IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 22, Issue 4, Ser. II (Jul. – Aug. 2020), PP 21-30
www.iosrjournals.org

An Intelligent Machine Learning Approaches for Predicting Coronary Artery Disease

Sivasubramaniyan S[1], Varsha Srinivasan[2], Srivarshini M[3], Janarthanan P[4]
[1,2,3,4](Computer Science and Engineering, Anna University,India)

Abstract:
Coronary Artery Disease (CAD) destroys the internal layer of the artery. Consequently, this destruction leads the fatty sediments to escalate the injury. CAD is one of the common significant reasons of death all around the world, thus early detection of CAD will facilitate scale back these rates. The medical industries gather a large number of facts which include some unknown data to make the choice effective. They also use some excellent data processing methods. The CAD prediction indicates the probability of patients getting artery disease. In this research, we propose various Machine Learning (ML) methods to predict the CAD with the help of historical data. These ML methods enable the system to learn over several datasets to acknowledge valuable understanding. The programmable capability of ML in examining, interpreting, and processing data-set is beneficial to decision-makers in the medical field. This method uses 10 medical parameters to forecast artery disease which is obtained from KEEL (Knowledge Extraction based on Evolutionary Learning). An experiment is performed with algorithms like Naive Bayes, Decision Tree, Neural Network (MLP Classifier), Logistic Regression, and Random Forest with necessary performance metrics like accuracy, precision, recall.

Key Word*: Coronary Artery Disease (CAD;, KEEL (Knowledge Extraction based on Evolutionary Learning);Machine Learning(ML); Accuracy; Precision; Recall.*

Date of Submission: 17-07-2020 Date of Acceptance: 01-08-2020

I. Introduction

Machine learning is abruptly piercing several areas inside the healthcare industry, from diagnosis to prognosis, with significant potential of remodeling the medical landscape. The platform of medicine has so far relied massively on heuristic methods, where information is obtained by practice and self-learning, which is necessary within the profoundly changeable health care circumstance. The progress in learning and knowledge of diseases has been correlated with the growth of information and data gradually because of elevations in devices that produce qualitative and quantitative analyses of the physiological parameters. Such a huge data area is fit to the application of machine learning. When ML was still in its nascence, it was assumed that the achievement of an intellectual system that can acquire and progress would rely on the capability to gather and store huge numbers of data in an information base. The improvements made in mathematical resources as data storehouses and distribution within the earlier decade have been a distinguished enabler in providing the potential to machine learning practices in the medical field. The analysis of health data is typically based on comparing extracted health measurements to predefined thresholds. Symptoms can be detected when the measurement is higher or lower than a threshold[4]. The enormous volume of data is a key resource to be processed and analyzed for obtaining knowledge that allows aid for saving costs and choice making[9]. Coronary Artery Disease is also known as Coronary Heart Disease[20]. The basic symptoms of CAD are Chest pain(angina), pressure or tightness in chest, shortness of breath, and artery attack. It is the common type of artery disease found in the U.S.A, where the lethal rate counts 3,70,000 a year. CAD can be predicted using algorithms of machine learning like Random Forest, Naive Bayes, Logistic Regression, Decision Tree(j48), and Neural Network [10, 29, 30]. These approaches have been broadly investigated in wide areas like medical applications for the purposes like screening, risk stratification, prediction, and assisted decision-making. The quantity of research differs due to the mortality rates among various diseases. In other words, more important diseases have attracted more research and focus.

II. Problem Statement

Artery disease is supervised effectively with a mix of lifestyle changes, medicine, and, in some cases, surgery. The functioning of the artery can be improved by minimizing the impact of CAD with the right treatment. The anticipated results are used to suppress and thus, reduce the cost of surgery and other medical expenses. The purpose of this analysis is to explicitly predict the presence of CAD with the attributes (dataset) procured from South African Artery Disease-KEEL. Judgments are often made by intuition and knowledge

instead of the knowledge enriched data hidden within the information set and databases. This practice lands up in undesired errors, biases, and excessive medical costs which influences the kind of service that caters to patients. Processing contains large potential for the medical industry to facilitate health models to periodically use data and analytics to identify inefficiencies and best practices that enhance care to decrease costs.

III. Related Works

The main target in both Artificial Neural Network and pre-processing of features was the improvement of characteristics and dismissal of issues produced by the anticipated model. To eradicate irrelevant features, the $\chi 2$ statistical model was used[1]. A novel health analysis approach for artery failure prediction could be practiced to anticipate artery failure strokes. Event Processing is coupled with mathematical procedures that collect health parameters. The process collected data by executing analysis rules to trigger alarms if an artery failure has been detected[2]. This technique introduced the feasibility of non-invasive electrophysiological pattern approximation employing artery motion imaging[3]. CNN combines the whole design with the collaborative practice for discrete neural networks in groups. CNNE has experimented widely on a variety of standard barriers in neural networks and machine learning[4]. The model developed to forecast the response to biventricular pacing based on our personalized models with concordance to the BSPM signals[5].

The combined new procedures were generally recognized as hybrid techniques. The system includes a neural network utilizing time series of artery rate[6].

The wearable device with wireless sensors could monitor the artery activity of the user's daily life. It could also generate a huge volume of data without complications. Although the change in rhythm (ECG) or artery rate or morphological design can be verified efficiently by a cardio specialist[7,8].

Sensitivity(i) intimates the rate of true positive events for class (i), specificity(i) estimates the proportion of true negative events for class (i), PPA(i) Is the true positive measure of events among all the classified events in class (i). Myocardial infarction is the diseased state of the artery that leads to the damage in the depolarizing myocardium (artery muscle), resulting in an artery attack. The effectiveness of each algorithm was tested using the Classification Matrix but here we ought to use a confusion matrix[21]. By using a neural network, it can be efficiently performed [11-19]. The Artery murmurs were generated by intense blood flow producing waves around the tissue. Several chronic diseases that create murmurs and irregularities of HSs manifest much earlier in phonocardiography are indicated by symptoms[23]. The classifications of artery sound using artificial neural networks emphasize the detection of abnormalities. The PCG signal of a normal artery consists of two different movements[24].

IV. Proposed Work

In this research, many independent variables such as age, medical history, etc. are being used along with a dependent variable (CAD class) during the training phase to build a model based on classification. The model is used to forecast the predicted variable value in the test dataset as accurately as possible. Fig. 4.1 shows the methodology adopted in this research to deal with the prediction of CAD. Then, the data are pre-processed and split into testing and training datasets. Min-Max scaling is applied to normalize the data and SoftMax function is utilized which takes logits as inputs. The TensorFlow framework has been employed for dataflow graphs and ReLU is used as an activation function. Using Recall, Precision, and Accuracy, we evaluate the models. Finally concluding the finest predicted model based on the high accuracy[25-28].

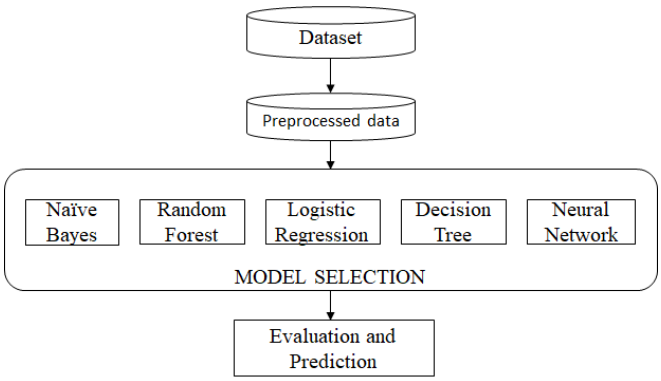

Fig.1. Proposed System.

Dataset Description:

The 462 instances (observations) of the data-set were acquired from South African Heart Disease-KEEL which is a subset of larger data-set. There are 10 instances out of which 9 are independent factors and 1 dependent factor, CAD is the dependent variable. The dependent variable CAD has two possible outcomes one is positive (1) and the other is negative (0). The data-set is obtained from high risk monitored patients.

Dataset Pre-Processing:

Data chosen may not be clear as it may contain noise or some missing values. The processing of unclear data should be eliminated to urge good and ideal results. The data cleaning method is enhanced to process ambiguous data. Filling missing values and removing noise can be performed using techniques like filling with common values in missing places. The Data-set is converted into a format to produce an accurate output[22]. For every value in an exceedingly feature, MinMaxScaler subtracts the minimum value within the feature and divides by the range. The range is the distinction between the first maximum and the original minimum. MinMaxScaler preserves the shape of the initial distribution. It doesn't meaningfully change the knowledge embedded within the initial data. It is essential to classify the testing data accurately and does not lessen the value of outliers. The computing range for the linguistics returned by MinMaxScaler is 0 to 1. In machine learning, the foremost goal of a predictive model is to come back with a hypothesis on the training data[24].

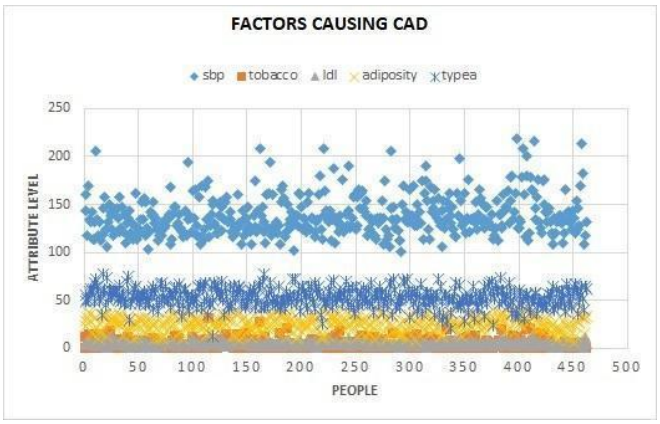

Fig. 2. SBP, Tobacco, LDL, Adiposity and Type-A Behaviour Attribute.

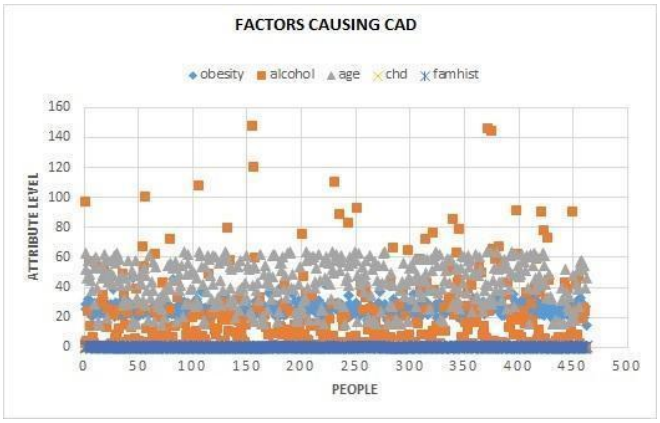

Fig. 3. Obesity, Alcohol, Age, CAD (Present/Absent) and Family History Attribute

The fig.1 and fig.2 graphically represents the factor causing coronary artery disease.

Naïve Bayes Algorithm:

Naive Bayes is a classifier formulated from the Bayes Theorem. It forecasts membership occurrences in every class, like the probability of a given datum belongs to a specific category. It shows the likelihood of every input attribute for the predictable state—the class with the best probability taken into account because of the presumably class. The naive Bayes is presented in Eqn. (1).

$$P(Y|Z) = \frac{P(Z|Y)P(Y)}{P(Z)} \qquad (1)$$

Where P(Y|Z) is Posterior Probability, P(Z|Y) is Likelihood, P(Y) is Class Prior Probability and P(Z) is Predictor Prior Probability.

Algorithm: Naïve Bayes
Input: A training dataset M, K=(k1,k2,k3…kn) value for predictor variable in the testing dataset.
Output: Classify whether CAD is present or absent.
BEGIN
1. FOR i=0 to i=N-1 DO
2. FOR c=1 to c=C-1 DO
3. $L_{ic} = \log \pi_c$
4. FOR j=1 to j=D-1 DO
5. IF $x_{ij} = 1$ THEN $L_{ic} = L_{ic} + \log \theta_{jc}$
6. ELSE
7. $L_{ic} = L_{ic} + \log(1 - \theta_{jc})$
8. ENDFOR
9. ENDFOR
10. $p_{ic} = \exp(L_{ic} - \text{logsumexp}(L_{i,:}))$
11. $y_i = \text{argmax}_c\, p_{ic}$
12. ENDFOR
13. END

Decision Tree(J48) Algorithm:

Itis a member of the supervised learning algorithm family. It is used for solving problems built on Regression and Classification. For training samples of data, the trees are constructed based on high entropy inputs. The trees are constructed using the DAC method. The objective of the algorithm is to construct a training model that could be used to forecast the category of the target variable by learning the simple rules concluded from training data. Since the attributes have many values, the Gain will select it is presented in Eqn. (2).

$$GainRatio(S,A) \equiv \frac{Gain\ (S,A)}{SplitInforamation\ \ (S,A)} (2)$$

$$SplitInformation(S,A) \equiv -\sum_{i=1}^{c} \frac{|S_i|}{|S|} log_2 \frac{|S_i|}{|S|} (3)$$

Where S_i is the subset of S for which A has the value v_i.Since the prediction is to define the presence and absence of CAD we use entropy for one attribute as represented in Eqn. (4).

$$Entropy = (-) \sum_{i=1}^{c} p_i * log_2(p_i) \qquad (4)$$

Where p_i is the amount of percentage of samples in a distinct class. When all the data points are in the same class then the entropy results in zero.

Algorithm: Decision Tree
Input: A training dataset M = $\{(X_1,y_1),(X_2,y_2)\ldots..(X_n, y_n)\}$ along with attribute S
Output: Classify whether CAD is present or absent.
1. gain ← null
2. for all attributes S in M do

3. information_gain ← InformationGain (a, Entropy)
4. if information_gain > gain then
a. gain ← information_gain
5. end if
6. end for
7. Best_split (M, S)
8. end procedure

Random Forest Classifier:
It is an algorithm based on classification consisting of many decision trees. It uses bagging and random features when building each independent tree to create an uncorrelated forest of trees. The prediction is more precise than that of any independent tree. It increases the predictive power of the algorithm. Random forest is the most uncomplicated and broadly used algorithm. Mathematically bagging and boosting is presented as in Eqn. (5) and Eqn. (6).

$$f_{bag} = f_1(x) + f_2(x) + \cdots + f_n(x) \quad (5)$$

$$f(x) = \sum_t A_t H_t(x) \quad (6)$$

Where f_1, f_2, f_n function denotes the average of all the distinct models and distinct learners. A_t is the calculated weight from the last iteration error. Generally, when the amount of trees in the forest is more the model does not cause overfitting.

Algorithm: Random Forest Classifier
Input: A training dataset M = $\{(X_1,y_1),(X_2,y_2)\ldots..(X_n, y_n)\}$ along with attribute S
Output: Classify whether CAD is present or absent.

Random_Forest(M, S)
1. A ← 0
2. while i=1 do
a) $boot\_strap^{(i)}$ ← a bootstrap sample
b) $random_i$ ← random_tree($boot\_strap^{(i)}$,S)
till number of trees
3. end for
4. return random
5. random_tree (boot_strap, S)
6. At each node
a) split on best feature
7. return tree
8. end function

Logistic Regression:
Logistic Regression is employed to predict the chances of being a case supporting the values of the variables which are independent. Input values (x) merged linearly utilizing coefficient values to infer an output value (y). A significant distinction from rectilinear regression is the modeled output value, either 1 or 0, rather than a numeric value. Logistic Regression represented in Eqn. (7).

$$y = \frac{e^{(b_0+b_1*x)}}{(1+e^{(b_0+b_1*x)})} \quad (7)$$

Where y is the determined output, b_o is the fractional expression and b_1 is the coefficient for the single input value (x).

Algorithm: Logistic Regression
Input: A training dataset M along with attribute S
Output: Classify whether CAD is present or absent
$y0, y1, y2, \ldots\ldots, y_n \leftarrow$ Encrypt_num(0)
total_iteration ← 50
$\alpha \leftarrow$ learning rate

a ← assign an integer
repeat
1. for j=0 to n do
2. $gradient_j \leftarrow$ Encrypt_num(0)
3. for i=1 to K do
4. $\hat{w}_j \leftarrow_{\text{sigmoid}} (y^T x^{(i)})$
5. $\hat{w}_j \leftarrow subtract(\hat{w}_j, y(i))$
6. $\hat{w}_j \leftarrow Add(\hat{w}_j, x_j(i))$
7. $gradient_j \leftarrow Add(gradient_j, \hat{w}_j)$
8. end for
9. $gradient_j \leftarrow Right\_shift(gradient_j, a)$
10. $N_j \leftarrow subtract(N_j, gradient_j)$
11. end for
12. until total iteration
13. return N

Neural Network Algorithm:

Neural Network (NN) is described by the link among the neurons, determining weight, and activation function. Ann's feed-forward variant is a multilayer perceptron. It has more than one perceptron. MLP consists of Input Layers, Hidden Layers, and Output Layers. In this arrangement, the two layers are shared. The other one can be the Input Layer; when the layer buffers the input signal, the next layer would be the output layer, which is responsible for generating the output of the network.

Algorithm: Neural Network
Input: A training dataset M along with corresponding attributes S
Output: Classify whether CAD is present or absent.
$W_i \leftarrow$ The weights for each layer
N ← Number of layers in the network
$F_{ij}^{(l)} \leftarrow$ Error for i, j
$p_{ij}^{(l)} \leftarrow 0$
procedure Backpropagation (M, S)
1. if (M, S) = {non-empty} then
2. for i=0 to b do
3. $f^l \leftarrow$ feedforward($x^{(i)}, W$)
4. $r^l \leftarrow f(N) - y(i)$
5. $p_{ij}^{(l)} \leftarrow p_{ij}^{(l)} + f_j^{(l)} p_i^{(l+1)}$
6. if j=0 do
7. $D_{ij} \leftarrow \frac{1}{m} t_{ij}^l$
8. else
9. $D_{ij} \leftarrow \frac{1}{m} t_{ij}^l + \lambda w_{ij}^l$
10. end if
11. end for
12. end procedure

V. Performance Evaluation

We have employed the training set for training the model and utilize the test set for validation point, ideally divide the data into 70:30 or 80:20. In this process, if there is a finite amount of data then there is a burst of high bias. Since we might miss some data about the knowledge which have not applied for training. The method is more appropriate to larger datasets and for similar distribution to train and test samples. We can manually split the information into the test and train set by using the slicing process. Then normalization makes training less delicate to the scale of attributes. Hence, we may preferably solve for coefficients. All the values between 0 and 1 remain visible within normalized data. The Min-Max scaling can be performed using equation (8).

$$data[each] = \frac{(data\ [each].\min(0))}{(data\ [each].\max(0))} \quad (8)$$

Logits gives input to the SoftMax function. The ranges of logits are as follows:
i) Range from ([0,1]) to R([-inf, inf])
ii) >0.5 corresponds to its value
iii) <0.5 corresponds to 0

Then the SoftMax function is additionally referred to as normalized exponential function. It takes input vector of k real numbers and anneals into a likelihood distribution consisting of k likelihoods. It is employed to map the non-annealed output of a framework to a probability distribution over predicted output. The SoftMax function is represented in Eqn. (9).

$$\partial(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}\ for\ i = 1,..,K\ and\ z = (z_j, \ldots, z_k) \in R^K \quad (9)$$

ReLU stands for Rectified Linear Units, is the most widely used activation function. Mathematically defined as y = max(0, x). It is essential because it doesn't saturate; the inclination is generally high (equal to 1) if the neuron stimulates. The classification models' performance derived by the ML is measured with the help of the confusion matrix. The evaluation of the model is performed with the confusion matrix[3]. It is a cross-tabulation which displays the number of instances assigned to each class that allows us to calculate the classification accuracy, precision, recall, false positives (FPs), false negatives (FNs), true positives (TPs), and true negatives (TNs). We have constructed a 2x2 confusion matrix for the two classes available in the dataset. They are:

Class a = Present (has CAD) Class b = Absent (no CAD)

True Positive (TP) expresses rightly predicted event values.

True Negative (TN) expresses rightly predicted no-event values.

False Positive (FP) expresses wrongly predicted event values.

False Negative (FN) expresses wrongly predicted no-event values.

There measures such as accuracy, error rate, recall, precision, F1-Score, root mean square error and mean absolute error playing a significant role in analyzing the best model. Accuracy is measured as the ratio of total true predictions in the data set. It is represented in Eqn. (10). The better accuracy is always 1 and the worst case is

$$0.\ Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (10)$$

Error rate is the overall number of false predictions by the model with reference to the overall predictions. Error rates are presented in Eqn. (11).

$$Error\ Rate = 1 - Accuracy \quad (11)$$

Recall is measured as the ratio of the number of correct positive prognosis to the total number of positives. It is also called as sensitivity or true positive rate. The best recall is 1, whereas the worst-case is 0. The sensitivity is represented in Eqn. (12).

$$Sensitivity = \frac{TP}{(TP+FN)} \quad (12)$$

Precision is the ratio of a number of records which are actually positive to the total number of records predicted as positive. It is represented in Eqn. (13).

$$Precision = \frac{TP}{(TP+FP)} \quad (13)$$

The weighted mean of Recall and Precision is called as F1-Score. Hence, this result uses both false negatives and false positives under consideration. The F1-Score delivers the balance between recall and precision. If the value of false negatives and false positives are different, it's better to compute both Recall and Precision. It is represented in Eqn. (14).

$$F1 - Score = \left(2 * \frac{(precision \ * recall \ )}{(precision \ + recall \ )}\right) \quad (14)$$

The root-mean-square-error is commonly used to estimate the variations between values forecasted by a model and the values are observed. It can also be referred to as the root-mean-square deviation, RMSD. The RMSE of predicted values at time t of a predicted variable y is presented in Eqn. (15).

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n}(\hat{y}-y)^2}}{n} \quad (15)$$

Mean absolute error is a quantity used to estimate the relationship between forecast and eventual outcomes. The mean absolute error is given in Eqn. (16).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i| \quad (16)$$

The mean absolute error value is an average of the absolute errors |e_i |=|f_i-y_i | , where f_i is the forecast and the true value. The table below represents the comparative study of the-algorithm.

Table no 1: Comparison of Algorithms.

Metrics	Algorithm									
	Naïve Bayes		Random Forest		Decision Tree		Logistic Regression		Neural Network [MLP Classifier]	
Confusion Matrix	[[36 25] [11 21]]		[[54 7] [18 14]]		[[52 9] [19 13]]		[[55 6] [20 12]]		[[59 4] [18 11]]	
Precision	0	0.77	0	0.75	0	0.73	0	0.73	0	0.77
	1	0.46	1	0.67	1	0.59	1	0.67	1	0.73
Recall	0	0.59	0	0.89	0	0.85	0	0.90	0	0.94
	1	0.66	1	0.44	1	0.41	1	0.38	1	0.38
F1-Score	0	0.67	0	0.81	0	0.79	0	0.81	0	0.84
	1	0.54	1	0.53	1	0.48	1	0.48	1	0.50
RMSE	62%		45%		55%		53%		49%	
MAE	39%		32%		30%		39%		24%	
Error Rate	39%		27%		30%		28%		24%	
Accuracy	**61%**		**73%**		**70%**		**72%**		**76%**	

Table no2: Macro and Weighted average for Precision, Recall and F1-Score.

Metrics	Average	Algorithm				
		Naïve Bayes	Random Forest	Decision Tree	Logistic Regression	Neural Network [MLPClassifier]
Precision	Macro avg	0.61	0.71	0.66	0.70	0.75
	Weighted avg	0.66	0.72	0.68	0.71	0.76
Recall	Macro avg	0.62	0.66	0.63	0.64	0.66
	Weighted avg	0.61	0.73	0.70	0.72	0.76
F1-Score	Macro avg	0.60	0.67	0.63	0.64	0.67
	Weighted avg	0.62	0.71	0.68	0.70	0.73

VI. Discussion

We consider a dataset of more than 400 patients and employed the algorithms such as Naive Bayes, Decision Tree(J48), Logistic Regression, Random Forest, Neural Network(MLP classifier) and concluded the results with performance metrics such as Precision, Recall, F1-Score with corresponding Macro average, and weighted average as presented in Table-I and Table-II. The experimental result shows that Neural Network (MLP classifier) outshines when compared to other algorithms which are presented in fig.3 and fig. 4. The accuracy values of Naïve Bayes, Random Forest, J48, Logistic Regression, and MLP classifier are 0.61, 0.73, 0.70, 0.72 and 0.76 respectively.

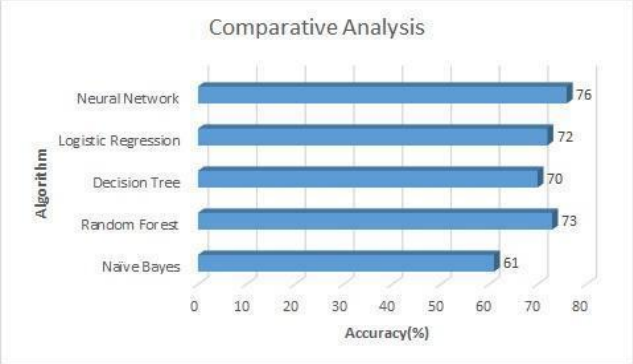

Fig. 4. Comparative Analysis of Algorithms

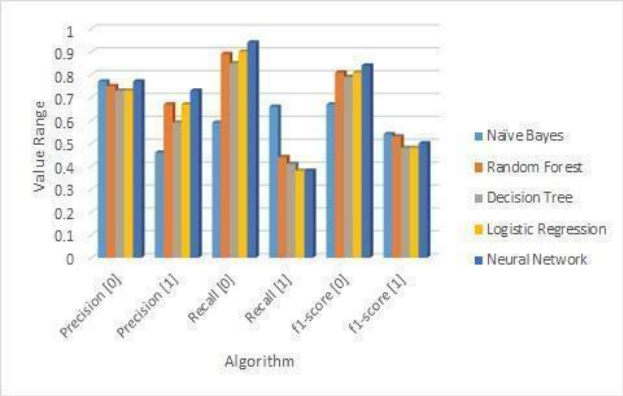

Fig. 5. Precision, Recall and F1-Score Analysis of Algorithms.

VII. Conclusion and Future Work

We experimented and analyzed the algorithms like Random Forest, Naïve Byes, Decision Tree, Neural Network(MLP Classifier), and Logistic Regression with various performance metrics to find an efficient approach to identify the artery disease. Early screening and detection of diseases benefit the patients by accelerating their treatment. It also helps the medical institutes and officials to greater distribute their resources and devise ways altogether to prevent or minimize the occurrence. In some cases of fatal diseases, early detection ends up in an increased probability of cure. Several research strategies are taken in the screening and prediction of diseases utilizing medical examination. There are various machine learning algorithms available to facilitate the prediction of CAD. This research work was an approach to focus on some of these available techniques of prediction and the performance measures related to them. In the future, we are planning to generate a system that foretells the disease based on the image and figure out the nature of disease present.

References

[1]. Yufa Xia, Huailing Zhang, Lin Xu, Zhifan Gao, Heye Zhang, Huafeng Liu, Shuo Li "An Automatic Cardiac Arrhythmia Classification System with Wearable Electrocardiogram", Institute of Electrical and Electronics Engineers(IEEE) Access, pp.51-56, vol. 6, 2018.

[2]. Liaqat Ali et al., "An Automated Diagnostic System for Artery Disease Prediction Based on $\chi 2$ Statistical Model and Optimally Configured Deep Neural Network", IEEE Access, vol. 4, 2019.

[3]. Senthilkumar Mohan, Chandrasegar Thirumalai, and Gautam Srivastava "Effective Artery Disease Prediction Using Hybrid Machine Learning Techniques", IEEE Access, 2019.

[4]. Afef Mdhaffar, Ismael Bouassida Rodriguez, Khalil Charfi, Leila Abid, and Bernd Freisleben "CEP4HFP: Complex Event Processing for Artery Failure Prediction", IEEE Transactions on NanoBioscience, vol.16, no.8, pp.708-717, 21017.

[5]. Adityo Prakosa et al. "Cardiac Electrophysiological Activation Pattern Estimation From Images Using a Patient-Specific Database of Synthetic Image Sequences", IEEE Transactions on Biomedical Engineering, vol.61, no.2, pp. 235-245, 2014.

[6]. Md. Monirul Islam, Xin Yao, and Kazuyuki Murase, "A Constructive Algorithm for Training Cooperative Neural Networks Ensembles", IEEE Transactions on Neural Networks, vol.14, no.4, pp.820-834,2003.

[7]. Sophie Giffard-Roisin et al. ,"Non-Invasive Personalisation of a Cardiac Electrophysiology Model from Body Surface Potential Mapping", IEEE Transactions on Biomedical Engineering, vol.64, no.9, pp.2206 - 2218, 2017.

[8]. C.A. Cheng, H.-W. Chiu, "An Artificial Neural Network Model for the evaluation of carotid artery stenting prognosis using a national-wide database", Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 2566-2569, Korea, 2017.

[9]. N. Al-milli,"Backpropagation Neural Network for Prediction Of Artery Disease", Journal of Theoretical Applied Information Technology, vol. 56, pp. 131-135, 2013.

[10]. R. Das, I. Turkoglu, A. Sengur, "Effective Diagnosis Of Artery Disease Through Neural Networks Ensembles", Expert System Application, vol. 36, no. 4, pp. 7675-7680, 2009.

[11]. Ishrat-Un-Nisa Uqaili and Syed Nadeem Ahsan, "Machine Learning-Based Prediction of Complex Bugs in Source Code", The International Arab Journal of Information Technology, vol. 17, no. 1, 2020.

[12]. D. K. Ravish, K. J. Shanthi, N. R. Shenoy, S. Nisargh, "Artery Function Monitoring Prediction And Prevention of Artery Attacks: Using Artificial Neural Networks", International Conference on Contemporary Computing and Informatics(IC3I), pp. 1-6, 2014.

[13]. Rosaria Silipo and Carlo Marchesi., "Artificial Neural Networks for Automatic ECG Analysis", IEEE. Trans. On signal processing, vol.46, no 5, pp 1417-1425,1998.

[14]. Jasleen Kaur and Jatinderkumar Saini, "Designing Punjabi Poetry Classifiers Using Machine Learning and Different Textual Features", The International Arab Journal of Information Technology, vol. 17, no.1, 2020.

[15]. J. S. Sonawane, D. R. Patil, "Prediction Of Artery Disease Using Multilayer Perceptron Neural Network", International Conference on Information Communication and Embedded System, pp. 1-6, Chennai, 2014.

[16]. N. Kumaravel, K. Sridhar, N. Nithiyanandam, "Automatic Diagnoses Of Artery Diseases Using Neural Network", Proceedings of the Fifteenth Biomedical Engineering Conference, pp. 319-322, India, 1996.

[17]. J. Nahar, T. Imam, K.S. Tickle, Y.-P.P. Chen, "Association Rule Mining to Detect Factors Which Contribute to Artery Disease in Males And Females", Expert Systems with Applications, vol.40, pp. 1086-1093, 2013.

[18]. Nazri Mohd Nawi, Rozaida Ghazali et al., "The Development of Improved Back-Propagation Neural Networks Algorithm for Predicting Patients with Artery Disease", Proceedings of the first international conference ICICA, vol. 6377, pp. 317-324, China, 2010.

[19]. Sang, H.O.: "Improving the Error Backpropagation Algorithm with a Modified Error Function". IEEE Transactions on Neural Networks, vol. 8, no.3, pp.799–803, 1997.

[20]. Swati Shilaskar et al., "Feature Selection For Medical Diagnosis: Evaluation For Cardiovascular Diseases", Journal of Expert System with Application, vol. 40, no.10, pp. 4146-4153, 2013.

[21]. Awang, R. & Palaniappan, S., "Intelligent Artery Disease Prediction System Using Data Mining Technique", International Journal of Computer Science and Network Security, vol. 8, no. 8, pp.83-92,2008.

[22]. R. Das, I. Turkoglu, A. Sengur,"Effective Diagnosis of Artery Disease Through Neural Networks Ensembles", Expert Systems with Applications, vol.36 pp. 7675-7680, 2009.

[23]. C. Ahlstrom, P. Hult, P. Rask, J.E Karlsson, E. Nylander, U. Dahlstro "Feature Extraction for Systolic Artery Murmur Classification", Annals of Biomedical Engineering, vol.34, no. 11, pp. 1666-77, 2006.

[24]. Metin Bilgin and Haldun Köktaş, "Sentiment Analysis with Term Weighting and Word Vectors", The International Arab Journal of Information Technology, Vol. 16, no. 5, pp.953-959,2019.

[25]. O. W. Samuel, G. M. Asogbon, A. K. Sangaiah, P. Fang, G. Li, "An Integrated Decision Support System Based on ANN and Fuzzy_AHP for Artery Failure Risk Prediction", Expert System Application, vol. 68, pp. 163-172, 2017.

[26]. Yanwei Xing, Jie wang, Zhihong Zhao Yonghong Gao, "Combination Data Mining Methods with New Medical Data to Predicting Outcome of Coronary Artery Disease", Convergence Information Technology International Conference, pp. 868-872, South Korea,2007.

[27]. S. Zaman, R. Toufiq, "Codon Based Back Propagation Neural Network Approach to Classify Hypertension Gene Sequences", International Conference on Electrical, Computer and Communication Engineering(ECCE), pp. 443-446, Bangladesh, 2017.

[28]. M. Ture, I. Kurt, A. Turhankurum, K. Ozdamar, "Comparing Classification Techniques for Predicting Essential Hypertension", Expert Systems with Applications, vol. 29, no. 3, pp. 583-588, 2005.

[29]. Kavitha Adhikesavan "An Integrated Approach for Measuring Semantic Similarity between Words and Sentences using Web Search Engine", The International Arab Journal of Information Technology, Vol.12, No. 6, pp. 589-596, 2015.

[30]. K. Uyar, A. Ilhan, "Diagnosis of Artery Disease Using Genetic Algorithm Based Trained Recurrent Fuzzy Neural Networks", Procedia Computer Science, vol. 120, pp. 588-593, 2017.

Sivasubramaniyan S, et. al. "An Intelligent Machine Learning Approaches for Predicting Coronary Artery Disease." *IOSR Journal of Computer Engineering (IOSR-JCE)*, 22(4), 2020, pp. 21-30.