PREDICTION OF HEART DISEASE USING DATA MINING

GROUP MEMBERS

1. P19101064 – SHAHID IQBAL
2. P19101063 – SANA ASHFAQ
3. P19101023 – IQRA MEHDI
4. P19101008 – ANUM ZEHRA (GROUP LEAD)

SUPERVISOR

DR. TEHSEEN A. JILANI

PROJECT DETAILS

MCS MORNING (FINAL)

DATA MINING AND DATA WAREHOUSING

WORKING ON WEKA AND SPSS

ABSTRACT

Our project is to predict the heart disease by examining the various attributes. In this project diverse strategies have been utilized to detect heart disease such as Decision tree, K-Means, Confusion Matrix. And among all these calculations the final result gives us the finest precision of 91.8%.

TABLE OF CONTENT

1. INTRODUCTION

In daily life many factors influence a human heart. Many problems are happening at a fast pace and new heart diseases are rapidly being recognized. In today's world of stress Heart, being an essential organ in a human body which pumps blood through the body for the blood circulation is fundamental and its health is to be conserved for a sound living. The health of a human heart is based on the encounters in a person's life and is completely dependent on proficient and personal behaviors of a person. There may also be a few genetic factors through which a sort of heart illness is passed down from eras. Concurring to the World Health Organization, every year more than 12 million deaths are happening around the world due to the different sorts of heart diseases which is additionally known by the term cardiovascular disease. The term heart disease includes numerous diseases that are diverse and particularly affect the heart and the arteries of a human being. Even youthful matured individuals around their 20-30 a long time of life expectancy are getting influenced by heart diseases. The increment within the possibility of heart disease among young may be due to the bad eating habits, lack of rest, anxious nature, depression, discouragement and various other factors such as obesity, poor diet, family history, high blood pressure, high blood cholesterol, idle behavior, smoking and hypertension.

The diagnosis of the heart diseases could be an exceptionally important and is itself the most complicated task in the medical field. All the mentioned components are taken into consideration when analyzing and understanding the patients by the specialist through manual check-ups at regular intervals of time. The symptoms of heart disease significantly depend upon which of the distress felt by a person. A few side effects are not usually identified by the common people. However, common symptoms include chest pain, breathlessness, and heart palpitations. The chest pain common to many types of heart disease is known as angina, or angina pectoris, and happens when a portion of the heart does not get sufficient oxygen. Angina may be activated by stressful events or physical effort and normally lasts under 10 minutes. Heart attacks can also happen as a result of different types of heart disease.

Data Mining is an important decision-making process information from past collections for future analysis or forecast. Information may be anonymous and may not be identified without using a data mine. The section says a single data mining process where the future result or predictions can be made based on historical data i.e., available. Digging for medical data has created a possible solution

combine classification techniques and deliver by computer database training that leads continuously to hidden tests patterns in medical data sets used for prediction of the patient's future status. So, using medical data to dig it is able to provide information about patient history and is capable provided clinical support through analysis. Clinical analysis in patients, these patterns are very important. In English, medical data mining uses classification algorithms that is an important part of diagnosing the possibility of a heart attack before it happened. Separation algorithms can be trained and tested to make decisive predictions a person's condition of heart attack.

2. DECISION TREE

2.1. INTRODUCTION

Decision Trees (DTs) are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. A tree can be seen as a piecewise constant approximation.

For instance, in the example below, decision trees learn from data to approximate a sine curve with a set of if-then-else decision rules. The deeper the tree, the more complex the decision rules and the fitter the model.

2.2. ADVANTAGES

Some advantages of decision trees are:

- Simple to understand and to interpret. Trees can be visualized.
- Requires little data preparation. Other techniques often require data normalization, dummy variables need to be created and blank values to be removed. Note however that this module does not support missing values.
- The cost of using the tree (i.e., predicting data) is logarithmic in the number of data points used to train the tree.
- Able to handle both numerical and categorical data. However, scikit-learn implementation does not support categorical variables for now. Other techniques are usually specialized in analyzing datasets that have only one type of variable. See algorithms for more information.
- Able to handle multi-output problems.
- to account for the reliability of the model.
- Performs well even if its assumptions are somewhat violated by the true model from which the data were generated.

2.3. DISADVANTAGES

- Decision-tree learners can create over-complex trees that do not generalize the data well. This is called overfitting. Mechanisms such as pruning, setting the minimum number of samples required at a leaf node or setting the maximum depth of the tree are necessary to avoid this problem.
- Decision trees can be unstable because small variations in the data might result in a completely different tree being generated. This problem is mitigated by using decision trees within an ensemble.
- Predictions of decision trees are neither smooth nor continuous, but piecewise constant approximations as seen in the above figure. Therefore, they are not good at extrapolation.

- The problem of learning an optimal decision tree is known to be NP-complete under several aspects of optimality and even for simple concepts. Consequently, practical decision-tree learning algorithms are based on heuristic algorithms such as the greedy algorithm where locally optimal decisions are made at each node. Such algorithms cannot guarantee to return the globally optimal decision tree. This can be mitigated by training multiple trees in an ensemble learner, where the features and samples are randomly sampled with replacement.

- There are concepts that are hard to learn because decision trees do not express them easily, such as XOR, parity or multiplexer problems.

- Decision tree learners create biased trees if some classes dominate. It is therefore recommended to balance the dataset prior to fitting with the decision tree.

3. TREE ALGORITHMS: ID3, C4.5

What are all the various decision tree algorithms and how do they differ from each other? Which one is implemented in scikit-learn?

3.1. ID3 (ITERATIVE DICHOTOMISER 3)

It was developed in 1986 by Ross Quinlan. The algorithm creates a multiway tree, finding for each node (i.e., in a greedy manner) the categorical feature that will yield the largest information gain for categorical targets. Trees are grown to their maximum size and then a pruning step is usually applied to improve the ability of the tree to generalize to unseen data.

3.2. C4.5

It is the successor to ID3 and removed the restriction that features must be categorical by dynamically defining a discrete attribute (based on numerical variables) that partitions the continuous attribute value into a discrete set of intervals. C4.5 converts the trained trees (i.e., the output of the ID3 algorithm) into sets of if-then rules. This accuracy of each rule is then evaluated to determine the order in which they should be applied. Pruning is done by removing a rule's precondition if the accuracy of the rule improves without it.

4. LOGISTIC REGRESSION

In statistics, multinomial logistic regression is a classification method that generalizes logistic regression to multiclass problems, i.e., with more than two possible discrete outcomes. That is, it is a model that is used to predict the probabilities of the different possible outcomes of a categorically distributed dependent variable, given a set of independent variables (which may be real-valued, binary-valued, categorical-valued, etc.).

```
NOM REG Heart Disease (BASE=LAST ORDER=ASCENDING) WITH Age Sex ChestPainType BP
Cholesterol
   FBSOver120 EKGResults MaxHR ExcerciseAngina STDepression SlopeOfST NoOfVesselsFluro
Thallium
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0)
PCONVERGE(0.000001)
   SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR)
REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=FIT PARAMETER SUMMARY LRT CPS STEP MFI.
```

Nominal Regression

Notes

Comments		
Input	Data	C:\Users\jojo \Desktop\HeartDisease.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	270
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the model.

Syntax		NOMREG HeartDisease (BASE=LAST ORDER=ASCENDING) WITH Age Sex ChestPainType BP Cholesterol FBSOver120 EKGResults MaxHR ExcerciseAngina STDepression SlopeOfST NoOfVesselsFluro Thallium /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001) /MODEL /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR) REMOVALMETHOD(LR) /INTERCEPT=INCLUDE /PRINT=FIT PARAMETER SUMMARY LRT CPS STEP MFI.
Resources	Processor Time	00:00:00.08
	Elapsed Time	00:00:00.08

Warnings

There are 270 (50.0%) cells (i.e dependent variable levels by subpopulations) with zero frequencies.

Case Processing Summary

		N	Marginal Percentage
HeartDisease	0	150	55.6%
	1	120	44.4%
Valid		270	100.0%
Missing		0	
Total		270	
Subpopulation		270[a]	

a. The dependent variable has only one value observed in 270 (100.0%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria -2 Log Likelihood	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept Only	370.959			
Final	179.598	191.361	13	.000

Goodness-of-Fit test:

	Chi-Square	Df	Sig.
Pearson	232.117	256	.856
Deviance	179.598	256	1.000

Pseudo R-Square

Cox and Snell	.508
Nagelkerke	.680
McFadden	.516

Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	187.628	8.031	1	.005
Age	180.063	.465	1	.495
Sex	188.408	8.810	1	.003
ChestPainType	191.342	11.744	1	.001
BP	184.646	5.048	1	.025
Cholesterol	182.847	3.249	1	.071
FBSOver120	181.571	1.973	1	.160
EKGResults	181.956	2.358	1	.125
MaxHR	183.687	4.089	1	.043
ExcerciseAngina	183.262	3.664	1	.056
STDepression	181.947	2.349	1	.125
SlopeOfST	180.862	1.264	1	.261
NoOfVesselsFluro	202.822	23.224	1	.000
Thallium	190.248	10.650	1	.001

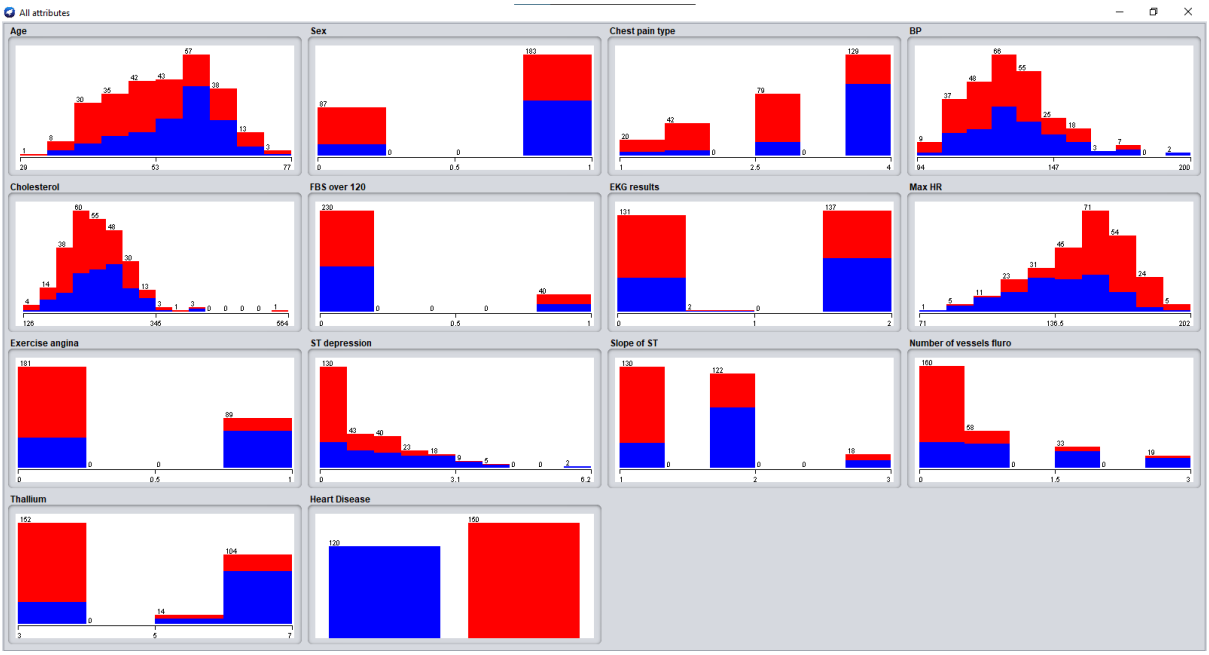
The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Parameter Estimates

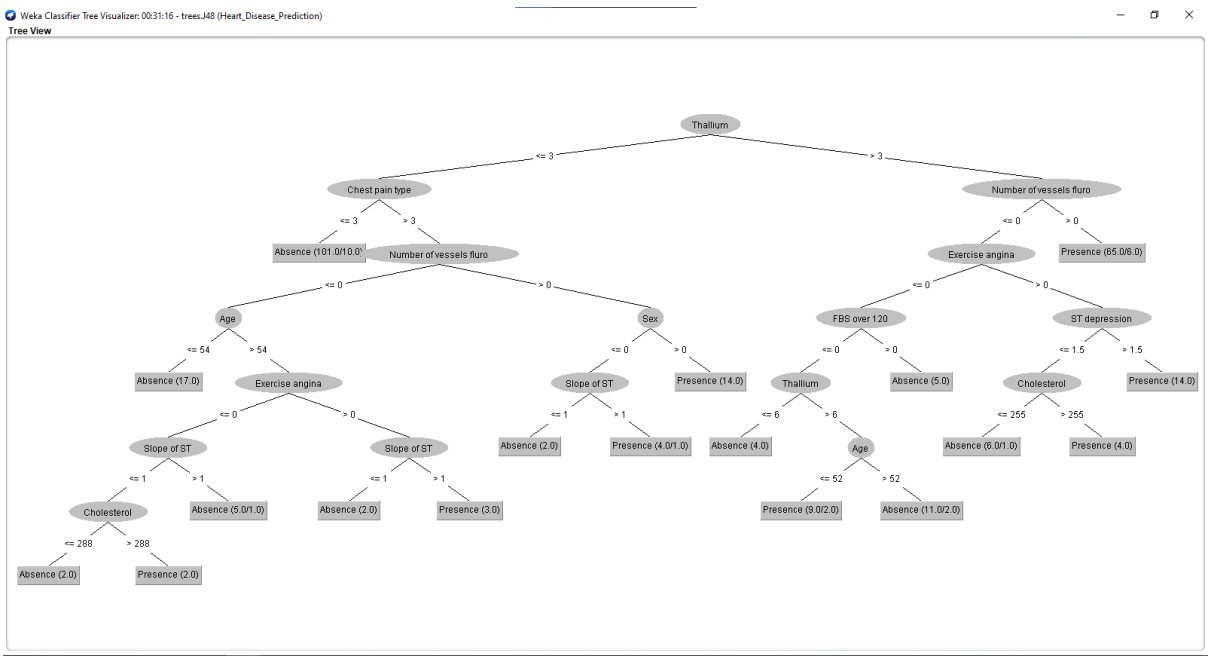
HeartDisease[a]		B	Std. Error	Wald	df	Sig.	Exp(B)		
0	Intercept	8.446	3.088	7.481	1	.006			
	Age	.017	.026	.462	1	.497	1.018		
	Sex	-1.542	.541	8.132	1	.004	.214		
	ChestPainType	-.701	.215	10.600	1	.001	.496		
	BP	-.025	.011	4.850	1	.028	.975		
	Cholesterol	-.007	.004	3.142	1	.076	.993		
	FBSOver120	.795	.575	1.913	1	.167	2.214		
	EKGResults	-.302	.198	2.325	1	.127	.740		
	MaxHR	.021	.011	3.957	1	.047	1.021		
	ExcerciseAngina	-.829	.431	3.701	1	.054	.436		
	STDepression	-.344	.227	2.291	1	.130	.709		
	SlopeOfST	-.442	.391	1.279	1	.258	.643		
	NoOfVesselsFluro	-1.165	.269	18.726	1	.000	.312		
	Thallium	-.341	.106	10.359	1	.001	.711		

5. DATA VISUALIZATION

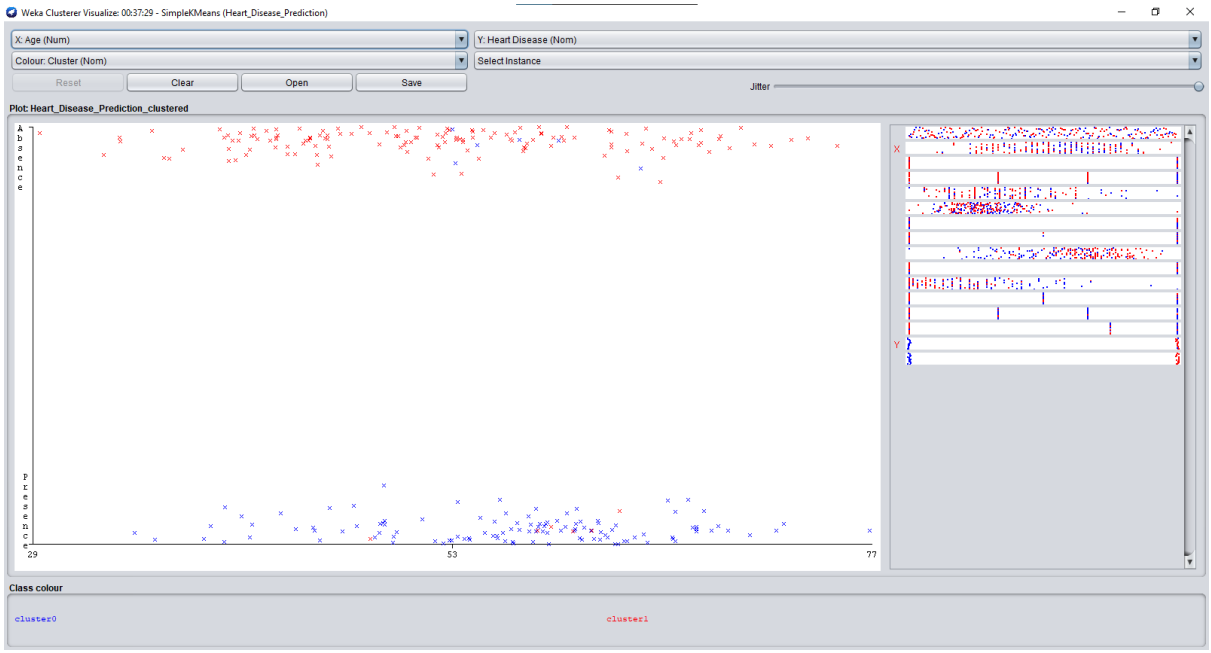
5.1. ALL ATTRIBUTES WRT HEART DISEASE



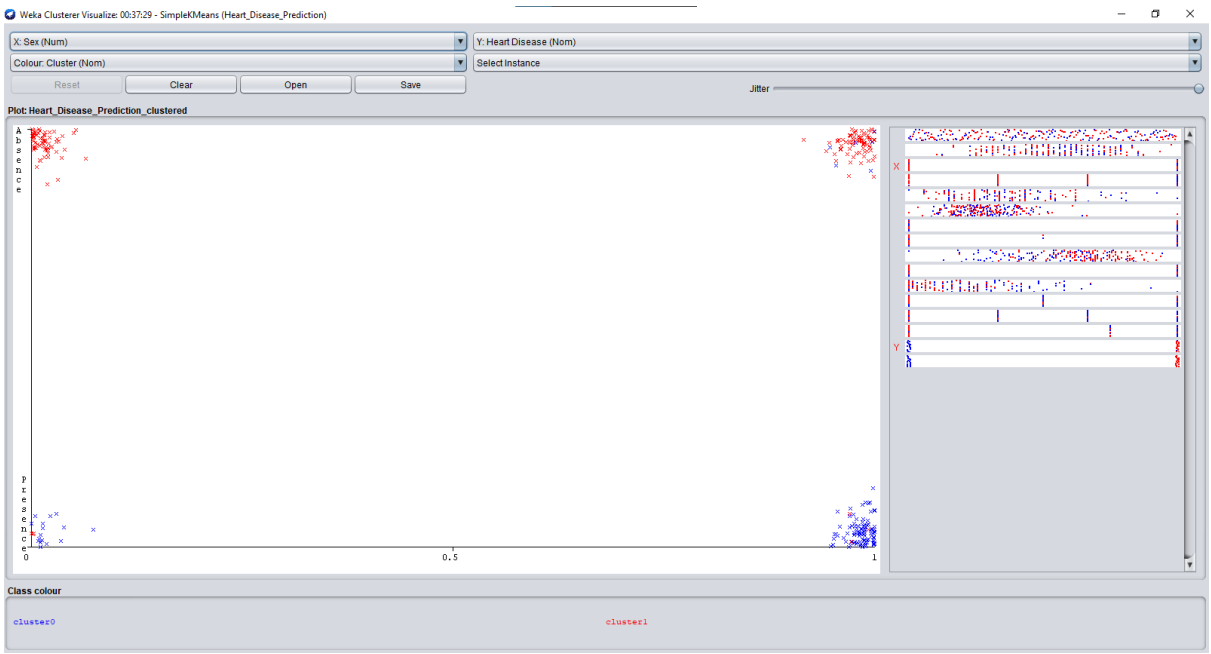
5.2. C4.5 IMPLEMENTATION IN WEKA USING JAVA LIBRARY J48



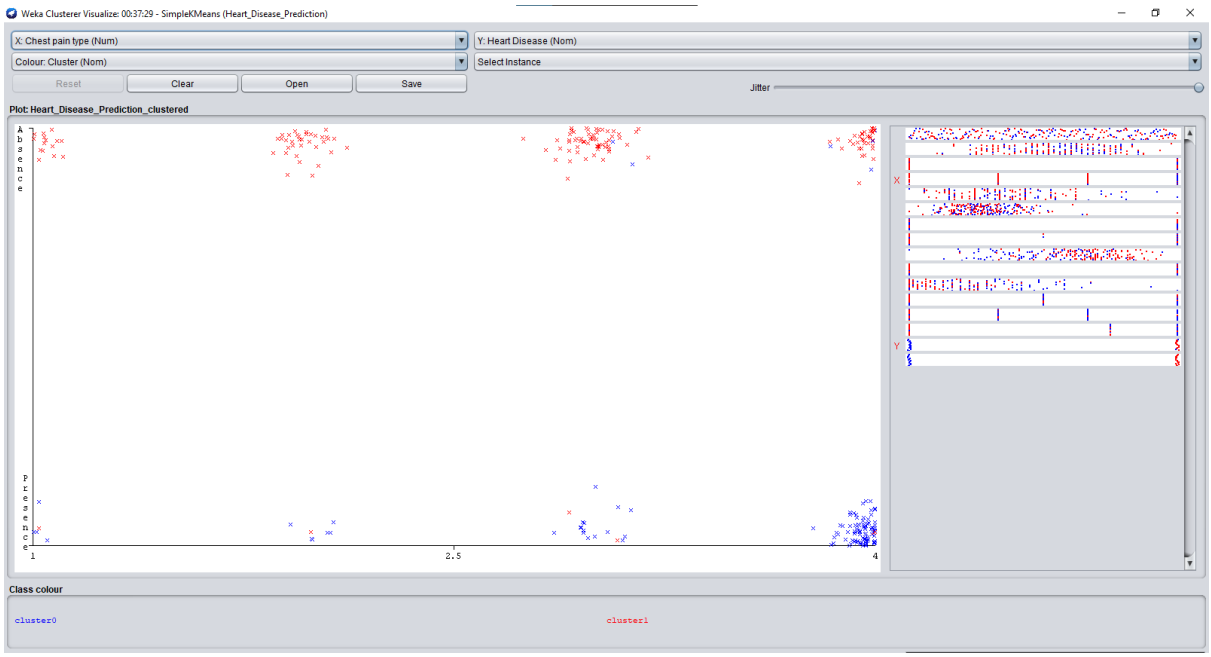
5.3. AGE VS HEART DISEASE



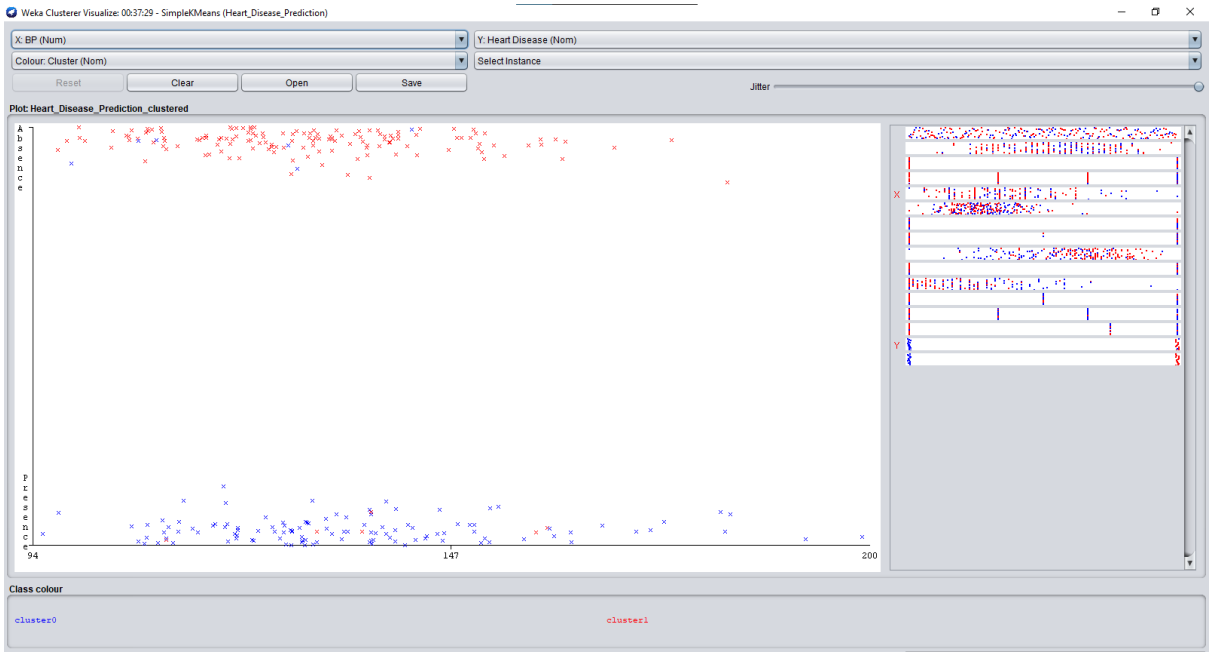
5.4. SEX VS HEART DISEASE



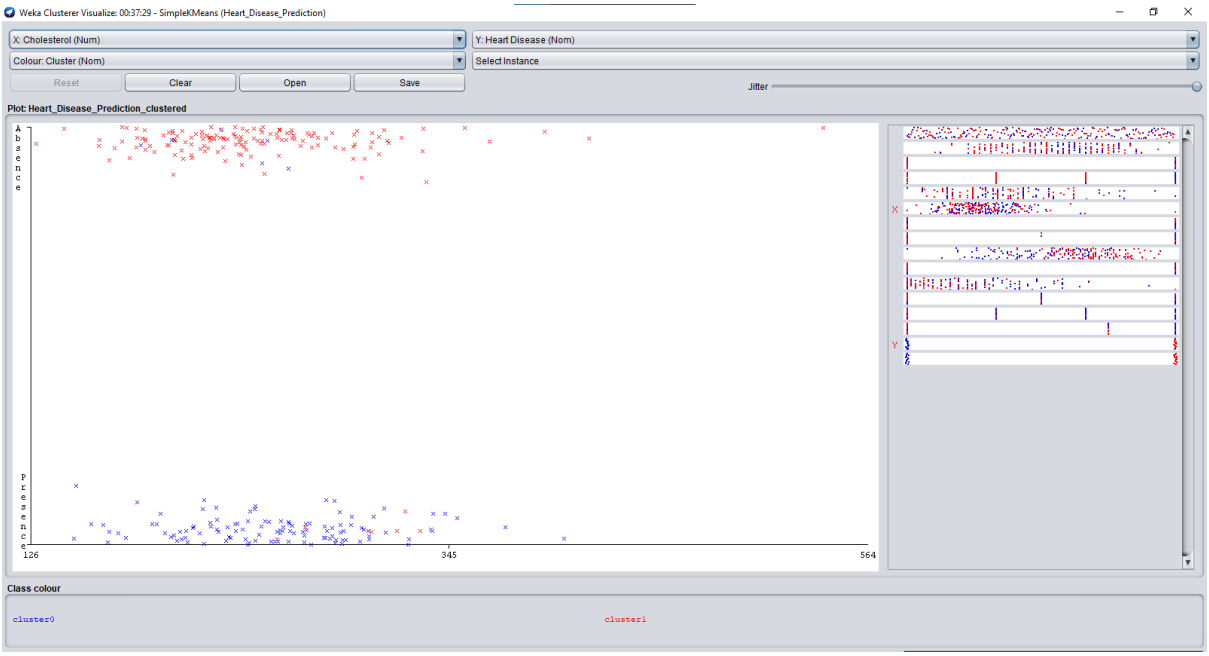
5.5. CHEST PAINT TYPE VS HEART DISEASE



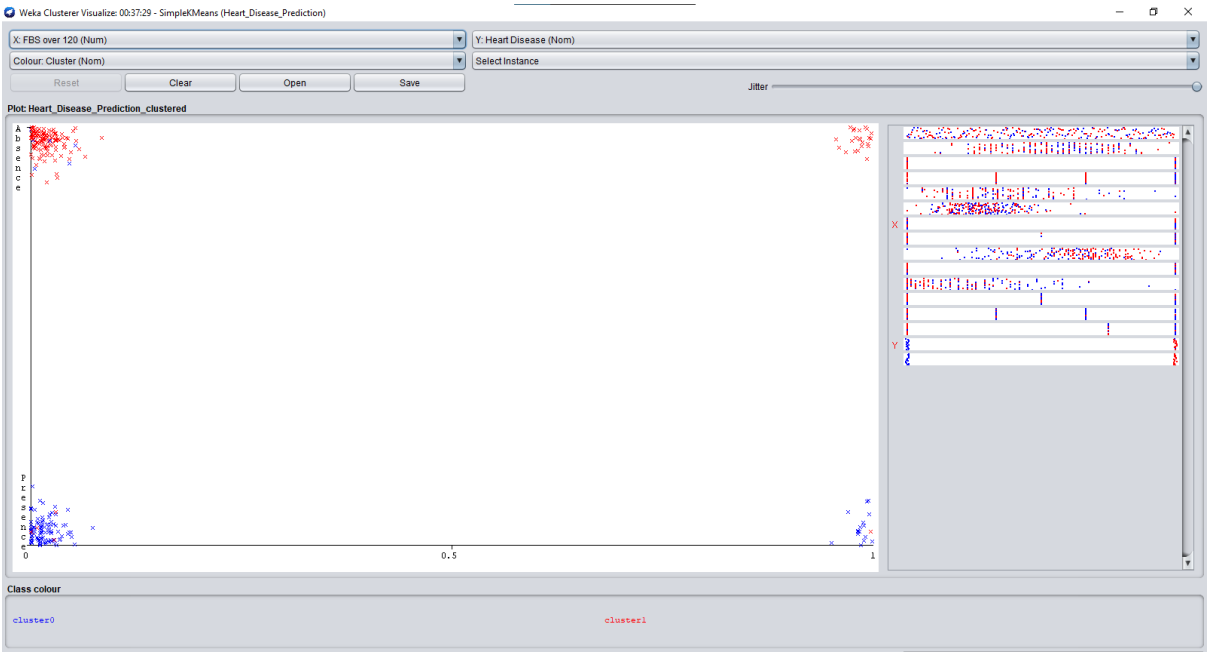
5.6. BP VS HEART DISEASE



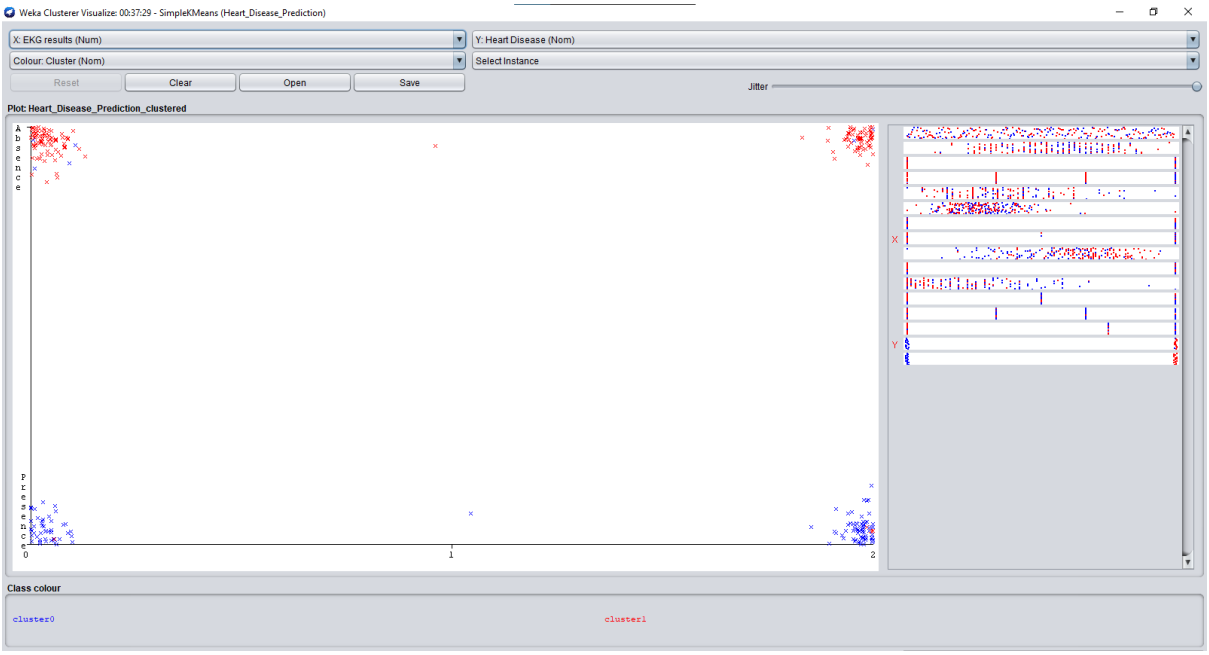
5.7. CHOLESTROL VS HEART DISEASE



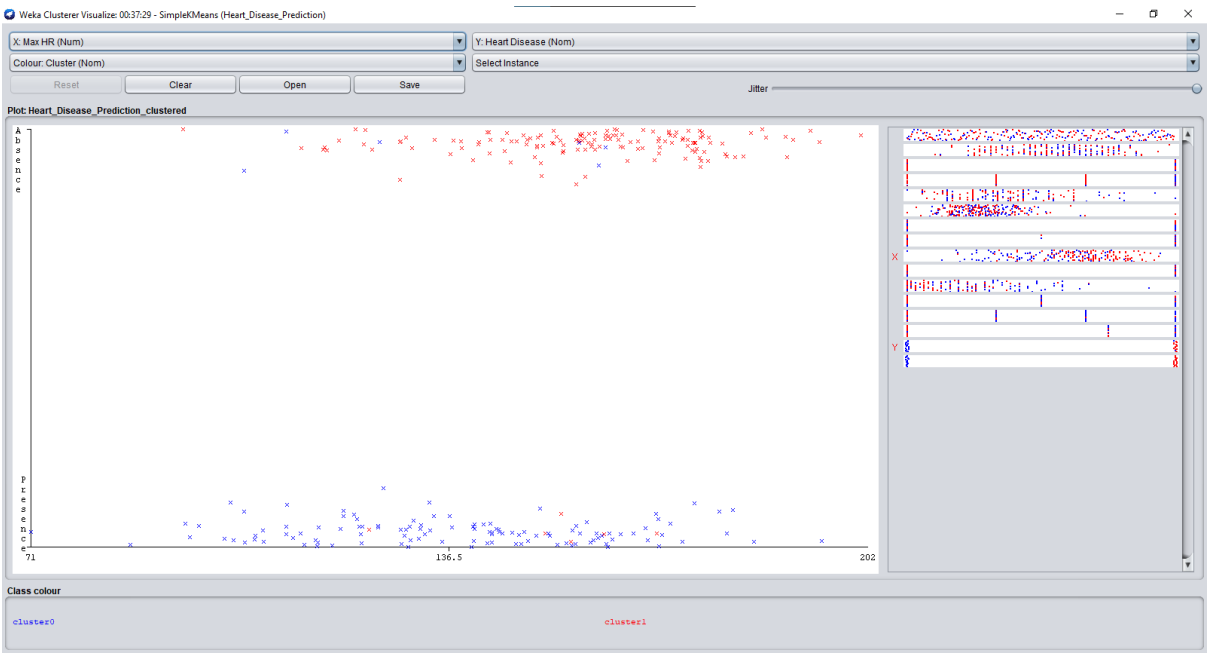
5.8. FBS OVER 120 VS HEART DISEASE



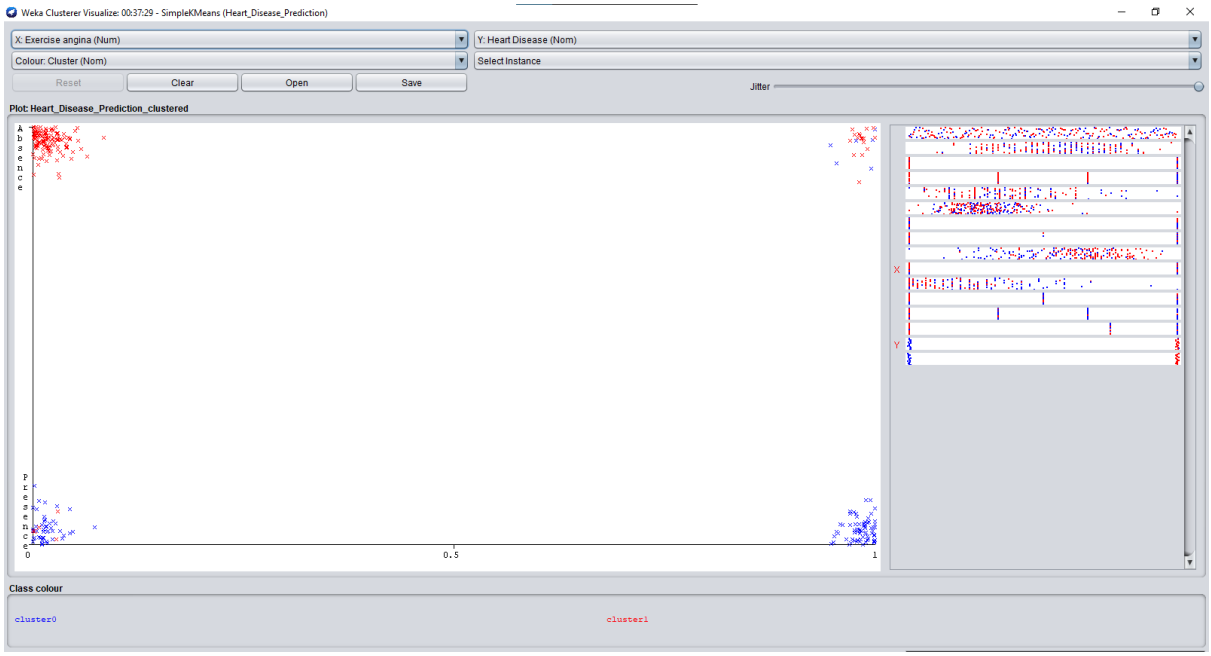
5.9. EKG RESULTS VS HEART DISEASE



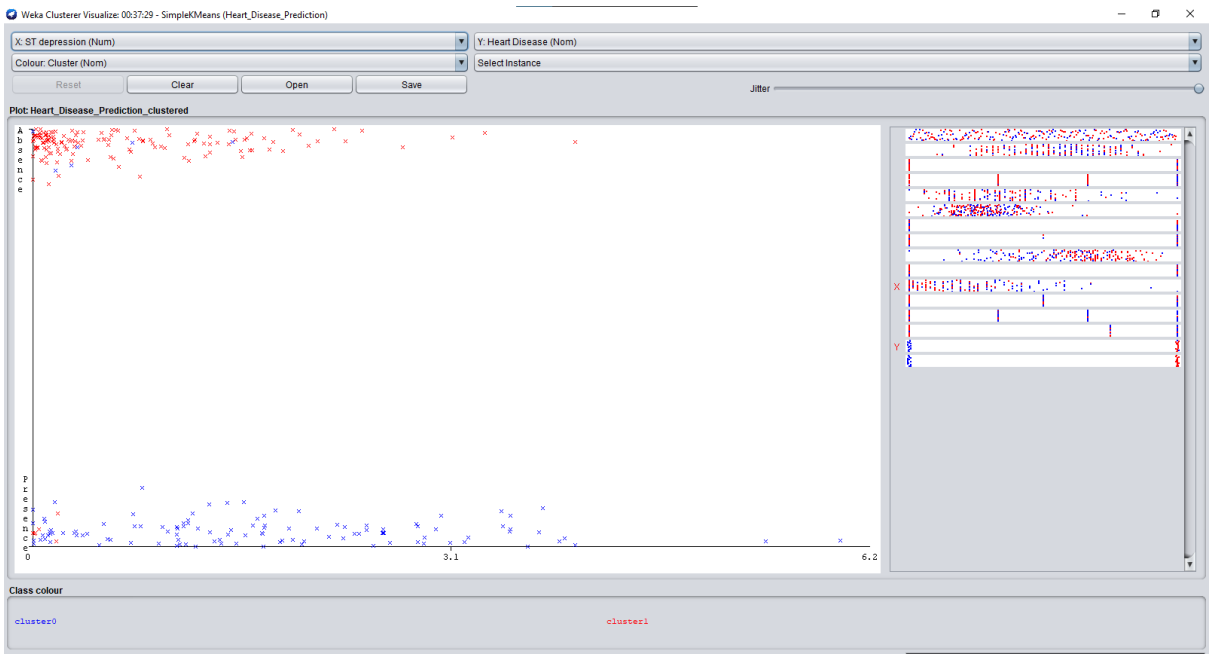
5.10. MAX HR VS HEART DISEASE



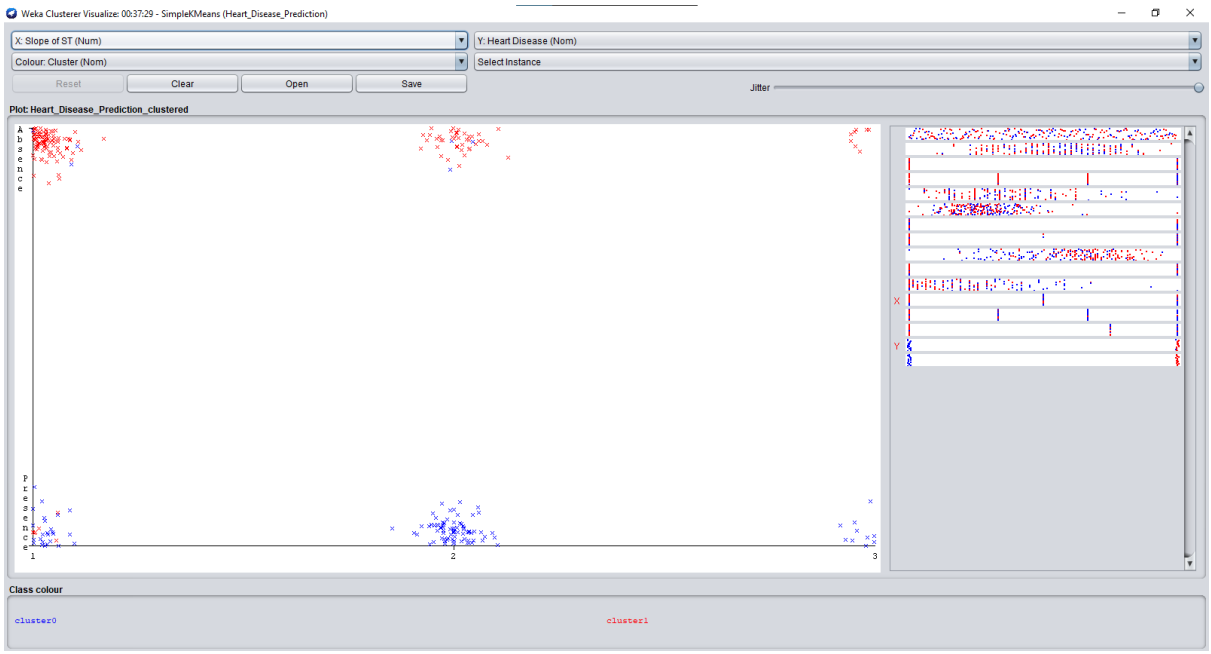
5.11. EXERCISE ANGINA VS HEART DISEASE



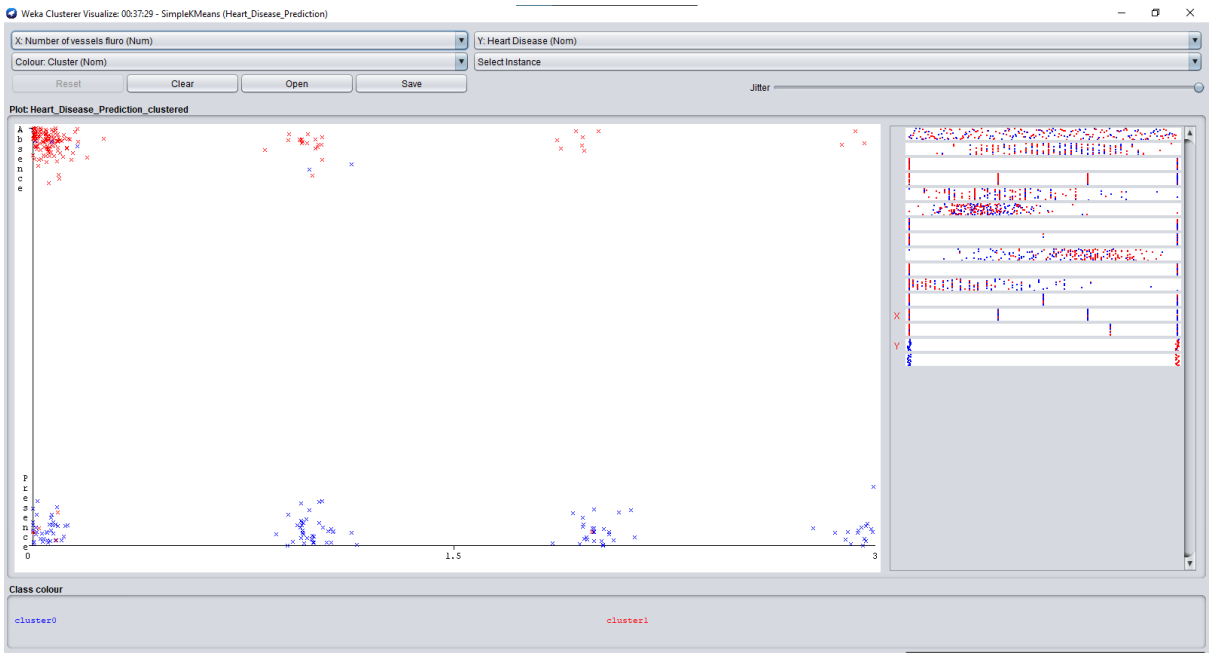
5.12. ST DEPRESSION VS HEART DISEASE



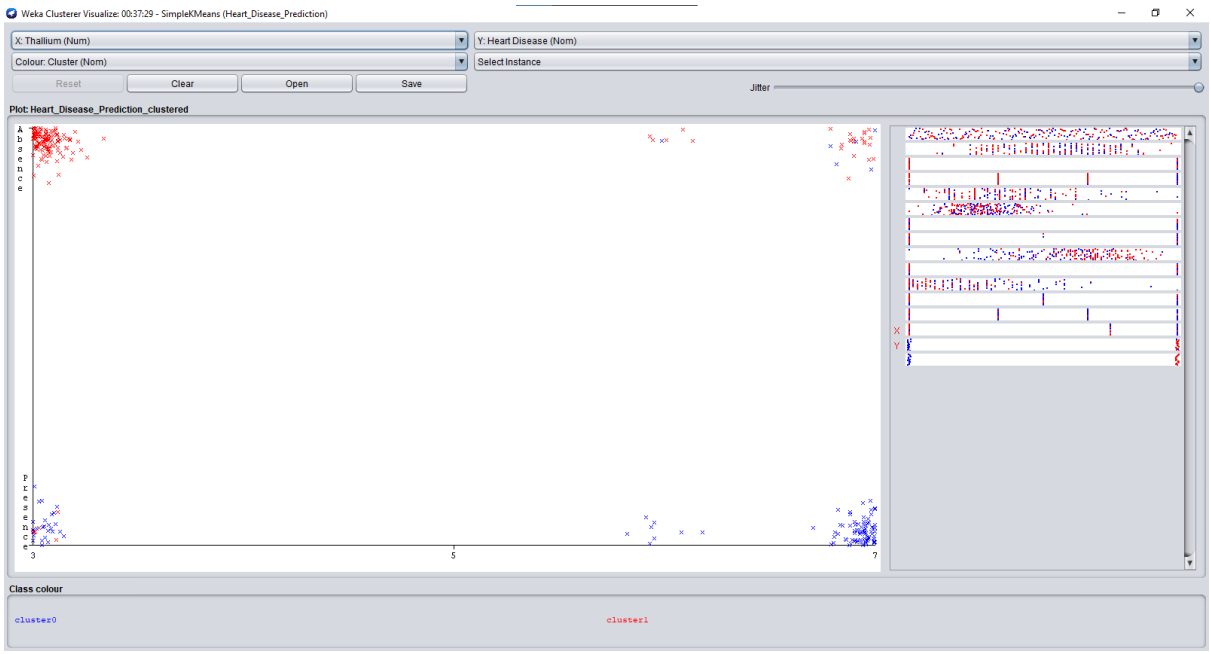
5.13. SLOPE OF ST VS HEART DISEASE



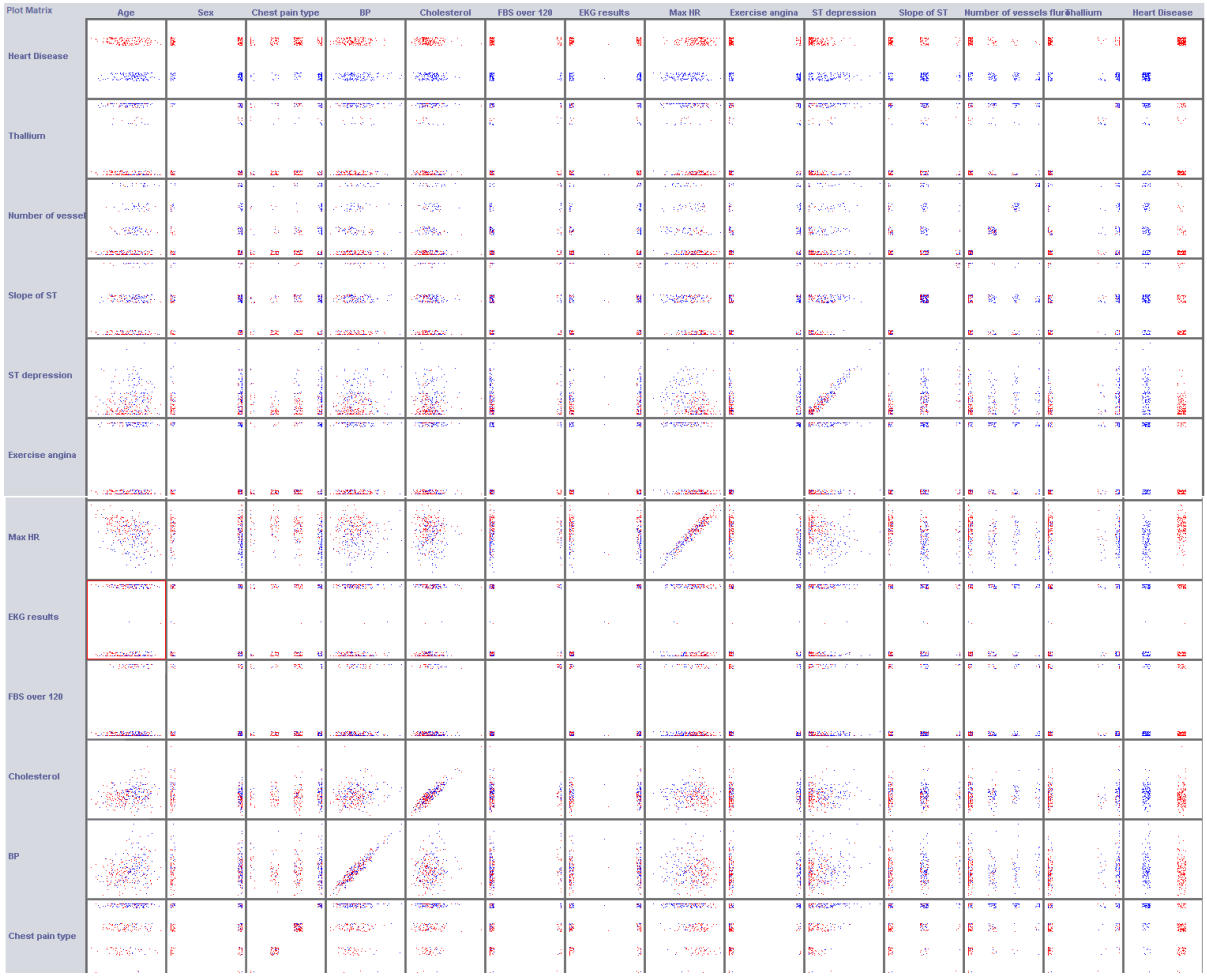
5.14. NO. OF VESSELS FLURO VS HEART DISEASE



5.15. THALLIUM VS HEART DISEASE



5.16. PLOT MATRIX



6. CONCLUSION

Following the algorithm and technique, we can deduce the presence of heart disease on the basis of some attributes. In light of this model, we can predict but prediction can't be 100% true. Therefore, we will increase the set of attributes for more accurate prediction in near future.