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Big data mining using supervised machine learning approaches for Hadoop with Weka distribution

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Abstract

Data is increasing very rapidly with the increase in technologies. To process this data and performing accurate mining to yield conclusions is a challenge. This domain to process and mining this big data is termed as big data mining. To store and process big data many open source tools were proposed and are present in Apache foundation. Apache Hadoop is the most widely used tool for big data processing. Apache Hadoop consists of two main components namely Hadoop distributed file system (HDFS) and map/reduce. HDFS is used to store the data in distributed form and map/reduce is used to process this distributed spread data. In the past many data mining and classification approaches have been proposed for big data in which for implementing machine learning no standard tool is used. And no generic topology for data flow is proposed to implement such model. And accuracy of classification for raw dataset is also poor. In this dissertation to perform big data mining Apache Hadoop and Weka is used. Weka is an open source tool for machine learning proposed by Waikato university of New Zealand. Here in this work Apache Hadoop is connected with Weka. Using this combination big data is stored on HDFS and processed using Weka using Knowledge flow of Weka. Knowledge flow provides a means to construct topologies using them HDFS components can be used to provide data to machine learning algorithms provided in Weka. In this work supervised machine learning approaches which include Naïve Bayes, Support vector machine, J48 are used for big data mining. The accuracy of these approaches is compared for raw data and normalized data given to the same topology. It is found proposed approach for big data mining yields better results as compared to the reference approach.

Keywords: Hadoop, Weka, Supervised machine learning.

I. INTRODUCTION

Big data is defined as large quantity of data which have need of new technologies and architecture to make possible to extort value from it by capturing and analysis process. New sources of big data include location specific data whichhas arrived from traffic management and from the tracking of personal devices such as Smartphone's. Big data has come into view because we are living inthe world which makes mounting use of data intensive technologies. Due to such large size of data it becomes very difficult to achieve effective analysis using existingtraditional techniques.

Since Big data is new upcoming technology in the market which can bring the huge benefits to the business organizations, it becomes necessary various challenges and issues associated in bringing and adopting to this technology are need to be understand. Big data concept means a dataset which continues grew so much that it becomes difficult to manage it using existing database models and tools. So at last Big data is data that exceeds the processing capacity of conventional database systems. The data is huge sized, moves too fast, or doesn't fit the structures of our database architectures. To gain value from this data, you must choose a substitute way to process it.

What are the problems?

There are many problems to handle big data like storage, processing etc.

a) Data integration – The structure of merging data is not so easy task with a reasonable cost.
b) Data volume – The ability to process the volume at a suitable rate so that the information is available to result analysers when they need it.
c) Skills availability –There are shortage of people. Who have the proficiency to bring all data mutually, analyse it and publish the results.
d) Solution cost –To ensure a positive ROI on a Big Data project; it is crucial to reduce the cost of the solutions.

What are the solutions?

Big data is very difficult to process and store. Mainly Hadoop is used to process the big data. Hadoop used HDFS to store the data efficiently and MapReduce framework for processing the data. MPI is also used to process the big data.

Big data define as the pool ofinformation's that is unable to handled or analysed using an existing or traditional data mining techniques or the tools. Constantly increase of computational power has brought tremendous flow of data in the past two decades. This remarkable flow of data is called as "big data" it cannot be deal with the aid of existing tools or any other procedure and this is more comprehensible to computers.

The size of BigData range from petabytes (PB) to Exabyte's (EB) or to zettabytes (ZB).The BigData created from the client server interaction which is known as customer call records or transaction histories etc.

Big Data system is getting lot of importance now a day from organisations to handle those data as well as using them in business growth.Some Big data examples such as data from Finance, Internet, Mobile device, Radio – Frequency Identification (RFID), Science, Sensor and Streaming are the top most seven data drivers.

BIG DATA HANDLING TOOLS

Hadoop

Hadoop is an Apache open source framework which supports java and also java code for implementation that allows distributed processing of large records across clusters of computers using easy programming models. The Hadoop framework application moving in an atmosphere that offer distributed storage and estimation across clusters of computers. Hadoop is made for level up from single server to thousands of equipment, each offering local calculation and storage [12].

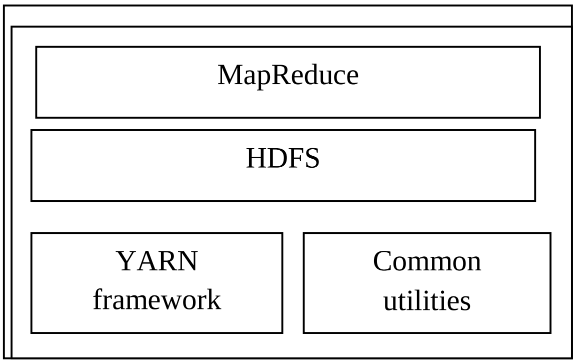


Figure: Architecture of Hadoop

Hadoop mainly consist of 2 components.

MapReduce

MapReduce applications can precede multiple terabytes of data in parallel on large clusters in a fault-tolerant manner and reliable. MapReduce is an estimation paradigm in which a function is divided into self-reliant units of work. Each of these units of process can be issued on any node in the cluster.

A MapReduce job divides the input data into several chunks that are processed by map jobs in similar way. The framework arranges the map outputs, which are then input to reduce tasks. Task's inputs and outputs are lain up in the file system. The

MapReduce framework and the HDFS (Hadoop Distributed File System) are classically on the same set of nodes, which allow the structure to schedule tasks on nodes that hold data [13].

The MapReduce framework having a single key Job Tracker and one secondary Task Tracker per node. The main node plan for job section tasks, re-executes, and monitors tasks abortive tasks. The secondary node processes as directed by the primary node. MapReduce have two phases

The map phase

The map section is the 1st a part of the data process sequence inside the MapReduce framework. Map functions serve as worker nodes which will process many smaller snippets of the whole data set. The MapReduce framework is liable for dividing the data set input into smaller chunks, and feeding them to a corresponding map function. after you write a map function, there's no got to incorporate logic to change the function to form multiple maps which will use the distributed computing design of Hadoop. These functions are oblivious to each data volume and also the cluster during which they're operative. As such, they'll be used unchanged for each little and huge data sets (which is commonest for those that are victimization Hadoop) [11].

The reduce phase

As with the map function, developers additionally should produce a reduce function. The key/value pairs from map outputs should correspond to the acceptable reducer partition such the ultimate results are aggregates of the suitably corresponding data. once the shuffle method is completed and therefore the reducer copies all of the map task outputs, the reducers will get into what's called a merge method. throughout this a part of the reduce part, all map outputs will be incorporate along to keep up their type ordering that's established throughout the map part. once the ultimate merge is complete then this reduce task of consolidating results for each key at intervals the incorporate output (and the ultimate result set), is written to the disk on the HDFS [11].

Data mining is that the extraction of knowledge from great deal of observational data sets, to seek out surprising relationship and pattern hidden in data, summarize the data in novel ways that during which to make it comprehendible and useful to the data users [1,2]. Web usage mining is that the appliance of data mining technique to automatically discover and extract useful information from a particular pc [2,3]. There are many major data processing techniques

Classification: Classification may be a one in all the classical data processing techniques that is predicated on machine learning. Essentially classification is applied to classify every item during a set of information into one in all predefined set of categories. Classification technique makes use of many mathematical techniques like linear programming, call trees, neural network and statistics.

Clustering: It is an unsupervised data mining technique that makes effective and helpful clusters, which useful and meaningful also. Cluster of objects which have similar characteristics using different clustering technique. The clustering technique specifies the classes and put objects in each class to whom they belong, while in the classification techniques, objects are assigned according to predefined classes.

Association: Association is one of the well-known data mining technique. In association, a pattern is found out based on a relationship between items in the same transaction. That’s why association technique is also known as relation technique.

Prediction: The prediction, as it name suggest, is one of a data mining techniques that seeks to discover relationship between independent variables as well as relationship between dependent and independent variables.

Sequential Patterns: Sequential patterns analysis is one of data mining technique that tries to find or identify similar patterns, trends or regular events in transaction data over a business period.

Decision trees: Decision tree is one of the most frequently used data mining techniques because its model is easy to interpret for users. In decision tree technique, structure of decision tree is such that the very first point is root, which is a simple condition or question that has multiple answers. Each answer then further leads us to a set of conditions or questions that help us found out the data on the basis of which we can make the final decision depending on it.

II. MACHINE LEARNING

In this section past many approaches for data classification have been proposed. Which includes Naïve bayes, Support vector machine, Random Forest, Decision tree, PART and all these methods are compared in table 1. Which consists of related work done in the past.

Machine learning may be a kind of AI (AI) that gives computers with the power to learn while not being expressly programmed. Machine learning focuses on the event of computer programs which will change once exposed to new information.

Machine learning tasks are generally classified into 3 broad classes, looking on the character of the learning "signal" or "feedback" offered to a learning system. These are[14]

- Supervised learning: the computer is bestowed with example inputs and their desired outputs, given by a "teacher", and also the goal is to learn a general rule that maps inputs to outputs.

- Unsupervised learning: No labels are given to the learning rule, going away it on its own to search out structure in its input. unsupervised learning will be a goal in itself (discovering hidden patterns in data) or a way towards an finish (feature learning).
- Reinforcement learning: A computer program interacts with a dynamic setting within which it should perform a precise goal (such as driving a vehicle or taking part in a game against an opponent [4]). The program is provided feedback in terms of rewards and punishments because it navigates its drawback area.

Bayes Classifier— It originates from previous works in pattern recognition and is joined to the family of probabilistic Graphical Models. For every category, a probabilistic outline is hold on. The chance of every attribute and also the probability of the category are keep during this outline. The graphical models are wont to show data concerning domains that are unsure in nature. Within the graphs [15], nodes depict variables and also the edges that connect corresponding random variable nodes are appointed weights that represent probabilistic dependencies. On encountering a brand new instance, the rule simply creates an update of the chances keep in conjunction with the particular category [12]. The sequence of training instances and also the existence of classification errors don't have any role during this method. So primarily it's to predict the category looking on the worth of the members of the category. This class consists of thirteen classifiers, however solely three of these are compatible with our chosen dataset.

Function classifier— It deploys the concept of regression and neural network. input data is mapped to the output. It employs the repetitive parameter estimation theme. Overall there are eighteen classifiers beneath this class, out of that only 2 are compatible with our dataset.

The main Objectives of this analysis includes:

A. huge data analysis using Apache Hadoop.
B. correct classification of this huge data using supervised machine learning.
C. Apache Hadoop and weka are going to be used for that huge information classification.
D. improvement in accuracy of classification over this dataset using correct discretization technique.
E. to possess high accuracy, True positive rate and preciseness and low false positive rate.

To evaluate the performance of the supervised machine learning approaches four analysis metrics are thought of. These are:

A. Accuracy – Accuracy will be outlined as properly classified instances divided by the full variety of instances in dataset.

B. preciseness - preciseness could be a measurement of what number of the properly classified instances that are relevant, i.e. it's a extremely specific metric that's best discovered in relevance different metrics like recall and accuracy.

C. True positive rate (TP) - variety of examples predicted positive that are literally positive.

D. False Positive rate (FP) - variety of examples foreseen positive that are literally negative.

Table 1

COMPARISON OF CLASSIFIERS			
CLASSIFIER	**CATEGORY**	**DESCRIPTION**	**REFERENCE**
Naive Bayes	Probability based classifier	This classifier is derived from Naïve Bayes conditional probability. This is suitable for datasets having less number of attributes.	[5]
Bayesian Net	Probability based classifier	Network of nodes based on Naïve Bayes classifier is termed as Bayesian Net. This can be applied to larger datasets as compared to Naïve Bayes.	[9]
Decision Tree (J48)	Tree based approach	It is enhanced version of C 4.5 algorithm and used ID3.	[15]
Random Forest	Tree based approach	It is also a decision tree based approach but have more accuracy as compared to J48.	[15]
Random Tree	Tree based approach	It generates a tree by randomly selecting branches	[15]

		from a possible set of trees.	
REPTree	Tree based approach	It uses gain and variance for prediction.	[12]
Support vector machine	Function based approach	It is a linear classification technique in which for every attribute a graph is plotted and a straight line is found such that it separates attribute instances into appropriate classes.	[31]
Multi layer perceptron	Neural Network	This classifier is based on Mc Colloch pit neuron having three layers namely input layer, hidden layer and output layer.	[8]

VI. PROPOSED WORK

In this paper a big data mining approach based on supervised machine learning is proposed. To handle big data Apache Hadoop is used for storage and processing. And to impart machine learning for big data mining and analysis Weka is used. Apache Hadoop and Weka are configured together using DistributedWekaHadoop package.

To enhance the accuracy of the approaches dataset is normalized using a method called supervised attribute level discretization.

A. DISCRETIZATION

Many Machine Learning (ML) algorithms are known to provide higher models by discretizing continuous attributes [14]. Naive bayes (NB) classifier needs the estimation of possibilities and also the continuous instructive attributes aren't very easy to handle, as they usually take too many various values for an instantaneous estimation of frequencies. to avoid this, a standard distribution of the continual values are often assumed, however this hypothesis isn't perpetually realistic. a similar development leads rules extraction techniques to make poorer sets of rules. DT algorithms perform a variety method of nominal attributes and can't handle continuous ones directly. As result, an outsized variety of ml and applied math techniques will solely be applied to information sets composed entirely of nominal variables. However, an awfully giant proportion of real information sets embrace continuous variables: that's variables measured at the interval or magnitude relation level. One answer to the present drawback is to partition numeric variables into variety of sub-ranges and treat every such sub-range as a class. This method of partitioning continuous variables into classes is sometimes termed discretization. Sadly, the quantity of how to discretize a continual attribute is infinite. Discretization could be a potential long bottleneck, since the variety of attainable discretization is exponential within the number of interval threshold candidates at intervals the domain [14]. The goal of discretization is to seek out a collection of cut points to partition the range into a little variety of intervals that have sensible category coherence, that is sometimes measured by an analysis operate. Additionally to the maximization of reciprocality between category labels and attribute values, a perfect discretization technique ought to have a secondary goal to reduce the quantity of intervals while not important loss of class attribute mutual dependence. Discretization is sometimes performed before the learning method and it are often broken into 2 tasks. The primary task is to seek out the quantity of separate intervals. solely many discretization algorithms perform this; usually, the user should specify the quantity of intervals or give a heuristic. The second task is to seek out the width, or the boundaries, of the intervals given the vary of values of a continual attribute. Usually, in discretization method, once sorting information in ascending or drizzling order with relation to the variable to be discretized, landmarks should be chosen among the complete dataset. In general, the algorithmic rule for selecting landmarks are often either topdown, that starts with an empty list of landmarks and splits intervals, or bottom-up, that starts with the entire list of all the values as landmarks and merges intervals. In each cases there's a stopping criterion, that specifies once to prevent the discretization method. Researchers within the ml community have introduced several discretization algorithms. Most of those algorithms perform an repetitive greedy heuristic search within the space of candidate discretizations, exploitation differing kinds of rating functions for evaluating a discretization. A recent outline of assorted varieties of discretization algorithms are usually found in [28].

The term “cut-point” refers to a true value inside the range of continuous values that divides the range into 2 intervals, one interval is a smaller amount than or equal to the cutpoint and therefore the alternative interval is bigger than the cut-point. for instance, an eternal interval [a, b] is divided into [a, c] and (c, b], wherever the worth c may be a cut-point. Cut-point is additionally called split-point. The term “arity” within the discretization context suggests that the amount of intervals or partitions. Before discretization of an eternal feature, arity may be set to k—the range of partitions within the continuous options. the most range of cut-points is $k - 1$. Discretization method reduces the arity however there's a trade-off between arity and its impact on the accuracy. A typical discretization method loosely consists of 4 steps: (1) sorting the continual values of the feature to be discretized, (2) evaluating a cut-point for ripping or adjacent intervals for merging, (3) according to some criterion, ripping or merging intervals of continuous value, and (4) finally stopping at some purpose. once sorting, following step within the discretization method is to seek out the simplest “cut-point” to separate a spread of continuous values or the simplest try of adjacent intervals to merge. One typical analysis perform is to see the correlation of a split or a merge with the category label. There ar various analysis functions found within the literature like entropy measures and statistical measures (more details within the following sections). A stopping criterion specifies once to prevent the discretization method. it's typically ruled by a trade-off between lower arity with a far better understanding however less accuracy and a higher arity with a poorer understanding however higher accuracy. the amount of inconsistencies (inconsistency is outlined later) caused by discretization—it shouldn't be abundant more than the amount of inconsistencies of the first data before discretization. 2 instances are thought of inconsistent if they're identical in their attribute values aside from their category labels. Generally, the discretization ways may be classified as: (1) supervised or unsupervised, (2) direct or progressive, (3) world or native, (4) static or dynamic, (5) Top down or bottom-up. We have a tendency to distinct these classes within the following section.

Feature generation is a three-step process: the first step is a pre-processing stage in which the speech utterance has to be normalized and eventually noise-filtered or smoothed. The second and third step correspond to the extraction of local and global features, as can be seen in Figure 4.5. Features can indeed be different in nature, depending on whether they capture local or global information. A speech utterance is typically segmented into small blocks in which local computations are performed (ex: energy, pitch of the window). Global features refer to all the computations performed with local features; they use information from the whole utterance, whereas local features are calculated for each block independently. The easiest ones are statistical overall values such as mean, maximum, minimum, median, variance, range or inter quartile range. More complex features include some in-between operations like the following:

- curve simplification in linear segments like slopes or constant levels (ex: stylization process of the pitch, macroscopic variations of the energy, etc...)
- combination of multiple local features (for example, mean energy of the voiced segments)
- histogram derivation (for musical features)

Feature extraction is generally considered as a process of mapping the original features (measurements) into more effective features. If the mapping is linear, the mapping function is well defined and the task is simply to find the coefficients of a linear function so as to maximize or minimize a criterion. To determine these mapping coefficients, we can use the linear algebra techniques for simple criteria and we can apply optimization techniques for complex criteria. Unfortunately, in many applications of pattern recognition, there are salient features which are non-linear mappings of original measurements. Since there is no general theory to generate such nonlinear functions systematically and find the optimum one, extraction of features becomes problem-specific. In large multi-dimensional data sets, it is usually advantageous to discover some structure from the data. Thus we assume that the data are governed by a certain number of underlying parameters (features). The minimum number of features required to account for the observed properties of the data is called intrinsic dimensionality of the data set.

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables.

STEP OF HADOOP WEKA CONNECTIVITY FOR BIG DATA MINING

Step 1: Start Hadoop daemons ,the Apache Hadoop startup daemons.

The daemons that are running on standalone cluster. It shows NameNode, DataNode, ResourceManager and NodeManager.

Step 2: Start Weka

A terminal in which command to start Weka jar is illustrated along with the Weka startup GUI.

Step 3: Weka package manager for Hadoop connectivity

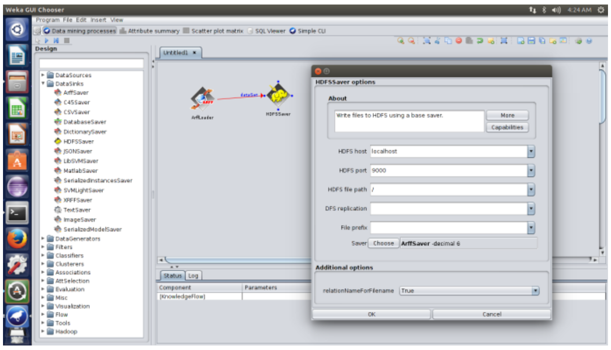
The Weka package manager to install Weka Hadoop distribution for Weka Hadoop connectivity.

Step 4: Weka Knowledge flow Hadoop machine learning execution.

A. *Putting data on HDFS from local file system.*

The Knowledge flow from Weka to load data from ARFF loader to HDFS saver.

The figure below shows the Apache Hadoop and Weka connectivity using Knowledge flow in Weka.



HDFSSaver options

About

Write files to HDFS using a base saver.

HDFS host: localhost

HDFS port: 9000

HDFS file path: /

DFS replication:

File prefix:

Saver: ArffSaver -decimal 6

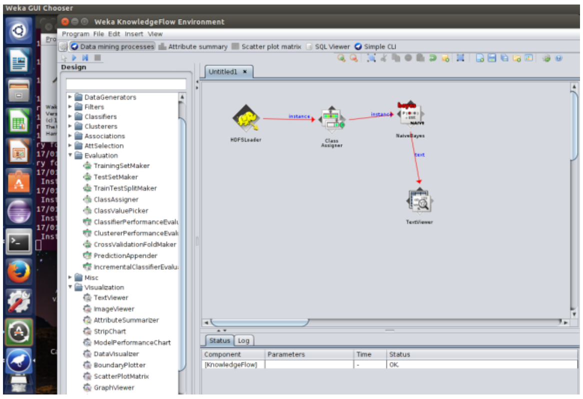
Additional options

relationNameForFilename: True

Component	Parameters
[KnowledgeFlow]	

Figure 1. Screenshot showing HDFS loader properties

Figure shows the complete Knowledge flow to load the data from HDFS and class assigner to pick the class from dataset and appropriate classifier which is Naïve Bayes here and Text Viewer to view the results of classification.



Component	Parameters	Time	Status
[KnowledgeFlow]		-	OK

Figure 2. Screenshot showing data processing

IV. RESULTS

A tool that is employed for each data processing and Machine Learning is weka. it was 1st enforced by The University of Waikato, New zealand, in 1997 [4]. It's a group of a massive range of Machine Learning and data processing algorithms. One drawback of this software package is that it supports data files solely written in ARFF (attribute relation file format) and CSV (comma separated values) format. Initially, it absolutely was written in C however later on it had been rewritten in JAVA language. It contains of a graphical user interface interface for interaction with the data files. It possesses forty nine knowledge pre-processing tools, fifteen attribute evaluators, seventy six classification algorithms and ten search algorithms for the aim of feature selection. It contains of 3 differing types of graphical user interfaces (GUI's):- "The Explorer", "The Experimenter", and "The knowledge Flow". Weka provides the chance for the development of any new Machine Learning algorithmic rule. It contains visualization tools and a collection of panels to execute the specified tasks.

1.NAIVE BAYES

The table below shows the accuracy, precision, false positive rate and true positive rate for the Naïve Bayes classifier applied. The table is shown for dataset which is not normalized.

BEFORE NORMALIZATION			
TP RATE	FP RATE	PRICISION	ACCURACY
0.862	0.095	0.893	86.17%

The table below shows the accuracy, precision, false positive rate and true positive rate for the Naïve Bayes classifier applied. The table is shown for dataset which is normalized. It is clear from the table that accuracy has increased considerably.

AFTER NORMALIZATION			
TP RATE	FP RATE	PRICISION	ACCURACY
0.980	0.020	0.981	98%

2) J48

The table below shows the accuracy, precision, false positive rate and true positive rate for the J48 classifier applied. The table is shown for dataset which is not normalized.

BEFORE NORMALIZATION			
TP RATE	FP RATE	PRICISION	ACCURACY
1	0	1	100%

The table below shows the accuracy, precision, false positive rate and true positive rate for the J48 classifier applied. The table is shown for dataset which is normalized.

It is clear from the table that accuracy has increased considerably.

AFTER NORMALIZATION			
TP RATE	FP RATE	PRICISION	ACCURACY
1	0	1	100%

3) SVM

The table below shows the accuracy, precision, false positive rate and true positive rate for the SVM classifier applied. The table is shown for dataset which is not normalized.

BEFORE NORMALIZATION			
TP RATE	FP RATE	PRICISION	ACCURACY
0.748	0.748	0.560	74.83%
AFTER NORMALIZATION			
TP RATE	FP RATE	PRICISION	ACCURACY
0.987	0.009	0.987	98.67%

The table above shows the accuracy, precision, false positive rate and true positive rate for the SVM classifier applied. The table is shown for dataset which is normalized. It is clear from the table that accuracy has increased considerably.

The graph below shows the comparison of accuracies of all the classifiers used in the dissertation for the dataset which is not normalized.

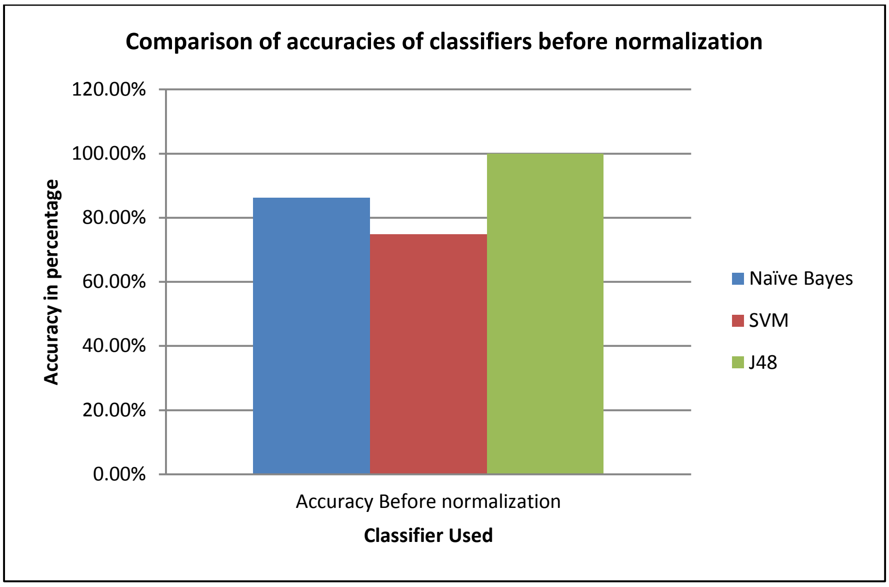


Figure 3: Comparision of accuracies without normalization.

The graph bleow shows the comparison of accuracies of all the classifiers used in the dissertation for the dataset which is normalized.

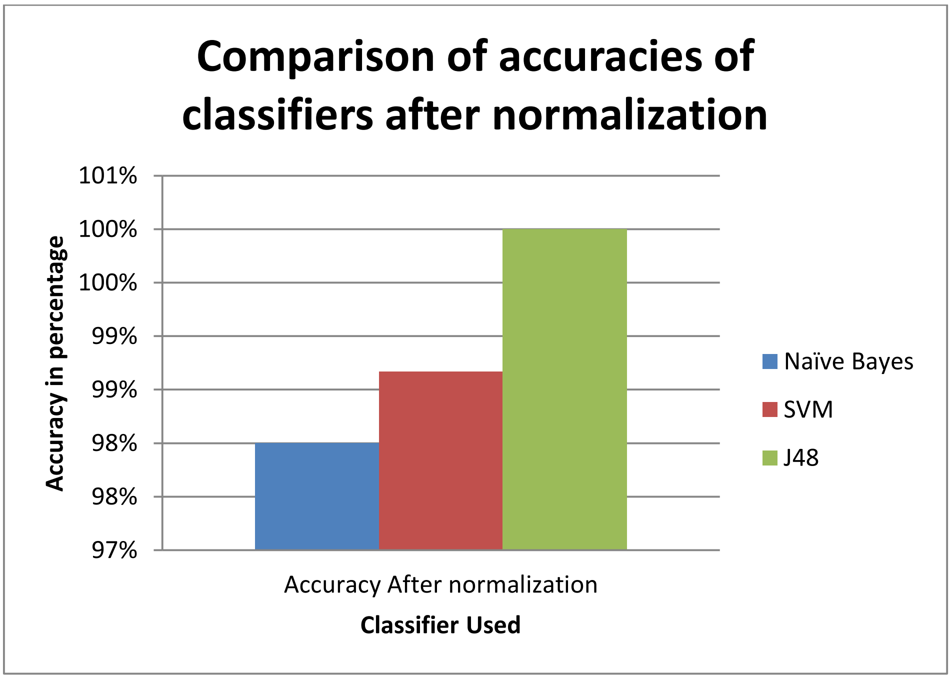


Figure 4. Comparision of accuracies after normalization

V. CONCLUSION

In this era of data analytics, machine learning has emerged as a vital domain of research. For classification and clustering of datasets different machine learning techniques have been Machine learning algorithms can be broadly classified as supervised and unsupervised approaches. In this dissertation supervised machine learning techniques which include Naïve Bayes, Support vector machine and J48 have been studied. But the objective of research is to increase the accuracy of classification for the raw datasets. Here normalization has been applied on the raw dataset and it is found that accuracy has been improved after supervised discretization of dataset.

In future the proposed scheme can be tested for other datasets also. And normalization and feature selection approaches can be studied and suitable can be applied.

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