

## Notice of Retraction

### **"Molecular Diagnostic and Using Deep Learning Techniques for Predict Functional Recovery of Patients Treated of Cardiovascular Disease,"**

by Ar Junejo, Yin Shen, Asif Ali Laghari, Xiaobo Zhang and Hao Luo  
in IEEE Access, Vol 7, August 2019

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Due to the nature of this violation, reasonable effort should be made to remove all past references to this paper, and refrain from future references to this paper.

Received July 28, 2019, accepted August 11, 2019, date of publication August 23, 2019, date of current version September 9, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2937290

# Molecular Diagnostic and Using Deep Learning Techniques for Predict Functional Recovery of Patients Treated of Cardiovascular Disease

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This work was supported in part by the National Natural Science Foundation of China under Grant 61100029.

**ABSTRACT** Today, with the development of industry and mechanized life style, the prevalence of the disease is rising steadily as well. Observing at the trend and lifecycle style, its predict that after ten years around 23.6 million people die because of Cardiovascular Disease (CVD). For that reason, aim to use Deep Learning Techniques (DLTs), to analysis stable CVD that would give valuable awareness to decrease misdiagnosis in the Robust Healthcare Industry (RHI). An objective of this paper is first, Molecular diagnosis (MD), and second using Deep Learning Techniques DLTs, to synthesis and characterize to accumulate (raw information) from CVD patients, those who admitted the emergency section between January (2018 to December 2019). We are using Artificial Neural Network (ANN), model characterize to predict CVD patients and configuration, Feature selection (FS), Mean Square Error (MSE), accuracy, sensitivity. The ANN accuracy is 98.4, K-nearest neighbor (KNN) accuracy is 98.01%, Naïve Bayes (NB), accuracy is 96.99%. Decision tree (DT), accuracy is 87.81%. Our robust data driven model explore the efficient accuracy rate to predict CVD patients. The ANN model in term of their efficient in disease analysis, and prognosis of the RHI.

**INDEX TERMS** Artificial neural network (ANN), cardiovascular disease (CVD), molecular diagnostic (MD), Robust Healthcare Industry (RHI).

## I. INTRODUCTION

Cardiovascular disease (CVD) arises when the blood vessel of the heart that normally provides blood and oxygen to the heart is completely blocked [1].

The human organ, is many molecular interaction networks, like self-possessed of millions of interacting Nano-cells. Intra-Body Biological Systems (IBBS) is nearly connected to individually each other and interact mainly through molecular transactions [2].

The statistics, report published by World Health Organization (WHO) [3], indicate that CVD, the number one reason for death, in the globe [4], [5], and about 17.7 million people annually die, which means 31% of all global deaths happened because of CVDs, in 2018 [6]. A significant point is that, about 80% of CVDs deaths are occurred because of heart attacks and/or strokes. Another point is that,

The associate editor coordinating the review of this article and approving it for publication was Masood Ur-Rehman.

above 75% of CVD mortalities happen in middle-income, and low-income countries. Based on these statistics, the estimation of CVDs patients may reach up to approximately 23.6 million in 2030 [7].

The American Heart Association (AHA) expressed that, different kinds of CVD are the number one killer for all American individuals. This constitutes an alarm for governments, and researchers to find, some solution to reduce the negative and destructive effects of this disease. The most distinct risk parameter of CVD, is shown in Fig.1.

Deep learning [9], is used to predict, examining, distinct (RHI) [10], [11]. In this article, initial describe the model for necessary intra-organ, molecular interaction, medium [12], i.e., action potential-based cardio molecular interaction medium.

Fluid-Structure interaction in a blood vessel network analysis of the displacements associated stresses of the walls of a part of an artery, and a few branches embedded within the muscular tissue, when laid open to the pressure caused by the

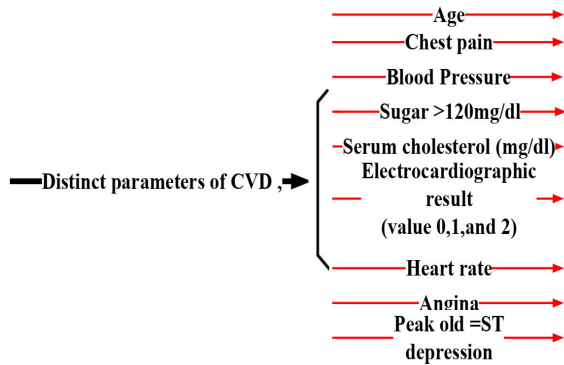


FIGURE 1. Distinct parameters of CVD [8].

heart’s beating [13]. The case study, is often wont to observe the chance for the failure of the artery given a convinced deformation within the artery.

The blood flow and fluid pressure are calculated within the first case study. The forces applied, by the fluid on the interior walls of the blood vessel, are used as loads for the structural analysis within the walls, and contiguous cardiac muscle tissue.

The equations for the fluid flow, are outlined within the blood vessel. The structural analysis, is outlined within the walls and therefore the tissue only, extremely nonlinear hyper-elastic model for the blood vessel walls and therefore the contiguous tissue.

In this study secondly, we endeavored to apply Machine Learning Techniques (MLTs), as Naïve Bayesian networks (BN), are powdered of a network like structures with accompanying conditional probabilities [14]. Decision tree (DT), utilize to represent the probability relationship between a feature, or to predict the value of a target variable supported many input variables.

The K-Nearest Neighbor (KNN), techniques are a non-parametric technique, used for classifier and regression [15]. The KNN, needs a distance metric which the most well-known of distance metric is the Minimum-Distance Classifier (MDC).

The MDC attempts to assign a classified variable to the most common category (class) amongst its neighbors, which means that it measures, the distance from neighbors and classify them. There are distinct distance measures but Euclidean distance, measures are the most commonly used distance measures. The learning process of the KNN, includes in choosing an appropriate parameter [16].

Fully connected neural network, model used for predicting, by CVD, such as in, coronary artery disease, to analysis heart disease, to construct risk parameters, heart disease [17]. In table.1 describes different DLT, and the table. 2 shows the related work.

The main contribution, of this paper is introduce classification performance, which combines with DLT, techniques as ANN, NB, DT, KNN.

Designing ANN, model with back propagation learning techniques, and feature selection, for classification of CVD.

TABLE 1. Machine learning techniques.

Techniques	Abbr. Name	Descriptions
Classification		Performance measurement
Naive Bayes	NB	Bayes theorem based probabilistic learner
Best-first decision tree	D T	Tree with binary splits on features
k-nearest neighbor	k-nn	Similarity analysis with k closest instances
Multilayer perception	MLP	Back propagation based neural network.
Regression	R	Regression is classifying values, whose value be influenced by the success of probability
Feature selection	FS	The process of select variables that predict the outcomes

Our techniques prove the accuracy rate and control the attributes which give more towards the predication. Further, it’s potential to reduction the undesirable effects of measuring noise, by injecting noise into information throughout the training techniques. Demonstrate of this draft is to point out the emerging response strategies for intra-organ, failures and molecular diagnostic of CVD, and to bridge the clinical information gap.

Our main research, can be summarized as follows.

Section II, is experimental detail, material, and dataset, molecular diagnosis of the CVD, distinct machine learning techniques, and the result. Section III is discussion, motivation and engineering finding. Section VI. is a conclusion and future work.

II. EXPERIMENTAL DETAIL AND RESULTS

A. MATERIALS AND DATA SET

Cardiovascular disease CVD, hospital dataset, accessible at UCI, laboratory (Molecular Diagnostics Laboratory) Shaukat Khanum hospital and research Centre was used in this study. Our dataset contains 294 samples. Total 14 attributes included, and six scenarios are considered. The table.no.3 is the list of the 14 attributes.

B. MOLECULAR DIAGNOSIS OF THE CVD

In this section, we try to find a solution, for how can interaction blood, within the blood vessel of the CVD. A special environment for implementing microscale interaction.

Actually, the treatment of the absorptions of distinct factors in the blood hopes, it’s become efficient for doctors, to help to identify a serious condition for patients. Due to the access of such data [20], it may be potential to activate not solely the first administration of the essential therapies, in efficient ways that however additionally the discharge of precise may molecular interaction, before arranged in the human organ. Meanwhile, the blood needs regarding one minute to finish the massive and tiny circulation, it’s a rare medium, to quickly transmit data, to distinct components of the organ [21].

TABLE 2. Show related work using different MLT techniques.

Author/	Year	Used Techniques	Result
Srabanti, Maji (2018) [18]		DT,	Hybrid DT, workout best aspect to individual techniques
Kumari,2017 [15]		RIPPER, DT, ANN,SVM	SVM is efficient techniques for CVD prediction and accuracy is also high.
Nikhar,2016 [1]		NB, DT	The compare DT, and NB, classifier the DT, the result is better than NB.
Ratnam, 2015 [16]		ANN, NB	It is used to reduce the number of clusters and the information attribute filtering is efficient for predicting CVD.
Nishara Banu,2014 [19]		C4.5,DT	The performance of DT, the techniques are restrained on the basis of data entropy.
Patel,2013 [17]		NB, NT	In the less number of attributes, focus on how can diagnose and analyzed CVD.

TABLE 3. List of the tributes.

Attribute	value
Age	38
Sex	02
Cp	04
trestbps	32
Chol	144
Fbs	02
Restecg	02
Thalach	73
Exang	07
Oldpeack	06
Slope	11
Ca	05
Thal	05
num	05

Therefore, considerate the interaction mechanisms, in the blood, is of great interest in the field of molecular diagnosis. The Fig.2 (A) is Normal and (B) Heart failure Cordial infarction [22].

However, in an exceedingly kind of CVD, with impaired pump perform, stroke volume (blood flow volume ejected per heart beat) drops and therefore the heart is unable to with efficiency pump oxygen-rich blood to the remainder of the body the heart is transformed from the underlying disease method, turning into enlarged with stiff muscle walls because it is being strained to carry a lot of oxygen-rich blood to pump to the organ. The weakened pumping volume ends up in straightforward weakness. It additionally causes blood and fluid to encouragement into the lungs, and also the organ, leading to breathlessness and generalized swelling, severally. Fig. 3. (A) Normal and (B) Artificial heart blood Vessel.

CASE I: In the domain, cardiac muscle, aorta and its branches vessels, with blood contained. The Naiver-Stokes equations in the blood and oxygen to the heart are narrowed [24]. At individually surface wherever the model carries a vessel, to a surprising finish, it characterizes the load with an identified pressure distribution. Synthesis of tissue and artery material process model.

Synthesis of Tissue and Blood Vessel Material Computational Model: The synthesis of rubber-like elastomers, is a

hard task for numerous reasons. The material can undergo very large strains. The stress-strain association, is mostly non-linear. Numerous rubber-like materials are generally not able to be compressed. It needs to revise standard displacement-based finite element formulations in order to arrive at correct results (mixed formulations). You must responsiveness to the description of stress, and strain measures. The analysis of nonlinear geometrically, the expectations about microscopic displacement are no longer valid. In table 4, describes the model parameters.

The liquid dynamics synthesis studies, the solution of the 3D Naiver equations. we can do so in both a stationary case, or in the time domain. To establish the Fig.4 describe the boundary conditions for the liquid – flow synthesis [25].

For the Time-dependent density functional theory (TDDFT) synthesis, the computational model deploys a circular function to vary the pressure distribution over time in equation.1 for COMSOL multiphysics none linear hyper elastic model

$$f(t) = \begin{cases} \frac{\sin\pi t}{3} & -\frac{1}{2}\text{Cos}\left(2\pi\left(t - \frac{1}{2}\right)\right) & 0 \leq t \leq \frac{1}{2}s \\ \frac{1}{2}s \leq t \leq \frac{3}{2}s & \end{cases} \quad (1)$$

First, observe the steady flow field in order to match its result to the transient case. Fig.5 explore a slice plot of the speed field (that provides values in m/s).

In the last model, analysis for the influence of outsized displacements, and for the hyper elastic performance of the biological tissues.

CASE II: Actually the heart, mechanisam, as transmitter (Tx), as source and Reciever (Rx) as destination like a transeiver, of the interaction system of the overall body organ. It hes characteristic signal producing and communication (interaction) mechanisam, which is of great prominence, and needs to be given special attention to understading the feature of transmission, of blood to every single cell, i.e., a destination inside the human organ.

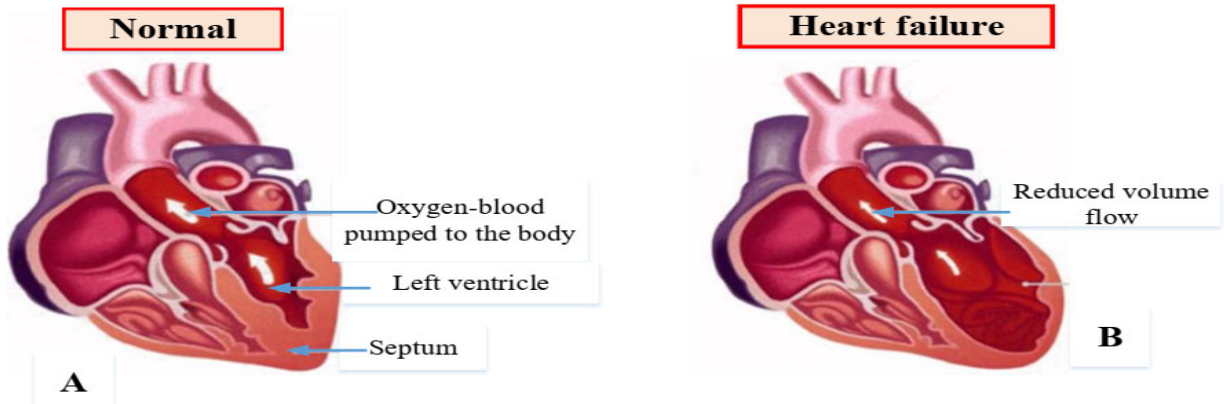


FIGURE 2. (A) Normal and (B) Heart failure (Cordial infarction caused by the rupture of plaque during coronary artery disease).

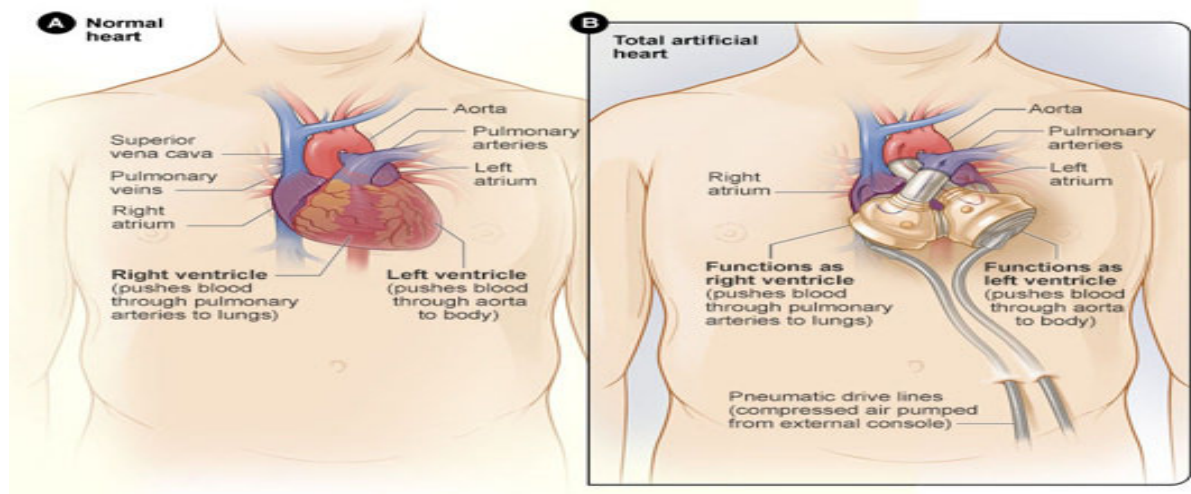


FIGURE 3. Normal and artificial heart blood vessel [23].

TABLE 4. Model parameters.

Attribute	value
Blood density	1060 kg/m <sup>3</sup>
Blood dynamic viscosity	0.005 Ns/m <sup>2</sup>
Artery density	960 kg/m <sup>3</sup>
Neo-Hookean hyperelastic behavior: the coefficient u	6.20 · 10 <sup>6</sup> N/m <sup>2</sup>
equal	20 μ
Bulk modulus equal	0.45
Poisson's ratio, v	1.0 · 10 <sup>7</sup> N/m <sup>2</sup> .
Lastic modulus equals	1200 kg/m <sup>3</sup>
Cardiac muscle- density	
Equivalent elastic modulus equals	1.16 · 10 <sup>6</sup> N/m <sup>2</sup> .

Molecular interaction system model, the essential components of a molecular interaction system are a source, destination, and medium. The source is a point placed at a distance (d) from the midpoint of the destination. It releases molecules that diffuse freely and individually from each other via Brownian motion. In precise, the molecules diffuse randomly over the medium, and the gesture of a molecule is not dependent on the gesture of any additional molecules [26].

For each information particle, the hitting ratio is stated as follow: -

$$R_{hit}(t) = \frac{r_r}{d + r_r} \operatorname{erfc} \left[ \frac{d}{\sqrt{4Dt}} \right] \quad (2)$$

where r, D, and d indicate the radius of the destination, the diffusion coefficient and the distance between  $T_x$ , and  $R_x$  [27].

The arrival of molecules is a binomial process in its nature. When considering a single emission of  $N^{Tx}$  molecules at  $t = 0$ ,  $N_1^{Rx}$  is expressed as a binomial random variable stated as follows:-

$$N_1^{Rx} \sim \mathcal{B} \left( N^{Tx}, P_1 \right) \quad (3)$$

where  $P_1$  denotes the predictable amount of molecules absorbed by the destination node through the initial symbol period, the binomial distribution with n success and trail probability p is indicate by  $\mathcal{B}(n; p)$ .

For broad circumstance with several emissions, in a period, the number of received molecules is affected by the existing



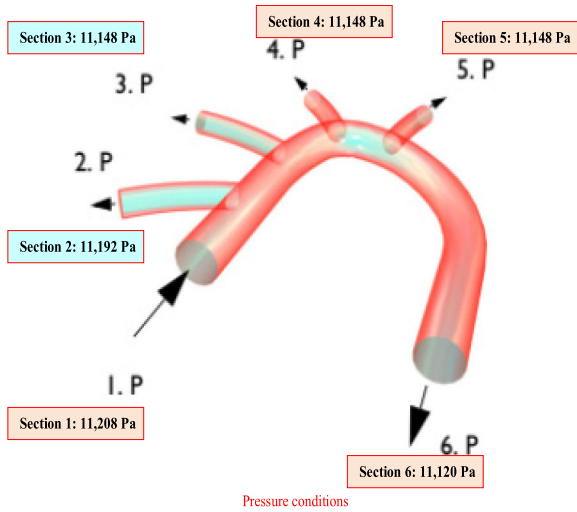


FIGURE 4. Boundary conditions.

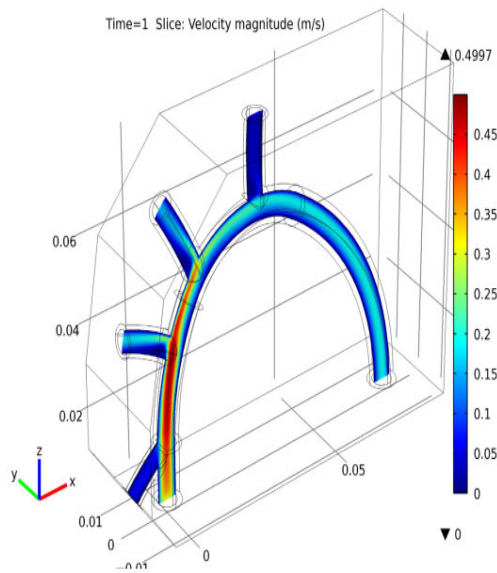


FIGURE 5. speed field color slice in the artery and its vessel branches, and displacement.

and the prior emissions. Hence, we get

$$N_i^{Rx} \sim \sum_{k=1}^i \mathcal{B}(N_k^{Tx}, P_{i-k+1}) \quad (4)$$

where  $N_k^{Tx}$  indicates the number of emitted molecules in the  $k^{th}$  symbol duration.

Due to the complexity of binomial random variables, the computational model is mostly approached by Gaussian model [27] given as follows.

$$N_i^{Rx} \sim \mathcal{N}\left(\sum_{k=1}^i N_k^{Tx} P_{i-k+1}, \sum_{k=1}^i N_k^{Tx} P_{i-k+1} (1 - P_{i-k+1})\right) \quad (5)$$

The  $N_i^{Rx}$  values are used to evaluate the CDF  $F_{N_i^{Rx}}(x)$  for Gaussian using the following equation

$$F_{N_i^{Rx}}(x) = P(N_i^{Rx} \leq x) \quad (6)$$

where  $P(\cdot)$  refers to the event probability.

$N_i^{Rx}$  is influenced by the present time and the prior emissions which are being processed by the transmitted bit values with continuous transmission of bit-0 indicates no emission, and the demodulation is done through simple thresholding. The demodulation function  $\delta(\cdot)$  receives the input  $N_i^{Rx}$  and the demodulated bits output according to the following equation:

$$Y_i = \delta(N_i^{Rx}) \begin{cases} 1 & \text{if } N_i^{Rx} \leq \varepsilon \\ 0 & \text{if } N_i^{Rx} > \varepsilon \end{cases} \quad (7)$$

where  $N_i^{Rx}$  and  $Y_i$  indicate the count of received molecules and the demodulated symbol in the  $i^{th}$  symbol period, although  $\varepsilon$  indicates the threshold value for demodulation.

The error probability of bit-1 for Gaussian model, using BCSK for the modulation and thresholding with  $\varepsilon$  for the demodulation is given as follows.

$$\begin{aligned} P_{e,1}^G &= P(N_i^{Rx}(t_1, t_1 + t_s) \leq \varepsilon) \\ &= \varrho\left(\frac{N_i^{Tx} P_{t_1}^{t_1+t_s} - \varepsilon}{\sqrt{N_i^{Tx} P_{t_1}^{t_1+t_s} (1 - P_{t_1}^{t_1+t_s})}}\right) \end{aligned} \quad (8)$$

where  $\varrho(\cdot)$  refer to the  $\varrho$ -function.

We designed the actual computational framework for molecular interaction which relies on the ideal information of the complete medium model. Due to that, we have optimized the BCSK modulation and the threshold demodulation, to reduce the error rate (BER). By using known learning techniques, we have discovered that the proposed technique achieved the same performance as the better performance.

### C. DEEP LEARNING TECHNIQUES

The MLT is used to predict the efficient retrieval of patient's diagnosis with CVD. The main aim is robust healthcare data drove, data leaning, missing data handling. Finally, an ANN model evaluation,

#### 1) CLASSIFICATION PERFORMANCE MEASUREMENT

The formula for the exploration of classification was discovered. (Positive class) in the Samples with the absence of CVD, and (Negative class). samples with the presence of CVD. Now the formula is defined as above through confusion matrix [28].

The rate of misclassification Proportion of inaccurately classified samples to the total number of samples is identified as the rate of misclassification.

There are two types of inappropriate classifications. If the presence of CVD was classified as the absence of CVD (E1), it is defined as type I error. If the absence of CVD was classified as the presence of CVD(E2), it is demarcated as a type II error.

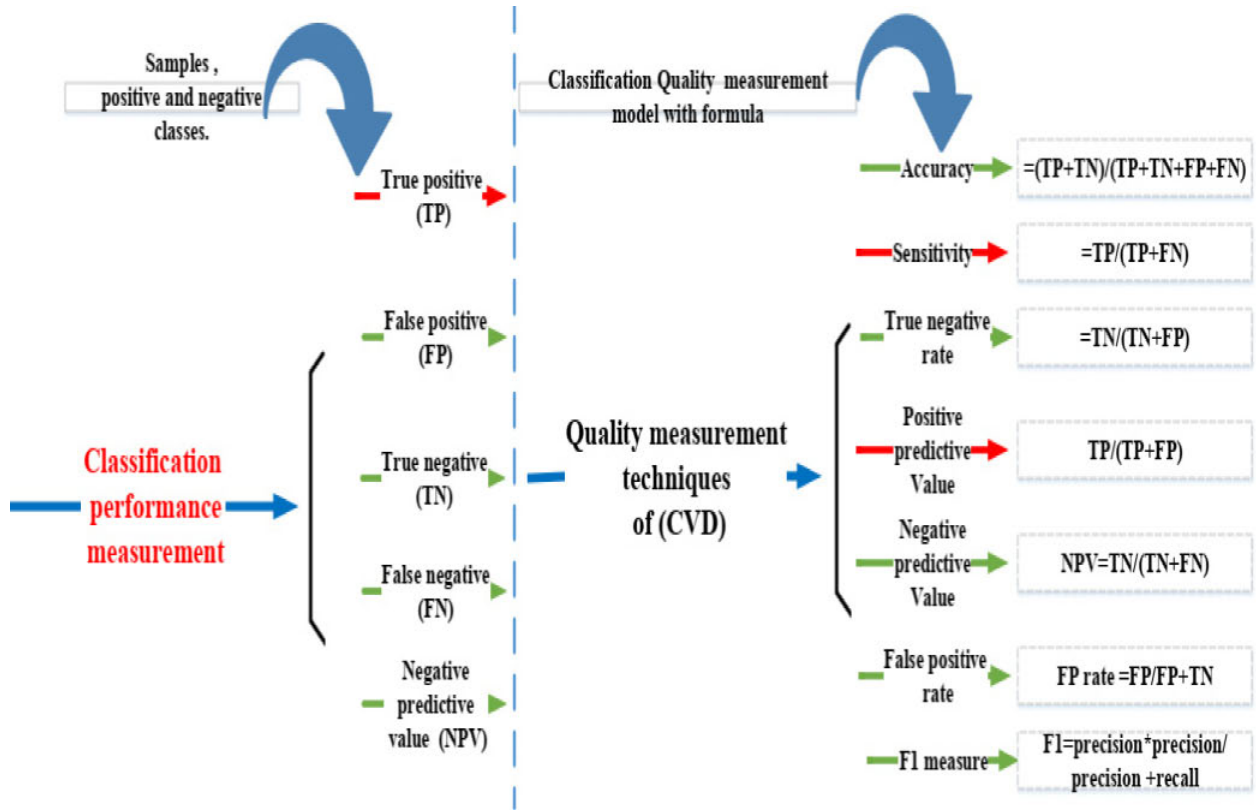


FIGURE 6. Quality measures for the characterization of classification formula.

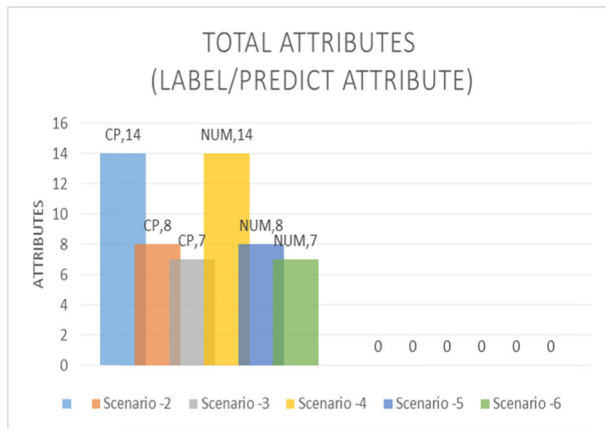


FIGURE 7. Describe Scenario-1 to scenarios-6 used for prediction CVD.

The rate of misclassification =  $\frac{E1+E2}{\text{total number of samples}}$ : The confusion matrix is describing the performant of the classifier model. The Classification measurement formula describes in the Fig.6 as TP, FP, TN, FN, NVP [29].

The following Fig.7 data are used in all scenarios-6 and compare the attributes and predicted attributes.

2) DECISION TREE

Decision tree (DT), utilize to represent the probability relationship between feature. In the Fig.8 DT, the result with respect to accuracy includes scenario-1 to scenario-6 [18].

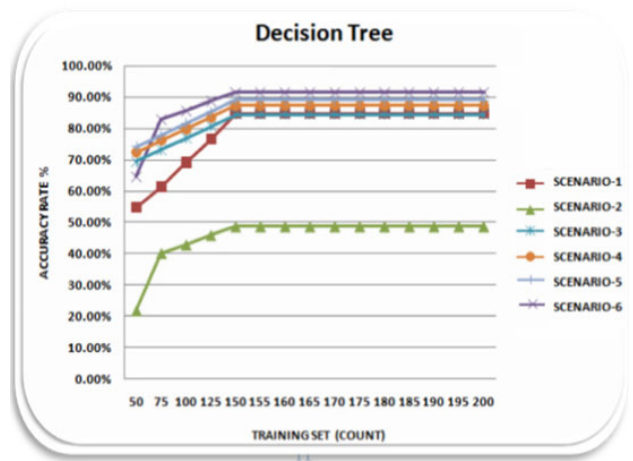


FIGURE 8. Accuracy rate with respect to scenario-6.

3) NAIVE BAYES NB

Bayesian networks BN, is conditional probability based structural network as in equation (2)

$$P(c|x) = \frac{P(x|y)P(y)}{P(y)} \tag{9}$$

The  $P(c|x)$ , is posterior probability, and given class (c), this supposition is called class conditional independence [31].

In the case of discrete variables X and Y are

$$P_{Y|X}(y|x) = \frac{P_{XY}(x,y)}{P_X(x)} = \frac{P_{X|Y}(x|y)P_Y(y)}{\sum_{y' \in Val(Y)} P_{X|Y}(x|y')P_Y(y')} \tag{10}$$

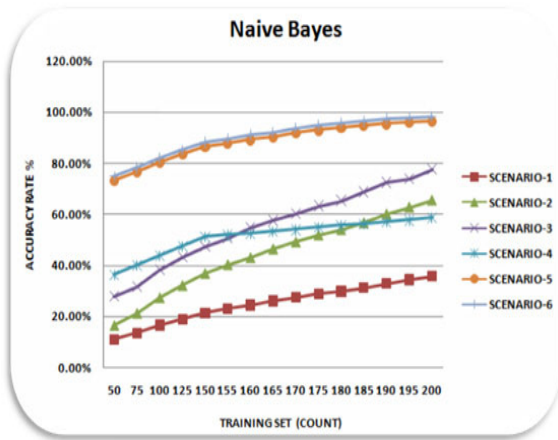


FIGURE 9. The accuracy rate of NB, in all scenario.

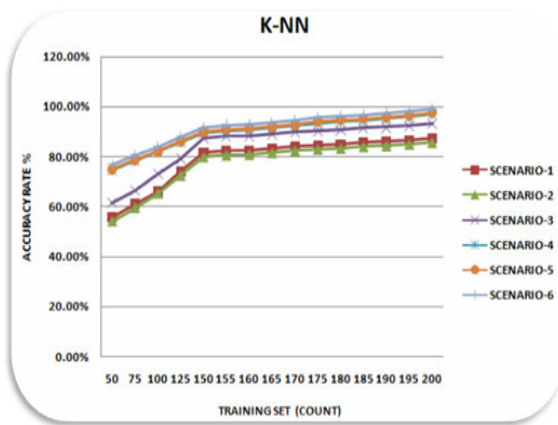


FIGURE 10. The accuracy rate of K-NN in all scenario.

If the random variable X and Y are continuous.

$$f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)} = \frac{f(x|y)P_Y(y)}{\int_{-\infty}^{\infty} f(x|y')f_Y(y')dy'} \quad (11)$$

Fig. 9 Accuracy rate of Naïve Bayesian NB, in all scenarios for CVD, this graph also states that scenario -6 has more accuracy compared to others scenarios-6.

4) K-NN

The K-NN techniques is a non-parametric technique intended for classifier and regression. The K-NN needs a distance metric which the most well-known of distance metric is the minimum-distance classifier (MDC). The MDC attempts to assign a classified variable to the common category (class) amongst its neighbors, which means that it measures the distance from neighbors and classify them.

There are distinct distance measures but Euclidean distance measures are the most commonly used distance measures. The learning process of the K-NN includes in choosing appropriate parameter k. Fig.10 report experimental results of K-NN with respect to accuracy rate in all scenarios for CVD, this graph also states that scenario-6 has more accuracy as compared to other scenarios-6 [32].

It is exploring that scenario-6 give an efficient result as compared to all other five.

5) ARTIFICIAL NEURAL NETWORK ANN, MODEL CONSTRUCTION AND EVALUATION

ANN model is analysis by a number of neurons n, a number of hidden layers m, transfer function, Multilayer Perceptron Neural Network (MLPNN) is one of the effective ANN for modeling and prediction, nonlinear and complex processes [33]. The number of output neuron is k,  $w_{ji}$  is the weight to the hidden neuron  $y_j$  from the input unit  $x_i$ ,  $w_{kj}$  represents the weight to output neuron  $z_k$ , from hidden neuron  $y_j$ . The biases are represented by  $b_j$  and  $b_k$  correspondingly.

• BPNN techniques

The BPNN acquire the standard of MLFF network which functions performing error control of each neuron. BPNN continue to updating its weight after processing the group of data until the error value is within the threshold.

• Fitting

The unsuitable number of hidden neurons cause also overfitting or under fitting, up thus far there is no actual formula for calculating the number of hidden neurons. Maximum of the time it is trial and error method. Though, there are numerous rules of thumbs for selecting the number of hidden neurons as: Hidden layer neurons is 2/3 of the magnitude of the input layers. Hidden layer neurons must twice of the number of neurons in the input. The size of the hidden layer neurons is in the middle of the input layer size and the output layer size. Fig.11. Flowchart for designing ANN.

The weight matrix {W}, a log-sigmoid function is assign as the activation function f, which offers data values between {1} and {0}. As a result, prior to the ANN, the feature data value essentials to be scaled to within the range of {0} to {1} as follows, where  $x$  is the input features before normalization  $x^*$  is the input features after the training,  $x_{min}$  is the least value of the input model feature and  $x_{max}$  is the maximum value of the input features. To output vector  $z$  and the  $k^{th}$  component  $z_k$  are calculated as

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (12)$$

$$z = f(Wx^* + b) \quad (13)$$

$$z_k(x, w) = f_1(b_k + \sum_{j=1}^m w_{kj}f_2(b_j + \sum_{i=1}^n w_{ji}x_n^*)) \quad (14)$$

The ANN is collected of two or more layers of processing elements which are linked by weighted connections as presented in Fig.6. The information flow is unidirectional, no feedback connections are present and each feed-forward network is tested with different hidden layer sizes. ANN also used for reducing the undesired effect of capacity noise error by inserting noise error in to (training) data. In the Fig.12 is Working procedure of ANN.

• Characterizing of the nonlinearity

The ANN is used for identification and characterization of structural nonlinearities by ANN and estimation of the



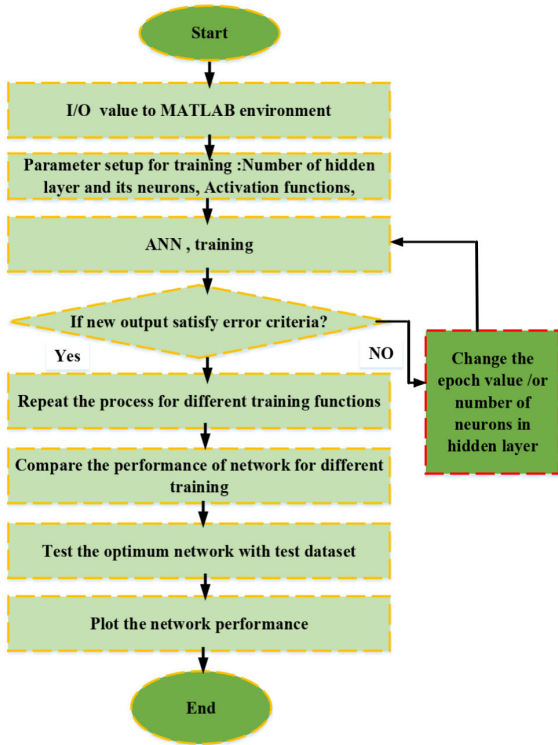


FIGURE 11. Flowchart of ANN, classification and parametric identification prediction.

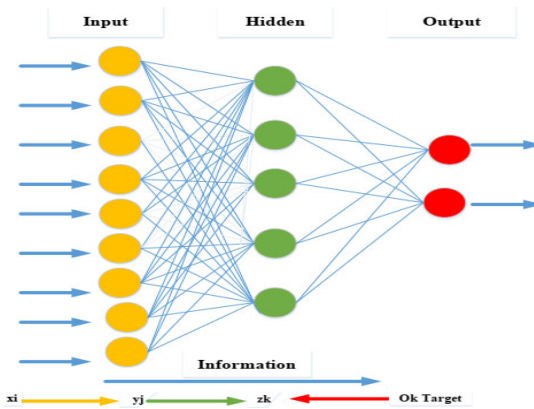


FIGURE 12. Working procedure of ANN.

parameters of the nonlinearity. The reason for using ANN in this regard is due to its an efficient structural nonlinear function in equation (13)

$$f : x \in R^D \rightarrow z \in R^1 \tag{15}$$

The function (f) is explored the below equation

$$f(x) = b_2 + w_2 * (fA(b_1 + w_1 * x)) \tag{16}$$

wherever x, is the input vector, z, the output, scalar bias is the b, and w is the weight matrix [18].

TABLE 5. Model parameters.

Model Parameters	Value
The input model neurons	9
The Hidden layer (number)	1
The Hidden layer (number of neurons)	5
The Output model (neurons)	2
Techniques (Gradient reduction) MSE,	0.002
Validation	0.07
Testing	0.07
validation= testing	0.075

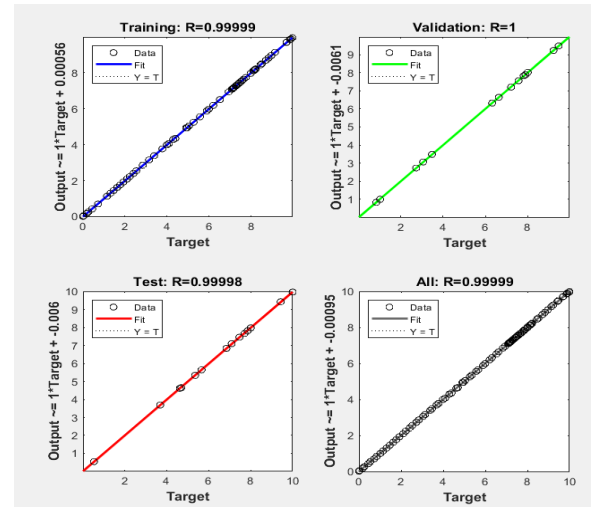


FIGURE 13. Regression analysis.

6) REGRESSION

The regression includes fitting an equation as,

$$i = 1/(1 + e(x) + x1) * f \tag{17}$$

Input vector = I, output value  $x \theta =$  bias term,  $x_1 =$  coefficient for single input value (i). In ANN, regression which is related to learning computations that explore data utilized for regression analysis to classify the CVD as Fig.13.

7) MEAN SQUARE ERROR (MSE)

$$e_{-}(i) = V_{-}(p \sim Dm, \quad i = 1, 2, 3, \dots) \tag{18}$$

where test error  $e_{-}(i)$ , desired a response from ANN -Dm, and  $V_{-}p$ - output predicted by ANN.

$$\text{Square error, } E = \sum_i e_i^2 \tag{19}$$

$$\text{Mean square error, } = \frac{E}{n} = \frac{\sum e^2}{n} \tag{20}$$

$$\text{where } n = \sum i, \text{ RMSE} = \sqrt{\frac{E}{n}} = \sqrt{\frac{\sum_i e_i^2}{n}} \tag{21}$$

Conferring characterizing (linear regression) of the fully connected network,  $R^2 \approx 0.93$  the coefficient of determination variation in the model response is clarified by regression on desire output performance are in Fig.14.

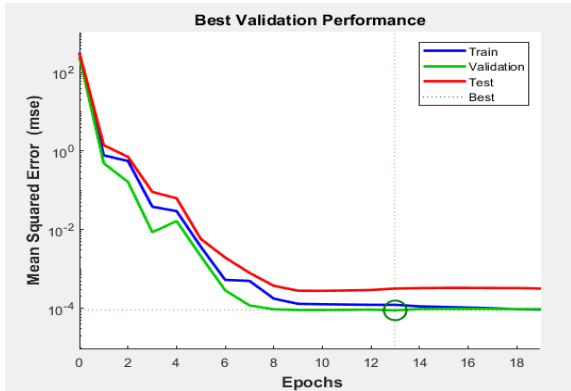


FIGURE 14. Performance evaluation of the trained network.

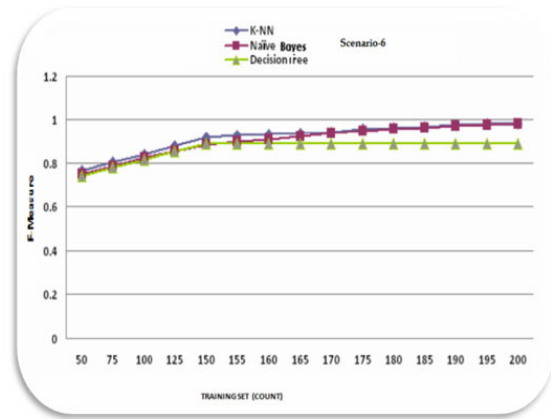


FIGURE 16. Result with respect to F-measure.

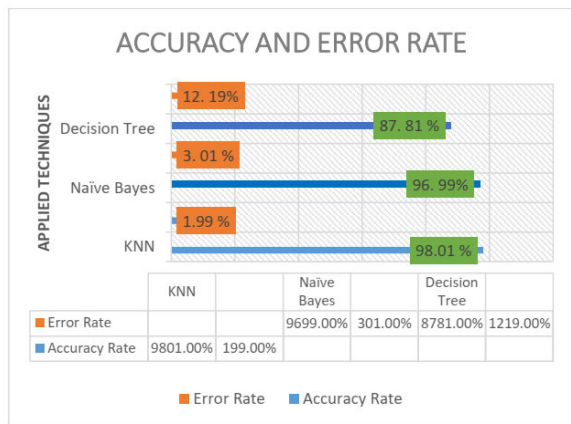


FIGURE 15. Comparison of three DLT, of different scenarios with respect to error rate and accuracy.

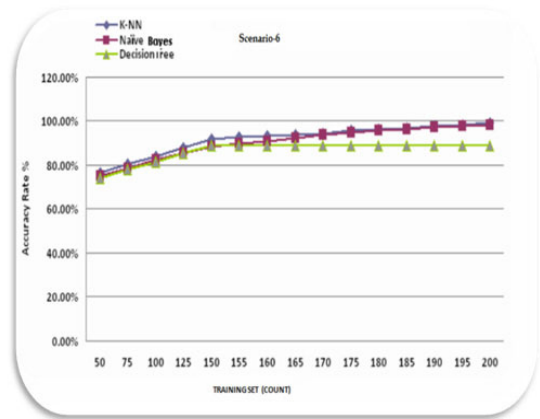


FIGURE 17. Result with respect to accuracy rate and perception.

8) FEATURE SELECTION

The actual Information Gain (IG) that is achieved by learning a variable A, which in the reduction entropy

$$IG(A) = H(S) \sum \frac{S1}{S} * H(Si) \quad (22)$$

The entropy of the certain dataset is H(S) and the (i<sup>th</sup>) subset of the entropy produced by (S), partitioning due to feature (A). It assistances to make ranking in the elaborate features due to the weight of these features. The IG variables value more than (0), were used to advanced computational models.

III. DISCUSSION

This draft, finding solution that fully connected ANN, enable to the analysis, of the desired variable and predict CVD, and efficient accuracy rate, our results might modification the means the way to reduce error- rate. Using MLT, to a distinct aspect of scenario-6 due to accuracy rate, In Fig.15 graph, K-NN techniques are more efficient than other.

Comparison between distinct DLT, of scenario-6 with respect to F-Measure, accuracy, and time in Fig.16, Fig.17, and Fig.18. From the following Fig.16 it is clearly shown that the K-NN techniques have more values as compared to others except for ANN,

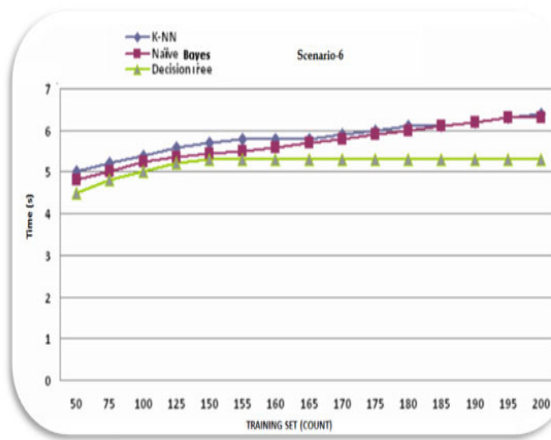


FIGURE 18. Result with respect to time(s).

Fig. 19 describe the graph, it is clearly shown that K-NN techniques have more TP, values and less FP, values, TN) values, and FN Values as compared to others.

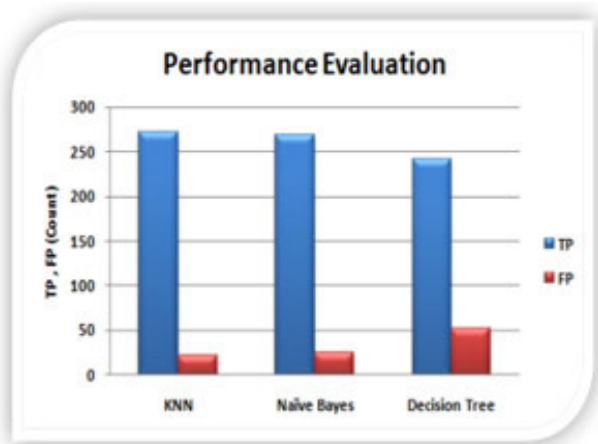


FIGURE 19. performance evaluation of distinct DLT.

#### A. MOTIVATION AND ENGINEERING FINDING

High-quality hospital decision, leads to efficient diagnosing, due to that required of the hour could be a robust clinical decision, at a low value. this may be achieved by applying advanced DLT, that helps in discouraging hidden patterns in RHI, we have a tendency to with success show that ANN techniques, properly predict CVD when deploying hospital information. the most engineering findings are:

The fully connected approach shows favorable accuracy rate with significant predictors which were self-sufficiently associated with stable CVD, based on comprehensive clinical data.

In order to reach to this point, some cases have a remarkable impact on the final results such as the synthesis and characterization of fitting parameters and afterward retraining and testing the systems using DLT, well-known classifiers were chosen which are: k-NN, DT, NB,

Molecular organ to organ interaction takes place in an emerging research field for nanoscale Medical Healthcare Industry MHI. In transient, exploration of the vital intra-body interaction source, and contribution to providing the reliability of all neural network systems, through nanoscale network relations broadens the contributions and encourages the development of health care industry HCI.

#### IV. CONCLUSION

In this article, we are using system Intel® Xeon® Processor cpu E5-2678 v3 @2.50GHzx48, Os type 64-bit, Memory 62.8GiB for evaluated, the efficiency of ANN. Firstly, demonstrate of this draft, is to focus, the molecular diagnosis, strategies for intra-organ failures. Secondly, using different Machine learning technique (MLT) for analysis, and predict functional recovery of patients treated of CVD. The classification and parametric identification of none linearity. ANN, performance, is better than the K\_NN, when test dataset is considered. Besides, the K\_NN accuracy rate shows better performance. We applied different feature selection methods to rank the attributes that give more towards the classifier

of CVD, that indirectly decrease the no of diagnosis tests to be taken by a patient. In the future work, therefore, more efficient and quality of RHI can be predictable, and which are not limited simples size.

#### REFERENCES

- [1] S. Nikhar, "Prediction of heart disease using machine learning algorithms," *Int. J. Adv. Eng., Manage. Sci.*, vol. 2, pp. 1–6, 2016.
- [2] A. Cheng, "Real-time cardiovascular diseases detection on a smartphone," Dept. Elect. Comput. Eng., Bioeng., Neurolog. Surg. Comput. Sci., 2011, vol. 4, p. 2.
- [3] M. Gómez-Recansens, S. Alfaro-Barrio, L. Tarro, E. Llauradó, and R. Solà, "A workplace intervention to reduce alcohol and drug consumption: A nonrandomized single-group study," *BMC Public Health*, vol. 18, Nov. 2018, Art. no. 1281.
- [4] U. R. Acharya, H. Fujita, M. Adam, O. S. Lih, V. K. Sudarshan, T. J. Hong, J. E. Koh, J. E. Koh, Y. Hagiwara, C. K. Chua, C. K. Poo, and T. R. San, "Automated characterization and classification of coronary artery disease and myocardial infarction by decomposition of ECG signals: A comparative study," *Inf. Sci.*, vol. 377, pp. 17–29, Jan. 2017.
- [5] M. Learning, "Heart disease diagnosis and prediction using machine learning and data mining techniques," *Rev. Adv. Comput. Sci. Technol.*, vol. 10, no. 7, p. 2137, 2017.
- [6] D. A. Tomar, "A survey on Data mining approaches for Healthcare," *Int. J. Bio-Sci. Bio-Technol.*, vol. 5, no. 5, pp. 241–266, 2013.
- [7] P.-N. Tan, *Introduction to Data Mining*, vol. 1, no. 1. New Delhi, India: Pearson, 2018.
- [8] G. Çelik, Ö. K. Baykan, Y. Kara, and H. Tireli, "Predicting 10-day mortality in patients with strokes using neural networks and multivariate statistical methods," *J. Stroke Cerebrovascular Diseases*, vol. 23, no. 6, pp. 1506–1512, 2014.
- [9] P. J. G. Lisboa, T. A. Etchells, I. H. Jarman, M. S. H. Aung, S. Chabaud, T. Bachelot, D. Perol, T. Gargi, V. Bourdès, S. Bonnevey, and S. Négrier, "Time-to-event analysis with artificial neural networks: An integrated analytical and rule-based study for breast cancer," *Neural Netw.*, vol. 21, nos. 2–3, p. 426, 2008.
- [10] I. T. M. Kurt, M. Ture, and A. T. Kurum, "Comparing performances of logistic regression, classification and regression tree, and neural networks for predicting coronary artery disease," *Expert Syst. Appl.*, vol. 34, no. 1, pp. 366–374, 2008.
- [11] A. Meharrar, M. Tioursi, M. Hatti, and A. B. Stambouli, "A variable speed wind generator maximum power tracking based on adaptative neuro-fuzzy inference system," *Expert Syst. Appl.*, vol. 38, no. 6, pp. 7659–7664, 2011.
- [12] H. Uguz, A. Öztürk, R. Saraçoğlu, and A. Arslan, "A biomedical system based on fuzzy discrete hidden Markov model for the diagnosis of the brain diseases," *Expert Syst. Appl.*, vol. 35, no. 3, pp. 1104–1114, 2008.
- [13] K. Thygesen et al., "Fourth universal definition of myocardial infarction (2018)," *Eur. Heart J.*, vol. 40, no. 3, pp. 237–269, 2019.
- [14] S. Ari and G. Saha, "In search of an optimization technique for artificial neural network to classify abnormal heart sounds," *Appl. Soft Comput.*, vol. 9, no. 1, pp. 330–340, 2009.
- [15] M. Kumari, "Comparative study of data mining classification methods in cardiovascular disease prediction," Citeseer, 2011, vol. 1.
- [16] D. Ratnum, "Disease forecasting system using data mining methods," in *Proc. Int. Conf. Intell. Comput. Appl.*, 2014.
- [17] S. B. Patel, P. K. Yadav, and D. P. Shukla, "Predict the diagnosis of heart disease patients using classification mining techniques," *J. Agricult. Vet. Sci.*, vol. 4, no. 2, pp. 61–64, 2013.
- [18] S. Maji, "Decision tree algorithms for prediction of heart disease," *Nature*, vol. 3, no. 45, pp. 447–453, 2018.
- [19] N. Bnu, "Disease forecasting system using data mining methode," in *Proc. Int. Conf. Intell. Comput. Appl.*, 2014.
- [20] D. Malak and O. B. Akan, "Molecular communication nanonetworks inside human body," *Nano Commun. Netw.*, vol. 3, pp. 19–35, Mar. 2012.
- [21] I. F. Akyildiz, M. Pierobon, S. Balasubramaniam, and Y. Koucheryavy, "The Internet of bio-nano things," *IEEE Commun. Mag.*, vol. 53, no. 3, pp. 32–40, Mar. 2015.
- [22] B. Atakan and O. B. Akan, "An information theoretical approach for molecular communication," in *Proc. IEEE Bio-Inspired Models Netw., Inf. Comput. Syst.*, Dec. 2007, pp. 33–40.

- [23] Y. Chahibi and I. Balasingham, "An intra-body molecular communication networks framework for continuous health monitoring and diagnosis," in *Proc. IEEE 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 4077–4088.
- [24] C. G. Giannopapa, "Fluid structure interaction in flexible vessels," Ph.D. dissertation, King's College London, London, U.K., 2004.
- [25] L. Felicetti, M. Femminella, and G. Reali, "Establishing digital molecular communications in blood vessels," in *Proc. 1st Int. Black Sea Conf. Commun. New. (BlackSeaCom)*, Jul. 2013, pp. 54–58.
- [26] X. Qian and M. Di Renzo, "Receiver design in molecular communications: An approach based on artificial neural networks," in *Proc. IEEE 15th Int. Symp. Wireless Commun. Syst. (ISWCS)*, Aug. 2018, pp. 1–5.
- [27] H. B. Yilmaz and C.-B. Chae, "Arrival modelling for molecular communication via diffusion," *Electron. Lett.*, vol. 50, no. 23, pp. 1667–1669, 2014.
- [28] J. Zhang, F. Lin, P. Xiong, H. Du, H. Zhang, M. Liu, Z. Hou, and X. Liu, "Automated detection and localization of myocardial infarction with staked sparse autoencoder and treebagger," *IEEE Access*, vol. 7, pp. 70634–70642, 2019.
- [29] A. K. Dwivedi, "Performance evaluation of different machine learning techniques for prediction of heart disease," *Neural Comput. Appl.*, vol. 29, no. 10, pp. 685–693, 2018.
- [30] S. Maji, "Decision tree algorithms for prediction of heart disease," in *Information and Communication Technology*, vol. 40. Springer, 2019, pp. 447–453.
- [31] A. Maleki and T. Do, "Review of probability theory," *CS*, vol. 229, no. 2, p. 1, 2000.
- [32] H. Yin and N. K. Jha, "A health decision support system for disease diagnosis based on wearable medical sensors and machine learning ensembles," *IEEE Trans. Multi-Scale Comput. Syst.*, vol. 3, no. 4, pp. 228–241, Oct./Dec. 2017.
- [33] A. Koyuncu, E. Cigeroglu, and H. N. Özgüven, "Localization and identification of structural nonlinearities using cascaded optimization and neural networks," *Mech. Syst. Signal Process.*, vol. 95, pp. 219–238, Oct. 2017.



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