SELECTION OF FEATURES ASSOCIATED WITH CORONARY ARTERY DISEASES (CAD) USING FEATURE SELECTION TECHNIQUES.

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Abstract:

In Machine Learning, Feature Selection is an interesting research area and it is the method of reducing the number of input attributes to reduce the computational cost and to improve the model performance. Further it is a current challenging issue in finding the optimal features with increase accuracy. The objective of this paper is to investigate some of the popular feature selection techniques on Z-Alizadeh sani dataset to determine the optimal features for efficient diagnosis of coronary artery disease (CAD). A total of seven feature selection techniques namely pearson correlation, chi-squared, feature importance, mutual information, lasso, random forest and recursive feature elimination are used. The performances of the selected features are examined by one of the best classifier linear support vector machine (SVM) is used. The result of the classification accuracy of whole features and for the newly reduced subset features are respectively 81.57% and 88.15%. The comparative performance evaluation metrics is also conducted in terms of accuracy, sensitivity and specificity.

Keywords: Coronary Artery Disease, Feature Selection, Support Vector Machine, Pearson Correlation, Chi-Squared, Feature Importance, Mutual Information, Lasso, Random Forest, Recursive Feature Elimination.

1. INTRODUCTION

The detection of useful and informative features for a given dataset is generally referred as Feature Selection, is an important and challenging research topic for disease diagnosis, disease prediction and disease classification. One of the main objectives for feature selection is to reduce the dimensionality. The presence of irrelevant and redundant feature in the dataset may weaken the performance of algorithms, usually leads to poor classification accuracy and also cause difficulty in understanding the information behind data. Feature Selection is consider as a fundamental problem and its role is critical in machine learning especially in the context associated with the irrelevant features [1]. Feature Selection methods use an evaluation measure to allocate scores to features and these scores are allocated according to the importance of features in determining the target labels. If the problem target is the disease diagnosis means there is a possible to identify the important features for that disease, which will help the physicians to diagnosis and treat disease using more efficient methods. Therefore most researchers used feature selection methods to identify important feature for diagnosing CAD. Feature Selection technique can improve learning performance, reduces computational complexity, building better systematic models and decrease the required storage. The feature selection technique in machine learning can be broadly classified into three categories: Filter Method, Wrapper Method and Embedded Method.

1.1 FILTER FEATURE SELECTION METHODS

Filter Methods are good for eliminating redundant, irrelevant, constant and duplicated features. Filter Approaches use an evaluation function supported the general characteristics of the dataset, by not considering any classification algorithm to select the subset of attributes or certain attributes. In this paper we investigate the filter based technique because it works faster, not dependent on classifiers, more scalable and less computational expense while dealing high dimensional data than wrapper based methods. Filter Feature Selection (FFS) technique is broadly classified into two categories such as i) Filter based Feature Ranking and ii) Filter based Subset Selection.

A. Filter based Feature Ranking (FBFR)

This technique rank features independently without involving any learning algorithm. Feature ranking consists of scoring each feature consistent with a specific method, and then selecting important features according to their scores [2]. Some commonly used filter-based feature ranking techniques are i) Statistics Based Scores: Chi-Square, Correlation and Clustering Variation ii) Probability Based Scores: Probabilistic Significance, InformationGain (IG), GainRatio and Symmetrical Uncertainty and iii) Instance-Based Techniques: ReliefF and ReliefFW iv) Classifier-based Techniques: OneRule [3].

B. Filter based Subset Selection (FBSS)

This technique estimate the group of features simultaneously rather than each individual feature like filter based feature ranking techniques and have the advantage of being able to select unique feature and detect redundant feature among features compares to ranking technique which evaluates each feature individually. The benefit of detecting redundant features is useful in reducing the size and improves the clear understanding of the final classification model [4]. Some commonly used filter based subset selection techniques are i) Correlation subset-based techniques and ii) Consistency subset-based technique. In Correlation based feature selection, the most important features are identified on the basis of high correlation and the remaining low correlated features are ignored for processing the model. In Consistency based feature selection, the most important features are identified on the basis of consistency values of each feature [5].

1.2 WRAPPER FEATURE SELECTION METHODS

Wrapper method will detect interaction between variables and evaluates all possible combination of subsets based on the classifier performance for classification tasks and clustering algorithm for clustering task. The evaluation is repeated for every subset, and therefore the subset generation depends on the search strategy, within the same way like filters. Wrapper Methods are slower in finding sufficiently good subsets and the computational cost is high while dealing large number of features than filters methods. Some of the wrapper methods are i) forward selection ii) backward elimination iii) recursive feature elimination and iv) bi-directional elimination (stepwise elimination) and v) exhaustive feature selection(subset selection).

1.3 EMBEDDED FEATURE SELECTION METHODS

Embedded Method combines the qualities of both filter and wrapper methods and it complete the feature selection process within the development of the machine learning algorithm itself. In other words, this method performs feature selection during the model training, which is why we call them embedded methods. A learning algorithm takes advantage of its own variable selection process and performs feature selection and classification or regression at an equivalent time. Embedded Method works faster and more accurate than filter method. Some commonly used embedded methods are i) lasso and ii) ridge regression are having inbuilt penalization function to reduce overfitting.

2. RELATED WORK

Table 1. Summarizes several existing work associated with the feature selection methodologies related to coronary artery disease.

S.No	Author	Objective	Dataset	Feature Selection Methods / Techniques
1	F Ghasemi et al [6]	Feature Selection in Pre-Diagnosis Heart Coronary Artery Disease Detection (2020)	Shahid Rajaee Hospital	Information Gain & Gini Index
2	Al-Tashi Q et al [7]	Feature Selection Method Based on Grey Wolf Optimization for Coronary Artery Disease Classification (2018)	Cleveland Heart disease dataset	Grey Wolf Optimization (GWO)
3	B. Kolukisa et al [8]	Evaluation of Classification Algorithms, Linear Discriminant Analysis and a New Hybrid Feature Selection Methodology for the Diagnosis of Coronary Artery Disease (2018)	Cleveland, Z-Alizadehsani and African Dataset	Hybrid Feature Selection (CS+IG+GR+RF)
4	J. Vijayashree at al [9]	A Machine Learning Framework for Feature Selection in Heart Disease Classification Using Improved Particle Swarm Optimization with Support Vector Machine Classifier (2018)	Cleveland heart disease database	PSO-SVM is best
5	C. B. Gokulnath et al [10]	An optimized feature selection based on genetic approach and support vector machine for heart disease (2018)	Cleveland heart disease database	Genetic Algorithm with SVM
6	C.-J. Qin et al [11]	Application Of Ensemble Algorithm Integrating Multiple Criteria Feature Selection In Coronary Heart disease Detection (2017)	Z-Alizadeh Sani CHD dataset	Filter FS Method (ANOVA, MI, CS) and Embedded FS Method (SVM.coef, RF.coef, LR.coef)
7	R. El-Bialy et al [12]	Feature Analysis of Coronary Artery Heart Disease Data Sets (2015)	Cleveland, Hungarian, V.A and Statlog Dataset	C4.5, Fast Decision Tree and Association Rules

8	N.A. Setiawan et al [13]	Benchmarking of Feature Selection Techniques for Coronary Artery Disease Diagnosis (2014)	Cleveland Dataset	MFS, CFS, WFS and RST
9	Mokeddem S et al [14]	Supervised Feature Selection For Diagnosis Of Coronary Artery Disease Based On Genetic Algorithm (2013)	UCI CAD dataset	Genetic Algorithm (GA) wrapped Bayes Naive (BN) is best
10	Alizadehsani R et al [15]	Diagnosis of Coronary Artery Disease Using Data Mining Techniques Based on Symptoms and ECG Features (2012)	Shaheed Rajaei Cardiovascular, Medical and Research Center	Ensemble Algorithm (SMO & NB)
11	Alizadehsani R et al [16]	Diagnosis of Coronary Artery Disease Using Data Mining Based on Lab Data and Echo Features (2012)	Shaheed Rajaei Cardiovascular, Medical and Research Center	Ensemble Algorithm (SMO & NB)
12	Rajeswari K et al [17]	Feature Selection in Ischemic Heart Disease Identification using Feed Forward Neural Networks (2012)	Hospital Data	Multilayer Feed Forward Neural Network
13	M. Anbarasi et al [18]	Enhanced prediction of heart disease with feature subset selection using genetic algorithm (2010)	Cleveland Heart Disease database	Genetic Algorithm
14	I. Babaoglu et al [19]	A comparison of feature selection models utilizing binary particle swarm optimization and genetic algorithm in determining coronary artery disease using support vector machine (2010)	Patient Data with EST and coronary angiography	BPSO, GA and SVM (All Features)

The abbreviation used in the table 1 are: **GA** – Genetic Algorithm, **SVM** – Support Vector Machine, **MLP** – Multi Layer Perceptron, **DT** – Decision Tree, **BFS** – Best First Search, **SFFS** - Sequential Floating Forward Search, **BPSO** – Binary Particle Swarm Optimization, **NB** – Naive Bayes, **SMO** – Algorithm for training SVM, **CS** – ChiSquared, **GR** – Gain Ratio, **IG** – InfoGain, **RF** – ReliefF, **LR** – Logistic Regression, **MFS** - Motivated Feature Selection ,**CFS** - Correlation based Feature Selection, **WFS** - Wrapper based Feature Selection **RST**- Rough Set based Feature Selection

3. METHODOLOGY

The proposed work related workflow is illustrated and displayed as within the following figure 1, and also this may be considered as proposed system methodology. The proposed work is divided into three levels. In the first level: Data Input process, Data Preprocessing (if the data contains missing value), Extraction of useful features using Feature Selection Techniques and finally the verification of useful features using Feature Evaluation & Validation using either ranking or by fixing threshold value. At the second level the dataset is divided into train data and test data with the selected features which will be applied to the traditional machine learning algorithm and compute the performance metrics. At the third level the proposed hybrid machine learning algorithm will be applied and compute the performance metrics. Finally the comparison will be displayed.

3.1 Block Diagram of Proposed Methodology

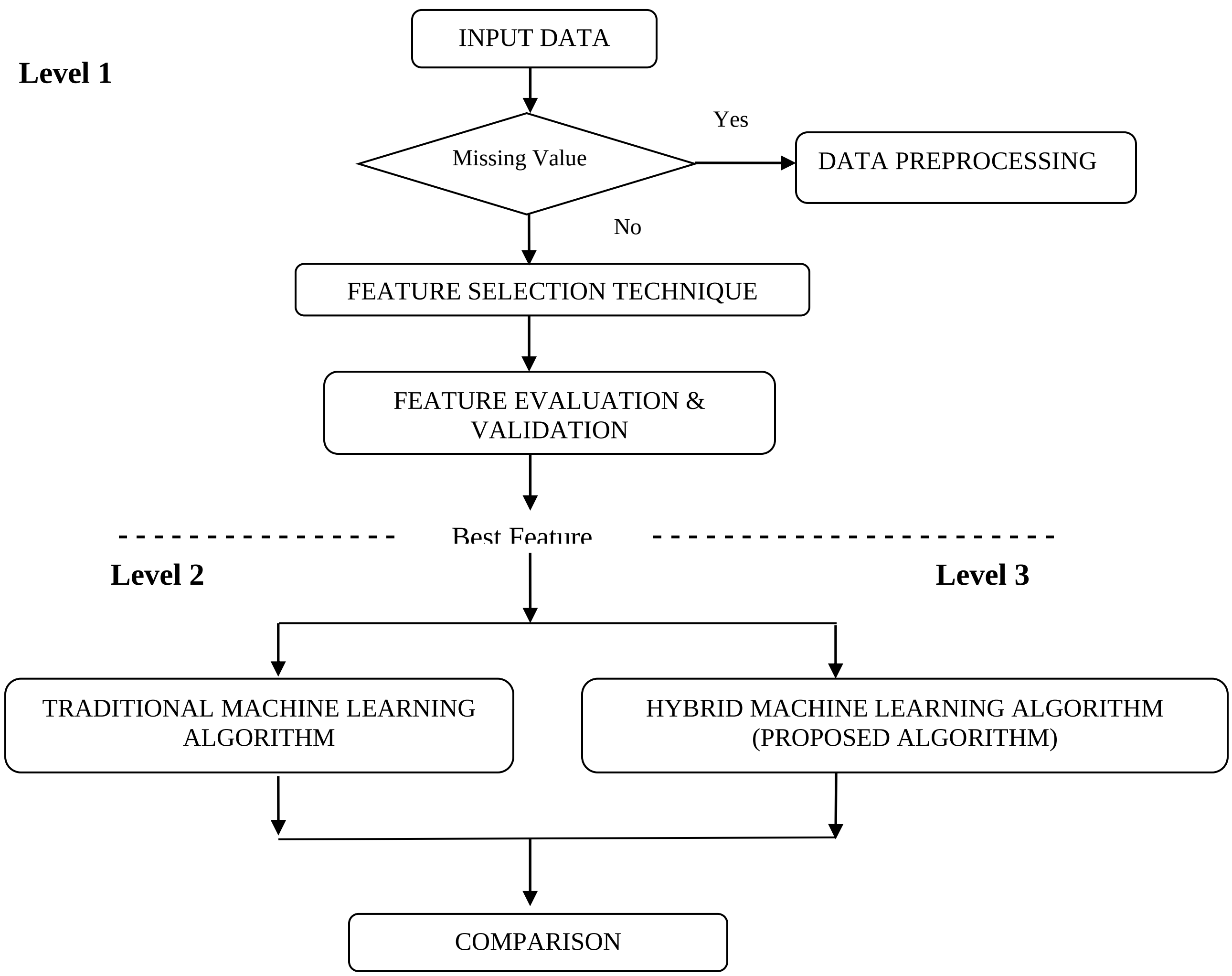

Fig 1: Proposed System Block Diagram

3.2 Dataset

The dataset named Z-Alizadeh Sani heart disease was collected from 303 patients annotated with 56 features; 55 of them were consider as input and one as output and also contains two main classes: CAD and Normal. Out of 55 features 29 integer, 5 float, and 21 categorical features with 216 CAD (sick) and 87 Normal (non CAD) patients. There is no missing data in the dataset but there is a need to transform the data fields into numerical for applying statistical feature selection technique. This dataset contains four main types of features: (1) demographic, (2) ECG, (3) symptoms and examination and (4) laboratory and echo. If a patient had the diameter that was >= to 50%, then he/she was categorized as a CAD patient, otherwise as a Normal patient.

3.3 Encoding and Feature Selection Methods

The Dataset contains some of the categorical values described have a small number of unique values so categorical encoding concept is employed which makes the machine learning algorithms to not overfit to unique values. Converting these categorical values into binary values allows the algorithms to process the data a less biased manner without losing any of the information.

In this paper we are investigating seven feature selection methods like pearson correlation, chi-squared, feature importance, mutual information, lasso, random forest and recursive feature elimination to the dataset for obtaining top 27 (50% features of the dataset) highly correlated dependent feature with the target feature and rank among the 27 features to select best features. Here the threshold value is set to 0.8, the features which are correlated greater than or equal to threshold value identified by correlation heatmap are removed from the dataset for effective accuracy result.

Pearson Correlation: Pearson correlation coefficient is a filter based feature selection method for understanding a feature’s relation to the response variable / target variable. It is used to measure the linear relationship between two variables. The absolute value of the pearson’s correlation between the numerical features and target in the dataset were checked and keep the top 27 features based on the criteria. The formula for pearson correlation coefficient is

$$r = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}}$$

Chi Squared: Chi-Square test is a filter based feature selection method and it calculates the chi-square metric between the numerical variables and the target, it only selects the variable with the high chi-squared values. Chi-squared is a statistical test compares the observed distribution between target and the various features in the dataset.

$$\chi_c^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Extra Tree Classifier: Extra Tree Classifier is a type of ensemble algorithm which combines the predictions from multiple trees. ETC is similar to the random forest and differs in the way of constructing decision tree in the forest. This technique gives you a score for each features of data, higher the score more relevant it is. To perform feature selection using ETC, each feature is ordered in descending order consistent with the Gini Importance of every feature and therefore the user selects the highest k features consistent with their choice.

Mutual Information: MI between two variables is a non negative value, which measures the dependency between two random variables X and Y. It is equal to zero if and only if two random variables are independent and higher values means higher dependency. It can reduce data dimension successfully and maintain or improve the accuracy of classification over by a set of all features. The mutual information is given by

Recursive Feature Elimination: RFE is a popular wrapper based feature selection method considers the selection of set of features as a search problem. The goal of this method is to take features recursively by considering smaller and smaller sets of features. The estimator is first trained with the initial set of features and then the importance of each and every feature is obtained either through a feature_importances_ attribute or a coef_attribute. Then, the smallest amount of important features is pruned from current set of features. That procedure is recursively repeated on the pruned set until the specified number of features to pick is eventually reached.

Lasso: Lasso (least absolute shrinkage and selection operator) is a embedded method and it use a algorithm that have built in feature selection methods and forces a lot of features to be zero. It provides good prediction accuracy because removing and shrinking the coefficients can reduce the variance without extensive increase of the bias, this is very useful when we have a large number of features and smaller number of observation.

Tree Based (Random Forest): It is an ensemble tree based algorithm and contains set of decision trees. First it selects random samples from the given dataset and for each sample. It construct a decision tree and get a prediction result from each of the decision tree and also performs the prediction result with the most votes as a final one.

4. EXPERIMENTAL RESULT

Table 2: Top most 50% of features relevant to CAD are selected using seven feature selection methods mentioned above are marked as True otherwise False. After evaluation count the number of true values for each attributes and extracts the attributes having the ranking value of 7, 6 etc.

Features	Pearson	Chi-2	RFE	Logistic	RF	ETC	MI	Total
Age	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	7
HTN	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	7
BP	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	7
Typical Chest Pain	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	7
Nonanginal	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	7
Tinversion	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	7
EF-TTE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	7
Region RWMA	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	7
DM	TRUE	TRUE	TRUE	TRUE	F	TRUE	TRUE	6
Dyspnea	TRUE	TRUE	TRUE	TRUE	F	TRUE	TRUE	6
Atypical	TRUE	TRUE	TRUE	F	TRUE	TRUE	TRUE	6
TG	TRUE	F	TRUE	TRUE	TRUE	TRUE	TRUE	6
ESR	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	F	6
K	TRUE	F	TRUE	TRUE	TRUE	TRUE	TRUE	6
PR	TRUE	F	TRUE	TRUE	TRUE	TRUE	F	5
Q Wave	TRUE	TRUE	TRUE	TRUE	F	F	TRUE	5
St Elevation	TRUE	TRUE	TRUE	TRUE	F	F	TRUE	5
St Depression	TRUE	TRUE	TRUE	TRUE	F	TRUE	F	5
Poor R Progression	TRUE	TRUE	TRUE	TRUE	F	F	TRUE	5
FBS	TRUE	TRUE	F	F	TRUE	TRUE	TRUE	5
HB	F	F	TRUE	TRUE	TRUE	TRUE	F	4
Lymph	TRUE	F	F	F	TRUE	TRUE	TRUE	4
Neut	TRUE	F	TRUE	F	TRUE	TRUE	F	4
PLT	TRUE	F	TRUE	F	TRUE	TRUE	F	4
BMI	F	F	F	F	TRUE	TRUE	TRUE	3
CRF	TRUE	TRUE	F	F	F	F	TRUE	3

Diastolic Murmur	TRUE	TRUE	TRUE	F	F	F	F	3
CR	TRUE	F	F	F	TRUE	TRUE	F	3
BUN	TRUE	F	F	F	TRUE	TRUE	F	3
Weight	F	F	F	F	TRUE	TRUE	F	2
Length	F	F	F	F	TRUE	TRUE	F	2
Current Smoker	F	TRUE	F	F	F	TRUE	F	2
FH	F	F	TRUE	TRUE	F	F	F	2
Airway disease	F	TRUE	TRUE	F	F	F	F	2
DLP	F	F	F	F	F	TRUE	TRUE	2
Weak Peripheral Pulse	F	TRUE	F	F	F	F	TRUE	2
Lung rales	F	F	TRUE	TRUE	F	F	F	2
Function Class	TRUE	TRUE	F	F	F	F	F	2
LowTH Ang	F	TRUE	TRUE	F	F	F	F	2
LVH	F	TRUE	TRUE	F	F	F	F	2
LDL	F	F	F	F	TRUE	TRUE	F	2
HDL	F	F	F	F	TRUE	TRUE	F	2
Na	F	F	F	F	F	TRUE	TRUE	2
WBC	F	F	F	F	TRUE	TRUE	F	2
VHD	F	F	F	F	F	TRUE	TRUE	2
Obesity	F	F	F	F	F	F	TRUE	1
Thyroid Disease	F	TRUE	F	F	F	F	F	1
Edema	F	TRUE	F	F	F	F	F	1
Fmale	F	TRUE	F	F	F	F	F	1
Male	F	F	F	F	F	F	TRUE	1
EX-Smoker	F	F	F	F	F	F	F	0
CVA	F	F	F	F	F	F	F	0
CHF	F	F	F	F	F	F	F	0
Systolic Murmur	F	F	F	F	F	F	F	0
Exertional CP	F	F	F	F	F	F	F	0

Table 3: Best Selected Features for CAD

14 Features	Age, DM, HTN, BP, Typical Chest Pain, Dyspnea, Atypical, Nonanginal, Tinversion, TG, ESR, K, EF-TTE, Region RWMA.
19 Features	Age, DM, HTN, BP, Typical Chest Pain, Dyspnea, Atypical, Nonanginal, Tinversion, TG, ESR, K, EF-TTE, Region RWMA, PR, Q Wave, St Elevation, St Depression, Poor R Progression, FBS.

The abbreviation used in the table 3 are: DM - Diabetes Mellitus, HTN – Hypertension, BP - Blood Pressure, TG – Triglyceride, ESR - Erythrocyte Sedimentation Rate, K – Potassium, EF - Ejection Fraction, Region with RWMA (Regional Wall Motion Abnormality)

4.1 SUPPORT VECTOR MACHINE

SVM is a supervised machine learning algorithm most commonly used to solve both classification and regression problems. It is widely used for classification task as it produces good accuracy with low computational power. SVM generated a line that best separates the two classes of data points. This classifier aims in forming a hyperplane which will separate the classes the maximum amount as possible by adjusting the distance between the data points. It plots a hyperplane for each attribute as a coordinate that's present within the dataset. Classification is performed by identifying the hyperplane that divides one class from the opposite class. Hyperplane are often decided supported several kernels. For this technique three kernels are used namely, 'linear', 'rbf' and 'poly' [20]. To examine the effect of selected features we used a well known classification technique namely support vector machine was applied between all the features and with selected features. The evaluation metrics is listed in the below table.

Table 4: Comparison of selected features with all features using SVM Classifier

SVM	All Features	19 Features	14 Features
Accuracy	81.57	86.84	88.15
Precision	65.38	77.27	80.95
Recall	77.27	77.27	77.27

45 (TP)	9 (FP)
5 (FN)	17 (TN)

Fig 2 (a) Confusion Matrix of all Features

49 (TP)	5 (FP)
5 (FN)	17 (TN)

Fig 2(b) Confusion Matrix of top 19 Features

50 (TP)	4 (FP)
5 (FN)	17 (TN)

Fig 2 (c) Confusion Matrix of top 14 Features

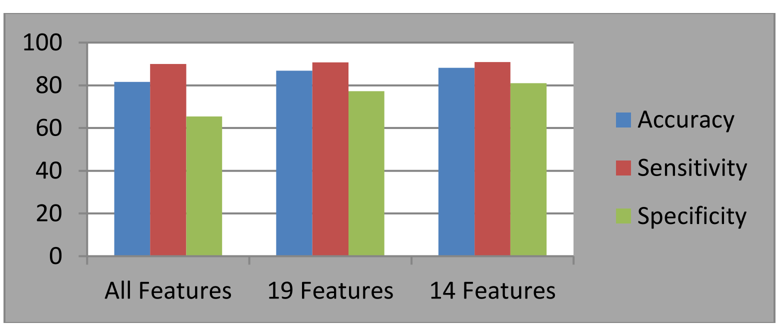

Fig 3: Result of Performance Metrics

5. CONCLUSION AND FUTURE WORK

CAD is one of the leading causes for death worldwide so it is important to extract the relevant features from the dataset to achieve highest detection performance. In this paper, the proposed method of feature selection used some of the filter, wrapper and embedded methods to select the most relevant features this brings the facility of all the methods to get high performance result. The performance metrics like accuracy, sensitivity and specificity are compared between all features and the reduced set of features are experimented through a well known machine learning classification algorithm namely support vector machine. The results of selected features are 88.15% accuracy, 90.5% sensitivity and 80.95% specificity improved than the original features. In the future, we will hybrid some other filter, wrapper and embedded feature selection method with classifiers by fixing threshold value can advance to better performance.

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