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Heart Disorder Prediction Using Machine Learning and Data Pitting Strategy

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Abstract—Heart Disorder is the main reason for death in the world over the last decade. Almost ten person dies of Heart Disorder about every minute in the India alone. Researchers have been using several data Pitting Strategies to help health care professionals in the diagnosis of heart disorder. However using data Pitting Strategy can reduce the number of test that are required. In order to reduce number of deaths from heart Disorders there have to be a quick and efficient detection Strategy. Decision Tree is one of the effective data Pitting methods used. This research compares different algorithms of Decision Tree classification seeking better performance in heart Disorder diagnosis using SL. The algorithms which are tested is C4.5 algorithm, Logistic model tree algorithm and Gradient Boosting algorithm. The existing datasets of heart Disorder patients from Cleveland database of UCI repository is used to test and justify the performance of decision tree algorithms. This datasets consists of 300 instances and 70 attributes. Subsequently, the classification algorithm that has optimal potential will be suggested for use in sizeable data. The goal of this study is to extract hidden patterns by applying data Pitting Strategies, which are noteworthy to heart Disorders and to predict the presence of heart Disorder in patients where this presence is valued from no presence to likely presence.
Keywords: Data Pitting; Decision Support System; Health disorder; Health records; Classification.

I. INTRODUCTION

Heart Disorder is the leading cause of death in the world over the past 15 years (World Health Organization 2007). Several different symptoms are associated with heart disorder, which makes it difficult to diagnose it quicker and better. Working on heart disorder patient's databases can be compared to real-life application. Doctors knowledge to assign the weight to each attribute. More weight is assigned to the attribute having high impact on disorder prediction. Therefore it appears reasonable to try utilizing the knowledge and experience of several specialists collected in databases towards assisting the Diagnosis process. It also provides healthcare professionals an extra source of knowledge for making decisions.

The healthcare industry collects large amounts of health-care data and that need to be mined to discover hidden information for effective decision making. Motivated by the world-wide increasing mortality of heart disorder patients each year and the availability of huge amount of patients' data from which to extract useful knowledge, researchers have been using data Pitting Strategies to help health care professionals in thediagnosis of heart disorder (Helma, Gottmann et al. 2000). Thus data Pitting refers to Pitting or extracting knowledgefrom large amounts of data. Data Pitting applications will be used for better health policy-making and prevention of hospital errors, early detection, prevention of disorders and preventable hospital deaths (Ruben 2009). Heart Disorder prediction system can assist medical professionals in predicting heart disorder based on the clinical data of patients [1]. Hence by implementing a heart disorder prediction system using Data Pitting Strategys and doing some sort of data Pitting on various heart disorder attributes, it can able to predict more probabilistically that the patients will be diagnosed with heart disorder. This paper presents a new model that enhances the Decision Tree accuracy in identifying heart disorder patients. It uses the different algorithm of Decision Trees.

II. BACKGROUND

Millions of people are getting some sort of heart Disorder every year and heart Disorder is the biggest killer of both men and women in the United States and around the world. The World Health Organization (WHO) analyzed that twelve million deaths occurs worldwide due to Heart Disorders. In almost every 34 seconds the heart disorderkills one person in world.

Medical diagnosis plays vital role and yet complicated task that needs to be executed efficiently and accurately. To reduce cost for achieving clinical tests an appropriate computer based information and decision support should be aided. Data Pitting is the use of software Strategies for finding patterns and consistency in sets of data. Also, with the advent of data Pitting in the last two decades, there is a big opportunity to allow computers to directly construct and classify the different attributes or classes.
Learning of the risk components connected with heart Disorder helps medicinal services experts to recognize patients at high risk of having Heart Disorder. Statistical analysis has identified risk factors associated with heart Disorder to be age, blood pressure, total cholesterol, diabetes, hyper tension, family history of heart disorder, obesity and lack of physical exercise, fasting blood sugar etc [3].

Researchers have been applying different data Pitting Strategies to help medicinal services experts with progressed exactness in the judgment of heart disorder. Neural network, Naive Bayes, Decision Tree etc. are some Strategys used in the diagnosis of heart disorder.

Applying Decision Tree Strategies has shown useful accuracy in the diagnosis of heart Disorder. But assisting health care professionals in the diagnosis of the world's biggest killer demands higher accuracy. Our research seeks to improve diagnosis accuracy to improve health outcomes.

Decision Tree is one of the data Pitting Strategies that cannot handle continuous variables directly so the continuous attributes must be converted to discrete attributes. Couple of Decision Tree use binary discretization for continuous-valued features. Other important accuracy improving is applying reduced error pruning to Decision Tree in the diagnosis of heart disorder patients. Intuitively, more complex models might be expected to produce more accurate results, but which Strategies is best? Seeking to thoroughly investigate options for accuracy improvements in heart Disorder diagnosis this paper systematically investigates comparing multiple classifiers decision tree Strategy.

This research uses Scikit-Learn(SL).The information of UCI repository regularly introduced in a database or spreadsheet. In order to use this data for SL tool, the data sets need to be in the ARFF format (attribute-relation file format). SL tool is used for to pre-process the dataset. After reviewing all these 70 different attributes, the unimportant attributes is dropped and only the important attributes(i.e. 14 attributes in this case) is considered for analysis to yield more accurate and better results. The 14th one is basically a predicted attribute, which is referred as Class. With thorough comparison between different decisiontree algorithms within SL tool and deriving the decisions out of it, would help the system to predict the likely presence of heart Disorder in the patient and will definitely help to diagnose heart Disorder well in advance and able to cure it in right time.

III. APPROACH AND METHODOLOGY

The following objectives are set for this heart prediction system.

- The prediction system should not assume any prior knowledge about the patient records it iscomparing.
- The chosen system must be scalable to run against large database with thousands of data.

This chosen approach is implemented using SL tool. SL is an open source software tool which consistsof an accumulation of machine learning algorithms for Data Pitting undertakings. It contains apparatuses for information pre-processing, classification, regression, clustering, association rules, and visualization [4]. For testing, the classification tools and explorer mode of SL are used. Decision Tree classifiers with Cross Validation 10-fold in Test mode is considered for this study.
The following steps are performed in SL.

- Start the SL Explorer.
- Open CSV dataset file and save in ARFF format
- Click on Classify tab and select C4.5 etc (from Trees)
- from choose button.
- Select appropriate Test mode option.
- Click on Start button and result will be displayed

Data

For comparing various Decision Tree classification Strategies, Cleveland dataset from UCI repository is used, which is available at Heart disorder. The dataset has 70 attributes and 301 records. However, only 13 attributes are used for this study & testing as shown in Table 1.

Table 1: SELECTED HEART DISORDER ATTRIBUTES

Name	Type	Description
Age	Continuous	Age Age in years
Sex	Discrete	0 = female 1 = male
Cp	Discrete	Chest pain type: 1 = typical angina, 2 = atypicalangina, 3 = non-anginal pain 4 =a symptom
Trest bps	Continuous	Resting blood pressure (in mm Hg)
Chol	Continuous	Serum cholesterol in mg/dl
Fbs	Discrete	Fasting blood sugar>120 mg/dl: 1-true 0=False
Exang Continuous Maximum heart rate achieved	Discrete	Exercise induced angina: 1 = Yes 0 = No
Thalach	Continuous	Maximum heart rate achieved
Old peak ST	Continuous	Depression induced by exercise relative to rest
Slope	Discrete	The slope of the peak exercise segment : 1 = up sloping 2 = flat 3 = down sloping
Ca	Continuous	Number of major vessels colored by fluoroscopy that ranged between 0 and 3.
Thal	Discrete	3 = normal 6 = fixed defect 7= reversible defect
Class	Discrete	Diagnosis classes: 0 = No Presence 1=Least likely to have heart Disorder 2= >1 3= >2 4=More likely have heart Disorder

This paper has emphasized specifically on decision tree classifiers for heart beat prediction within SL. Decision tree was considered here among all types of Data Pitting Strategies due to these below reasons. Decision tree filters are easy to implement and easy to understand. It is a method commonly used in data Pitting. Decision tree is one of the data Pitting Strategies demonstrating extensive achievement when contrasted with other data Pitting Strategies. It is a decision support system that uses a tree-like graph decisions. Decision trees are the most powerful approaches in knowledge discovery and data Pitting. Decision trees are highly effective tools in many areas such as data and text Pitting, information extraction, machine learning, and pattern recognition. It can handle input data like Nominal, Numeric &Text. It is able to process erroneous datasets or missing values.
A Decision Tree is used to learn a classification function which concludes the value of a dependent attribute (variable) given the values of the independent (input) attributes. Tree complexity has its effect on its accuracy. Usually the tree complexity can be measured by a metrics that contains: the total number of nodes, total number of leaves, depth of tree and number of attributes used in tree construction. Tree size should be relatively small that can be controlled by using a Strategy called pruning [5].

A correlation is based on affectability, specificity and precision by genuine positive and false positive in confusion matrix. To have a reasonable correlation between these algorithms, preparing time in seconds and treesize proportion for every system is considered with 10-fold stratified cross validation. The general approach took after for Decision Tree classification for satisfying the objective is:
Training => Algorithm => Model => Testing => Evaluation

Classification Tree Algorithms UsedC4.5 algorithm:

C4.5 is an open source Java implementation of the C4.5 algorithm in the SL tool. This algorithm utilizes an avaricious method to make decision trees for classification and uses decreased-error pruning [6]. Decision tree isbuilt by exaPitting information hubs, which are utilized to assess hugeness of existing highlights.C4.5 algorithm is an extension of ID3 algorithm and possibly creates a small tree. It uses divide and conquers approach to growing decision trees [7].At every node of the tree, the algorithm picks a attribute that can further part the samples into subsets. Every leaf node speaks to a class or decision.

Basic steps to construct tree are

- Check whether all cases belongs to same class, then the tree is a leaf and is labeled with that class.
- For each attribute, calculate the information and information gain.
- Find the best splitting attribute (depending upon current selection criterion).

C4.5 with Reduced error Pruning:

Pruning is very important Strategy to be used in tree creation because of outliers. It also addresses over fitting. Datasets may contain little subsets of instances that are not well defined. To classify them correctly, pruning canbe used. Separate and Conquer rule learning algorithm is basis to prune any tree. This rule learning scheme starts with an empty set of rules and the full set of training instances. Reduced-error pruning is one of such separate and conquer rule learning scheme. There are two types of pruning i.e.

- Post pruning (performed after creation of tree)
- Online pruning (performed during creation of tree).

After extracting the decision tree rules, reduced error pruning was used to prune the extracted decision rules. Applying reduced error Pruning provides more compact decisionrules and reduces the number of extracted rules.

The run-time complexity of C4.5 algorithm matches to the tree depth which is linked to tree size and number of examples. So their greatest disadvantage is size of C4.5 trees, which increases linearly with the number of examples. C4.5 rules slow for large and noisy datasets. Space complexity is very large as we have to store the values repeatedly in arrays.

Logistic Model Tree Algorithm:

Logistic Model Tree is the classifier for building logistic model trees, which consist of a decision tree structure with logistic regression function at the leaves. The algorithm can oversee parallel and multi-class target variables, numeric and nominal attributes and missing qualities [8]. A combination of learners that rely on simple regression models if only little and/or noisy data is available and add a more complex tree structure if there is enough data to warrant such a structure. LMT uses cost-complexity pruning. This algorithm is significantly slower than the other algorithms.

As in decision tree, the tested attributes is associated with every inner node. The attributes with k values, the node has k child nodes for nominal attributes and depending on the value of the attribute, the instances are sorted down. For the attributes of numeric, the node has two child nodes and comparing the attributes of tested value to a threshold (the instances are sorted down based on threshold [9].

Logistic Model Trees have been demonstrated to be extremely exact furthermore, smaller classifiers in diverse examination regions. Their most noteworthy weakness is the computational unpredictability of inciting the logistic regression models in the tree. Anyway the prediction of a model is acquired by sorting it down to a leaf what’s more, utilizing the logistic prediction model connected with that leaf. A solitary logistic model is less demanding to translate than C4.5 trees. However fabricating LMT’ stake longer time. It can likewise be demonstrated that trees produced by LMT are much littler than those produced by C4.5.

To construct a logistic model tree by developing a standard classification tree, building logistic regression models for all node, pruning a percentage of the sub-trees utilizing a pruning model, and combining the logistic models along a way into a solitary model in some manner is performed.

The pruning plan uses cross-validation to get more steady pruning results. In spite of the fact that this expanded the computational multifaceted nature, it brought about littler and for the most part more accurate trees. These thoughts lead to the following algorithm for developing logistic model trees:

This gives the logistic regression model at the base of the tree.

Like other tree impelling systems, LMT does not oblige any tuning of parameters. LMT produces a solitary tree containing double parts on numeric properties, multi-route parts on ostensible ones and logistic regression models at the leaves, and the algorithm guarantees that just applicable attributes are incorporated in the last.

Gradient Boosting algorithm:

Gradient Boosting is an ensemble classifier that consists of many decision trees. The output of the classes is represented by individual trees. The tree is constructed using algorithm as discussed.

Let N be the number of training classes and M be the number of variables in classifier.

- The input variable m is used to determine the node of the tree. Note that m<M.
- Choosing n times of training sets with the replacement of all available training cases N by predictingthe classes, estimate the error of the tree.
- Choose m variable randomly for each node of the tree and calculate the best split.
- At last the tree is fully grown and it is not pruned. The tree is pushed down for predicting a new sample. When the terminal node ends up, the label is assigned the training sample. This procedure isiterated over all trees and it is reported as random forest prediction.

Multi-classifiers are the aftereffect of joining a few individual classifiers. Troupes of classifiers towards expanding the execution have been presented. [5].

Random Forest (RF) is one of the case of such procedures. RF as a multi classifier formed by choice trees whereeach tree ht had been created from the set of information preparing and a vector θ t of arbitrary numbers indistinguishably disseminated and free from the vectors. Vectors θ1, θ 2 ,.., θ t-1 used to create the classifiers h1; h2; :::; ht-1 . Every decision tree is manufactured from random subset of the preparation dataset. It utilized a random vector that is produced from some altered likelihood dissemination, where the likelihood circulation is shifted to centre samples that are difficult to arrange. A Random vector can be joined into the tree-becoming process from various perspectives. The leaf hubs of each one tree are named by evaluations of the back dissemination over the information class names. Every interior hub contains a test that best parts the space of data to be arranged. Another, concealed occasion is ordered by sending it down every tree and conglomerating the arrived at
leaf appropriations.

There are three methodologies for Random Forest, for example, Forest-RI(Random Input choice) and Forest-RC(Random blend) and blended of Forest-RI and Forest-RC.

The Random Forest procedure has some desirable qualities, for example

- It is not difficult to utilize, basic and effortlessly parallelized.
- It doesnt oblige models or parameters to choose aside from the quantity of indicators to pick atarbitrary at every node.

- It runs effectively on extensive databases; it is moderately strong to anomalies and commotion.
- It can deal with a huge number of information variables without variable deletion; it gives evaluationsof what variables are important in classification.
- It has a successful system for assessing missing information and keeps up accuracy when a vast extentof the data are missing, it has methods for adjusting error in class populace unequal data sets.

Evaluation of Classification Algorithms

The execution of Classification algorithm is generally analyzed by assessing the affectability, specificity, and accuracy of the classification. The sensitivity is proportion of positive instances that are correctly classified as positive (i.e. the proportion of patients known to have the Disorder, who test positive for it).The specificity is the proportion of negative instances that are correctly classified as negative (i.e. the proportion of patients known notto have the disorder, who test negative for it).The accuracy is the proportion of instances that are correctly classified. To quantify the dependability of the execution of proposed model, the information is isolated into preparing and testing data with 10-fold stratified cross validation these values are defined as,

Sensitivity = True Positive/(True Positive + False Negative) Specificity = True Negative/(True Negative +False Positive) Accuracy = (True Positive + True Negative) / (True
Positive + True Negative+ False Negative+ False Positive)

All measures can be ascertained focused around four qualities specifically True Positive, False Positive, False Negative, and False Positive where,

- True Positive (TP) is various effectively classified that an instances positive.
- False Positive (FP) is a number of incorrectly classified that an instance is positive.
- False Negative (FN) is a number of incorrectly classified that an instance is negative.
- True Negative (TN) is a number of correctly classified that an instance is negative.
- F-Measure is a way of combining recall and precision scores into a single measure of performance.
- Recall is the ratio of relevant instances found in the search result to the total of all relevant instances.
- Precision is the proportion of relevant instances in the results returned.
- Receiver Operating Characteristics (ROC) Area is a traditional to plot this same information in anormalized form with 1-false negative rate plotted against the false positive rate.
- For every algorithm, the test choice cross-validation were utilized. As opposed to holding a part fortesting, the cross-validation repeats the training and testing process a few times with random forest

samples. The standard for this is 10-fold cross-validation. The data is partitioned arbitrarily into 10 sections in which the classes are represented in the same proportions asin the full dataset(stratification).Each one section is held out thus and the algorithm is trained on the nine remaining parts; then its error rate is computed on the holdout set. At long last, the 10 error estimates are found the middle value of to yield an overall error estimate. For C4.5 and Random Forest, all the tests were run with ten different random seeds. Choosing the different random seeds is carried outto normal out statistical variations.

IV. RESULTS

The decision tree classification was performed using C4.5algorithm, logistic model trees algorithm and Gradient Boosting algorithm on UCI repository. The experimental results is under the framework of SL 3.6.10. All experiment were performed on Core I3 with 2.4GHz CPU and 4GB RAM. The exploratory results are divided into a few sub thing for less demanding examination and assessment.

A. C4.5 with Reduced Error pruning Algorithm

The sample of C4.5 algorithm is connected on UCI repository and the confusion matrix is produced for class having 5 conceivable qualities are demonstrated in Fig 2. The confusion matrix is imperative viewpoint tobe considered. From this matrix, classifications can be made. The results of the C4.5 algorithm are indicated in Table 2.

———Confusion Matrix————

a	b	c	d	e	
146	8	4	6	0	|a = 0
31	9	9	6	0	|b = 1
9	5	13	8	1	|c = 2
11	7	10	4	3	|d = 3
2	5	3	3	0	|e = 4

TABLE II. CLASSIFICATION RESULT FOR C4.5

	Train Error	Test Error
C4.5	0.1425484	0.1864215

C4.5 model sacrifices error rate for a clearer decision process and as a result the error is acceptable.

B. Logistic Model Tree Algorithm

The example of logistic model trees algorithm is connected on UCI repository and the confusion matrix is produced for class gender having two conceivable qualities are indicated in Fig 4. The results of LMT algorithm are demonstrated in Table 3.

————Confusion Matrix————

a	b	c	d	e	
148	12	2	1	1	|a = 0
31	10	6	8	0	|b = 1
8	12	4	10	2	|c = 2
4	11	11	7	2	|d = 3
0	5	2	6	0	| e = 4

TABLE IIICLASSIFICATION RESULT FOR LOGISTIC MODEL TREEALGORITHM

	Train Error	Test Error
Logistic Model Tree Algorithm	0.1156716	0.137931

C. Gradient Boosting algorithm

The example of Gradient Boosting algorithm is connected on UCI repository and the confusion matrix is created forclass having 5 qualities are demonstrated in Fig 5. The result ofthe Gradient Boosting algorithm are demonstrated inTable 4.

————Confusion Matrix————

a	b	c	d	e	
152	7	2	3	0	|a = 0
34	4	10	5	2	|b = 1
10	11	7	7	1	|c = 2
5	11	12	5	2	|d = 3
1	5	2	3	2	| e = 4

TABLE IV. CLASSIFICATION RESULT FOR GRADIENT BOOSTING ALGORITHM

	Train Error	Test Error
Gradient Boosting Algorithm	0	0.3

As is mentioned above, we use random forest to choose key variables to project our data on. Since the model isflexible, the0 train error is explainable while the 0.2 test error is acceptable.

As is mentioned above, we use random forest to choose key variables to project our data on. Since the model isflexible, the0 train error is explainable while the 0.2 test error is acceptable.

V. COMPARISON OF METHODOLOGIES

TABLE V. COMPARISON OF DIFFERENT ALGORITHM RESULTS

	C4.5	Logistic Model Tree Algorithm	Gradient Boosting Algorithm
Train Error	0.1425484	0.115678	0
Test Error	0.1864215	0.137931	0.3

When comparing the results with LMT and Gradient Boosting algorithm, C4.5 algorithm achieved higher sensitivity and accuracy while LMT achieved higher specificity than C4.5 and Gradient Boosting algorithm. So overall from Table 10 and Table11, it is concluded that C4.5 (with Reduced Error Pruning) has got the best overall performance.

Also, C4.5 algorithm utilization reduced-error pruning form less number of trees. The LMT algorithm manufactures the littlest trees. This could show that cost-many-sided quality pruning prunes down to littler trees than decreased lapse pruning, yet it additionally demonstrate that the LMT algorithm does not have to assemble huge trees to group the information. The LMT algorithm appears to perform better on data sets with numerous numerical attributes, while for good execution for3 algorithm, the data sets with couple of numerical qualities gave a superior execution. We can see from the outcomes thatC4.5 is the best classification tree algorithm among the three with pruning system.

VI. CONCLUSION

By analyzing the experimental results, it is concluded thatC4.5 tree Strategy turned out to be best classifier for heart disorder prediction because it contains more accuracy and least total time to build. We can clearly see that highest accuracy belongs to C4.5 algorithm with reduced error pruning followed by LMT and Gradient Boosting algorithm respectively. Also observed that applying reduced error pruning to C4.5 results in higher performance while without pruning, it results in lower Performance. The best algorithm C4.5 based on UCI data has the highest accuracy i.e. 59.47% and the total time to build model is 0.04 seconds while LMT algorithm has the lowest accuracy i.e 57.67% and the total time to build model is 0.39seconds.

In conclusion, as identified through the literature review, we believe only a marginal success is achieved in the creation of predictive model for heart Disorder patients and hence there is a need for combinational and more complex models to increase the accuracy of predicting the early onset of heart disorder.

VII. FUTURE WORK

There are many possible improvements that could be explored to improve the scalability and accuracy ofthis prediction system. Due to time limitation, the following research/work needs to be performed in the future.

- Like to make use of testing different discretization Strategies, multiple classifiers Voting Strategy and different Decision tree types like information gain, gain ratio and Gini index. Eg. Experiment need to perform on use of Equal Frequency Discretization Gain Ratio Decision Trees by applying nine Votingscheme in order to enhance the accuracy and performance of diagnosis of heart Disorder.
- This paper proposes a framework using combinations of support vector machines, logistic regression and decision trees to arrive at an accurate prediction of heart disorder. Further work involves development of system using the mentioned methodology to be use for checking the imbalance with other data Pitting models.
- Like to explore different rules such as Association, Clustering, K-means etc for better efficiency and ease of simplicity.

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