+FP}{TP+FP+TN+FN} \times \frac{TP+FN}{TP+FP+TN+FN} \tag{12}$$

$$p_{class2} = \frac{FN+TN}{TP+FP+TN+FN} \times \frac{FP+TN}{TP+FP+TN+FN} \tag{13}$$

### 4.3 Mean Absolute Error

The average difference between predicted and actual value in all test cases called average prediction error which otherwise refers to the mean of the absolute values of each prediction error on all instances of the given test data set.

$$MAE = 1/n \sum\_(i=1)^{\wedge}n|e\_i| \tag{14}$$

### 4.4 Standard Deviation

Standard deviation measures the spread of the data about the mean value.

$$\sigma = \sqrt{\left(\left(\sum(x\_i - \mu)^{\wedge}2\right)/N\right)} \tag{15}$$

### 4.5 Median

The median is the middle number sorted in ascending, or descending list of numbers and can be more descriptive data set than the average.

$$\frac{n+1}{2} \tag{16}$$

Tab. 3 shows by using validation data set, the detailed prediction has been done in the form of confusion matrices and error rate obtained using SVM.

**Table 3:** Confusion matrix and error rate obtained using SVM

| Confusion matrix | | | Error rate 0.5913 |
|---|---|---|---|
| | Normal | Abnormal | |
| Normal | 200 | 180 | |
| Abnormal | 195 | 170 | |

Tab. 4 shows the performance metrics and the results obtained by the proposed method where each metric is calculated accordingly.

Fig. 5 gives the chart model evaluation using SVM and it proves the performance of classification accuracy 81.2187%, Sensitivity 93.2031% and Specificity 89.8655%. Tab. 5, it shows the comparison of existing systems and proposed systems for predicting cardiovascular disease.

**Table 4:** Performance metrices of KNN, SVM and Naive Bayes

| Performance Metrics | SVM |
|---|---|
| Time | 0.04 |
| Kappa statistics | 0.6233 |
| Standard deviation | 0.3108 |
| Mean absolute error | 0.5377 |
| Median | 0.5515 |
| Accuracy (%) | 81.2187 |
| Sensitivity (%) | 93.2031 |
| Specificity (%) | 89.8655 |
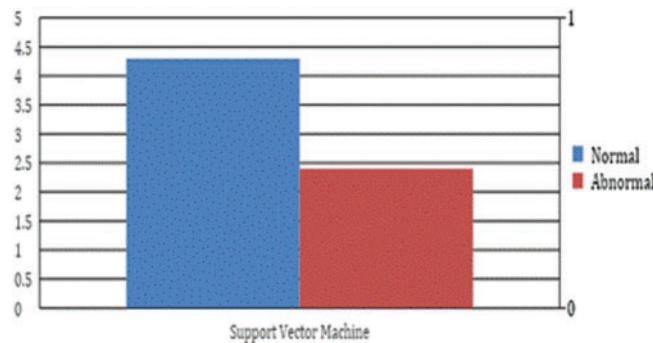


**Figure 5:** Performance of the support vector machine

**Table 5:** Comparison of existing and proposed system

| S.no. | Authors | Methodology | Accuracy (%) |
|---|---|---|---|
| 1. | Islam et al. [29] | Naïve Bayes, Logistic regression | 80 |
| 2. | Haq et al. [31] | KNN, ANN, Naïve Bayes, Decision tree | 89 |
| 3. | Dinesh et al. [40] | Gradient boosting, random forest, Naïve Bayes, Logistic regression | 88 |
| 4. | Bhardwaj et al. [38] | Genetically Optimized Neural Network | 93.24 |
| 5. | Proposed system | SVM | 95 |

Fig. 6 is a graphical representation of a comparison of existing system with the proposed method for predicting cardiovascular disease in the early stage with more accuracy when compared to other machine learning techniques.
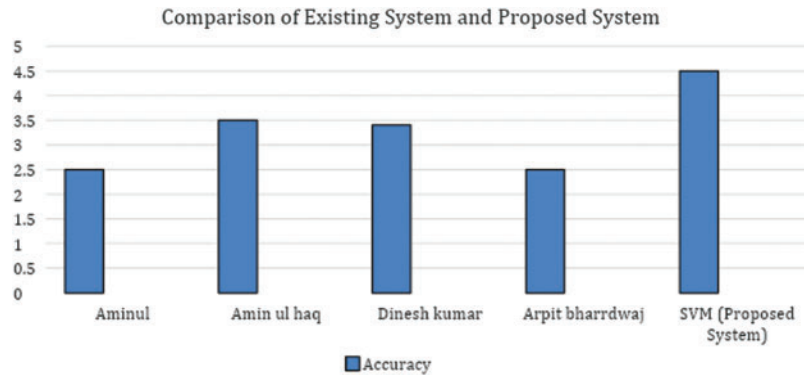
**Figure 6:** Comparison of existing and proposed system

## 5  Conclusion and Future Scope

In this study the occurrence of CVD is more in humans because of genetic disorder when compared to other health issues. Therefore, medical practioner are in need of suitable technique or model to predict primarily. Nowadays, machine learning techniques are adapted in medical science for such decision-making situations. The proposed system designed under supervised learning using SVM plays efficiently in decision appealing and retrieving proficiency from an enormous amount of data thereby delivering better patient care and productivity. This system proves as an excellent model in addressing the classification problems and go-to method for any type of prediction problem. In this research paper, the classification techniques used for identifying cardiovascular in patients gives more prediction accuracy compare to other technical approaches. Future research is required to validate the algorithm for a huge population in taking many risk parameters into consideration.

**Conflicts of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

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