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Comparative Analysis of Data mining Methods to Analyze Personal Loans Using Decision Tree and Naïve Bayes Classifier

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Abstract: The data mining classification techniques and analysis can enable banks to move precisely classify consumers into various credit risk group. Knowing what risk group a consumer falls into would allows a bank to fine tune its lending policies by recognizing high risk groups of consumers to whom loans should not be issued, and identifying safer loans that should be issued on terms commensurate with the risk of default. So research en for classification and prediction of loan grants. The attributes are determined that have greatest effect in the loan grants. For this purpose C4.5, CART and Naïve Bayes are compared and analyzed in this research. This concludes that a bank should not only target the rich customers for granting loan but it should assess the other attributes of a customer as well which play a very important part in credit granting decisions and predicting the loan defaulters.

Index Terms: C4.5, CART, Naïve Bayes, Type II error.

1. Introduction

The decision-making of accepting or rejecting a client's credit by banks is commonly executed via judgmental techniques and credit scoring models. Most banks and financial institutions use the judgmental approach which is based on the 3C's, 4C's or 5C's which are character, capital, collateral, capacity and condition. However, to improve assessment of credit applicants, banks can use credit scoring or predictive models to classify the applicants[1].A bank loans officer needs analysis of his/her data in order to learn which loan applicants are safe" and which are risky" for the bank. To understand that information, classification is a form of data analysis that can be used to extract models describing important data classes or to predict future data trends. The purpose of this research is to assign credit applicants to either a 'good credit' group that is likely to repay financial obligation or a 'bad credit' group whose application will be denied because of its high possibility of defaulting on the financial obligation[6].The achievement of this research paper is to classify the attributes using the prediction methods to classify as a good or bad customer The prediction is bounded to only the German data so, it might be more accurate if larger dataset with more relevant attributes are taken and tested.

The research only compared three classifiers, i.e. C4.5, CART and Naïve Baye's. The area for improvements in this paper can be implemented using other methods like Neural Network, SVM, Clustering, etc.

2. Related Work

Banks also soften their lending standards; they lend more to borrowers with a bad credit history and with high uncertainty. Lower interest rates by contrast reduce the credit risk of outstanding loans. Especially for any credit-granting institution, such as commercial banks and certain retailers, the ability to discriminate between good customers and bad ones is crucial. The need for reliable models that predict defaults accurately is imperative so that the interested parties can take either preventive or corrective action (Wang et al., 2005).In this section, here are some issues of research problems and future research directions in this field.

2.1 Behavioral Scoring

Behavioral scoring is a dynamic process while credit scoring can be reviewed as a static process which deals with only new applicants. Thomas in 2000A.D has introduced a dynamic systems assessment model for behavior scoring, which may become a research trend in future. Hsieh 2004 A.Destablished a two-stage hybrid model based on SOM and Apriori for behavior management of existing customers in banks [5]. First, SOM was used to classify bank customers into three major profitable groups of customers: revolver users, transactor users and convenience users based on repayment behavior and recency, frequency, monetary behavioral scoring predicators. Then, the resulting groups of customers were profiled by their feature attributes determined using an Apriori association rule inducer.

2.2 The More Complex a Model, the Better the Classifier?

New models are getting more complex and difficult, while the implementation cost of these models becomes much higher. Credit scoring cards and logistic regression are still the widely-used methods for credit scoring.

2.3 Incorporate Economic Conditions into Credit Scoring?

According to Xiao-lin and Yu ZhongType I and Type II are two kinds classification error of scoring system. For banks, Type I error classify good customer as bad one and reject their loans, which will reduce banks' profit. In contrast, Type II error classify bad customer as good one and provide loans, which will bring loss to banks. The researches focus more on Type II error because it is generally believed that it may bring about more serious damage to credit institutions. In addition, Type II error is also a criterion to evaluate a credit model. SVM is considered having an advantage over ANN because that its fitness function has the ability to control Type II. However, it should not been ignored that reducing Type I can also cause an increase in revenue[5]. Chuang and Lin (2009) presented a reassigning credit scoring model (RCSM) in order to decrease Type I error. First they used ANN to classify applicants as ac- accepted good or rejected bad credits. Then the CBR-based classification technique was used to reduce Type I error by reassigning the rejected good credit applicants to conditional accepted class and provide a certain amount of loans to them. In short, how to decrease losses and at the same time maximize the revenues is a major research direction in future work.

2.4 Credit Risk Analysis

The FICO credit score model takes into consideration five factors to create a model for credit scoring [6]:

Using Principal Component Analysis in Loan
Payment history (35% significance);
Outstanding credit balances (30% significance);
Credit history (15% significance);
Type of credit (10% significance);
Inquiries (10% significance).

Using simple classification tree for credit scoring model. Aktan employed the most commonly used decision tree algorithm CART that is always preference for the best effective variable to split ten de. Therefore, the order of the split node can reflect the important variable in the credit scoring. The variable, income, customer type and education level are important. It shows that average correct classification rates of training and testing are 72.89%and 65.58% respectively. For training set, 100 customers with good credit are classified as bad credit customers for training and 141 customers with bad credit are classified as good credit cutomers.64 customers with good credit are classified as bad credit customers and 63 customers with bad credit are classified as good credit customers for testing. The result is shown below [6].

3. Research Methodology

Classification is learning a function that maps an item into one of a set of predefined classes. It is the type of data analysis that can be used to extract models to describe important data classes or to predict future data trends. The classification process consists of two phases; the first phase is learning process, the training data will be analyzed by the classification algorithm. The learned model or classifier is represented in the form of classification rules. Next, the second phase is classification where the test data are used to estimate the accuracy of the Classification model or classifier. If the accuracy is considered acceptable, the rules can

be applied to the classification of new data [3].This section is about the framework for comparing the performance of the classification algorithms of decision trees: CART,C4.5 and Naïve Bayes classification with the role play of the attributes in them to predict loan grants data is taken from data sets[9]. It consists of 1000 data, among which 60% are used for training and remaining 40% are utilized for testing purpose that are work

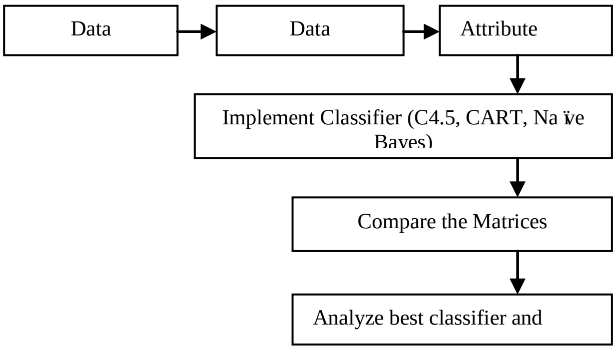

Fig.1. Research Methodology

3.1 Loan Prediction Using C4.5

C4.5 is an algorithm used to generate a decision tree developed by Ross Quinlan. C4.5 is an extension of Quinlan's earlier ID3 algorithm. The decision trees generated by C4.5 can be used for classification, and for this reason, C4.5 is often referred to as a statistical classifier [7].

C4.5 algorithm:

For the classification the total number of good and bad in loan grants is found out from the data set. Information gain is calculated for the whole dataset i.e. Info (D) and then for each attribute the normalized information gain is calculated individually i.e. Info(D) .Gain(A) is calculated subtracting the information gain and information gain of individual attribute for that particular attribute.

$$\mathrm{IG(A)=H(S)}-\sum_{t\epsilon T} p(t)H(t)$$

Where,

H(S) - Entropy of set *S*, and H(S) = $-\sum_{x\in X} p(x)log_2\, p(x)$
T- The subsets created from splitting set S by attribute A such that
P(T)- The proportion of the number of elements in t to the number of elements in set S
H(t)- Entropy of subset t

The process is repeated for all the attributes and selected the highest normalized information gain for a decision node. The features of the attribute may be nominal or categorical like if age is attribute with its category like youth, middle-aged and senior. For each category the table with the remaining attributes is made.

Again, recursion is done until leaf node is not found.

3.2 Loan Prediction Using Cart

Classification and regression trees (CART) is a non-parametric decision tree learning technique that produces either classification or regression trees, depending on whether the dependent variable is categorical or numeric, respectively.

CART algorithm:

It will search for all possible variables and all possible values in order to find the best split – the question that splits the data into two parts with maximum homogeneity. The process is then repeated for each of the resulting data fragments which use impurity functions like Gini splitting index and Towing splitting index [6]. Here Gini splitting rule (or Gini index) is used for the loan prediction. It uses the following impurity function:

Splitting Criteria:

Gini index is measured to find the impurity of *D*, a data partition or set of training tuples, as

$$\mathrm{Gini(D)}= 1-\sum_{i=1}^{m} Pi^2$$

where *pi* is the proabability that a tuple in *D* belongs to class *Ci* . The sum is computed over *m* classes.

Here ,splitting is compulsory binary so, data *D*is splittedinto *D*1 and *D*2. The partitioning is done as follows

$$\mathrm{Gini_A(D)}=\frac{|D1|}{|D|}\mathrm{Gini(D1)}+\frac{|D2|}{|D|}\mathrm{Gini(D2)}$$

The reduction in impurity that would be incurred by a binary split on a discrete or continuous-valued attribute *A* is

$$\Delta Gini(A)=Gini(D)-Gini_A(D)$$

The process is repeated for each attributes and decision for the rootnode is made for the lowest valued $Gini_A(D)$[6]. Again if the attribute purpose is chosen as the root node then its features like personal loan and business loan is splitting binary and made the table for only each features in both sides.Recursion is done until leaf node is found.

3.3 Loan Prediction Using Naive Bayes

A Naïve Bay's classifier estimates the class-conditional probability by assuming that the attributes are conditionally independent, given the class label y. The conditional independence assumption can be formally stated as follows:

$$P(X|Y=y) = \prod_{i=1}^{d} P(Xi|Y=y),$$

Where each attribute set X={X_1, X2… $X_{d\}}$ consists of d attributes[8].

Naïve Bayes algorithm

1. From data set D Associated class label n dimensional attribute vector X=(x1, x2, x3,…, xn), depiction n measurement made on the tuple from n attributes. A1, A2, A3… An
2. Suppose we have m classes c1, c2, …, cm Giving tuple X, classifier will predict X belongs to highest posterior probability, condition on X.
   X∈Ci if P(Ci|X) > P (Cj|X) for 1 <= j <=m, j | Ci, for which P(Ci|X) is maximized is called maximum posterior hypothesis;

$$P(Ci|X) = \frac{P(X|Ci)P(Ci)}{P(X)}$$

3. P(X) is constant for all classes maximize P (X|Ci) P (Ci).
   If Class prior probability are not known, commonly assume that P(C1)=P(C2)=…=P(Cm) maximize P (X|Ci)
   Else Maximize P (X|Ci) P(Ci)

$$P(C_i) = \frac{|Ci,D|}{|D|}$$

4. Calculate P(X|Ci) is extremely expensive Naïve assumes class conditional independence is made.

$$P(X|C_i) = \prod_{k=1}^{n} P(Xk|Ci),$$
$$= P(Xi|Ci).P(X_2|Ci)\ldots P(Xn|Ci)$$

Where X_k is the value of attribute, A_k for X .
If A is category

$$P(X_k| C_i) = \frac{\#\ of\_tuple\_of\_class\_Ci\_inD\_have\_value\_Xk}{|Ci,D|}$$

4. Results and Discussion

The German loan dataset consist of 1000 dataset 60 % of data is used for the train set and 40 % is used for the test set. Experiments for CART and C4.5 using German data set are summarized below.

Table 1. C4.5 train

Attributes	Confusion Matrix				Precision	Recall	F_Score	Accuracy	CCI	Time	No. Of Leaf	Size Of Tree
	TP	FN	FP	TN								
category1	398	25	67	110	85.5914	94.08983	89.63964	398.18333	508	0.2	52	75
category2	404	19	54	123	88.20961	95.50827	91.71396	404.205	527	0.1	7	13
category3	398	25	67	110	85.5914	94.08983	89.63964	398.18333	508	0.2	52	75
category4	394	29	110	67	78.1746	93.14421	85.00539	394.11167	461	0	16	23
category5	359	64	70	107	83.68298	84.86998	84.2723	359.17833	466	0.5	18	27
category6	423	0	177	0	70.5	100	82.69795	423	423	0	1	1
category7	405	18	110	67	78.64078	95.74468	86.35394	405.11167	472	0.1	38	53
category8	423	0	177	0	70.5	100	82.69795	423	423	0	1	1
category9	406	17	94	83	81.2	95.98109	87.974	406.13833	489	0.4	33	45
category10	403	20	52	125	88.57143	95.27187	91.79954	403.20833	528	0.2	87	113

Here out of 600 data are used for training in both the C4.5 and CART method. Category 1, 2,3,10 is better for correctly classified instances out of 600 data during train phase. The categories 4,6,7,8 shows that the false positive rate is large compared to other categories. Categories 6,8,11shows all data are true positive so, there will be loss if the banks take true negative data as good one .The precision ,accuracy is higher for category 1,2,5,10 compared to other categories.

Table 2. CART train

Attributes	Confusion Matrix				Precision	Recall	F_score	Accuracy	CCI	Time	No of leaf	Size of tree
	TP	FN	FP	TN								
category1	389	34	91	86	91.962175	91.962175	91.962175	389.14333	475	2.78	6	11
category2	399	24	97	80	94.326241	94.32624	91.96217494	399.13333	479	1.61	7	13
category3	389	34	91	86	91.962175	91.96217	94.32624113	389.14333	475	3.22	6	11
category4	417	6	149	28	98.58156	98.58156	91.96217494	417.04667	445	0.42	3	5
category5	411	12	111	66	97.163121	97.16312	98.58156028	411.11	477	1.09	12	23
category6	423	0	177	0	100	100	97.16312057	423	423	0.69	1	1
category7	423	0	177	0	100	100	100	423	423	1.05	1	1
category8	423	0	177	0	100	100	100	423	423	0.66	1	1
category9	398	25	90	87	94.089835	94.08983	100	398.145	485	1.39	9	17
category10	399	24	97	80	94.326241	94.32624	94.08983452	399.13333	479	1.59	7	13
category11	423	0	177	0	100	100	94.32624113	423	423	0.44	1	1

From the above table correctly classified instance out of 600 instances is higher in categories 9,2,10 in the case of CART. In confusion matrix category 6, 7, 8, 11shows the worst case as false positives are 177 and true positive values are 423 for all these categories.

Table 3. Naive Bayes train

Attributes	Confusion Matrix				Precision	Recall	F_Score	Accuracy	CCI	Time
	TP	FN	FP	TN						
category1	375	48	82	95	82.05689	88.65248	85.22727	78.33333	470	0.02
category2	383	40	94	83	80.2935	90.54374	85.11111	77.66667	466	0
category3	375	48	82	95	82.05689	88.65248	85.22727	78.33333	470	0.02
category4	393	30	117	60	77.05882	92.9078	84.24437	75.5	453	0.02
category5	368	55	117	60	75.87629	86.99764	81.05727	71.33333	420	0.03
category6	414	9	164	13	71.6263	97.87234	82.71728	71.16667	427	0.03
category7	388	35	128	49	75.1938	91.72577	82.64111	72.83333	437	0.02
category8	400	23	157	20	71.81329	94.56265	81.63265	70	420	0.02
category9	379	44	89	88	80.98291	89.59811	85.07295	77.83333	467	0.02
category10	379	44	94	83	80.12685	89.59811	84.59821	77	462	0.02
category11	423	0	177	0	70.5	100	82.69795	70.5	423	0.02

Here, out of 600 data sets the higher correctly classified instances is high in categories 1, 3, i.e 470 and lower in category 5,6,8 i. e . 420, 414 and 400 respectively. The accuracy is high in categories, 1,3 i.e. it is 78.3333% and lower in category 8 .FP rate is rate is high in categories 4,5,6,7,8,11 and lower in 1,2,3,9,1 [1]0.

Table 4. C4.5 test

Attributes	Confusion Matrix				Precision	Recall	F_score	Accuracy	CCI	Time
	TP	FN	FP	TN						
category1	266	11	45	78	85.5305	96.029	90.47619	86	344	1.89
category2	264	13	56	67	82.5	95.307	88.44221	82.75	331	0.75
category3	265	12	101	22	72.4044	95.668	82.42613	71.75	287	0.25

category4	236	41	65	58	78.4053	85.199	81.6609	73.5	294	0.22
category5	269	8	96	27	73.6986	97.112	83.80062	74	296	0.28
category6	277	0	123	0	69.25	100	81.83161	69.25	277	0.45
category7	277	0	123	0	69.25	100	81.83161	69.25	277	0.45
category8	277	0	12	0	95.8478	100	97.87986	95.847751	277	0.22
category9	257	20	62	61	80.5643	92.78	86.24161	79.5	318	0.5
category10	267	10	62	61	81.155	96.39	88.11881	82	328	0.86
category11	277	0	123	0	69.25	100	81.83161	69.25	277	0.11

Here out of 400 data are used for testing in both the C4.5 and CART method. The categories 6, 7,8,11 are not good for attributes for classification as there precision 69% only. The category 8 shows the best as its precision and accuracy is 95%.

Table 5. CART test

Attributes	Confusion Matrix				Precision	Recall	F_score	Accuracy	CCI	Time
	TP	FN	FP	TN						
category1	244	33	48	75	83.5616	88.08664	85.7645	79.75	319	1.89
category2	259	18	62	61	80.6854	93.50181	86.62207	80	320	0.75
category3	277	0	123	0	69.25	100	81.83161	69.25	277	0.25
category4	238	39	56	67	80.9524	85.92058	83.36252	76.25	305	0.22
category5	260	17	80	43	76.4706	93.86282	84.27877	75.75	303	0.28
category6	277	0	123	0	69.25	100	81.83161	69.25	277	0.45
category7	277	0	123	0	69.25	100	81.83161	69.25	277	0.45
category8	277	0	123	0	69.25	100	81.83161	69.25	277	0.22
category9	246	31	55	68	81.7276	88.80866	85.12111	78.5	314	0.5
category10	259	18	62	61	80.6854	93.50181	86.62207	80	320	0.86
category11	277	0	123	0	69.25	100	81.83161	69.25	277	0.11

In the above table category 3, 6, 7,8,11 shows higher false positive values so these are the worst attributes while category 2,5,10 are the best categories. Category 5 consists of only4 attributes.

Table 6. Comparison of accuracy for C4.5, CART and Na ïve Bayes

Attributes	Confusion Matrix				Precision	Recall	F_score	Accuracy	CCI	Time
	TP	FN	FP	TN						
category1	237	40	49	74	82.86713	85.55957	84.19183	77.75	311	0.06
category2	240	37	61	62	79.73422	86.6426	83.04498	75.5	302	0.03
category3	248	29	97	26	71.88406	89.53069	79.74277	68.5	274	0
category4	246	31	81	42	75.22936	88.80866	81.45695	72	288	0
category5	254	23	88	35	74.26901	91.69675	82.06785	72.25	289	0
category6	266	11	111	12	70.55703	96.02888	81.34557	69.5	278	0
category7	254	23	94	29	72.98851	91.69675	81.28	70.75	283	0
category8	264	13	111	12	70.4	95.30686	80.9816	69	276	0
category9	240	37	63	60	79.20792	86.6426	82.75862	75	300	0
category10	238	39	59	64	80.13468	85.92058	82.92683	75.5	302	0.02
category11	277	0	123	0	69.25	100	81.83161	69.25	277	0

Here, from the above figure we can see the accuracy is higher in C4.5 for the category in comparison to CART and Na ïve Bayes. The category 4 performed good because it contains only four attributes and its accuracy is higher .the category 6,7,11 are the worst ones and accuracy is same in C4.5, CART and Na ïve Bayes.

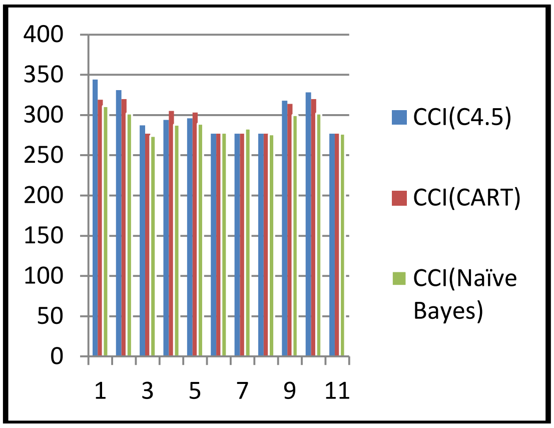

Fig.2. Comparison of correctly classified instances for C4.5, CART and Na ïve Bayes

We can see the CCI using Na ïve Bayes is remarkably higher compared to C4.5 and CART .the categories 1,4,9,10 are good ones while category 5, 11 are the worst ones.

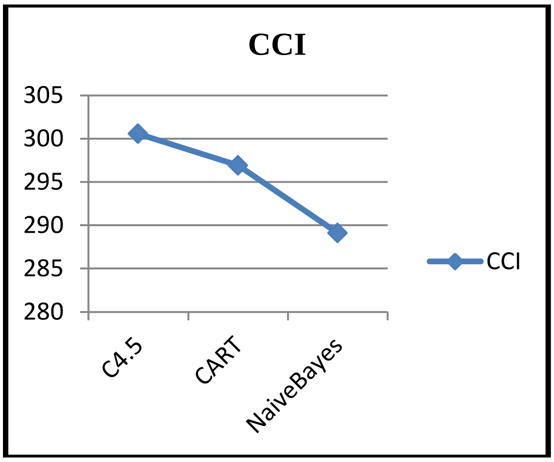

Fig.3. Average value of correctly classified instance for C4.5, CART and Na ïve Bayes

From the above figure, the accuracy is higher in C4.5 compared to classifier Na ïve Bayes and CART.

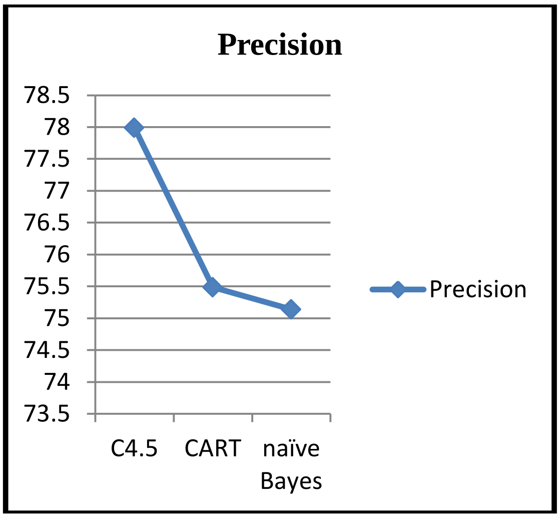

Fig.4. Average Precision value for C4.5, CART and Na ïve Bayes

The average precision is remarkably higher in C4.5 compared to CART and Na ïve Bayes. The average precision of C4.5 is 78%, CART is 75.5 and Na ïve Bayes is 75.1.

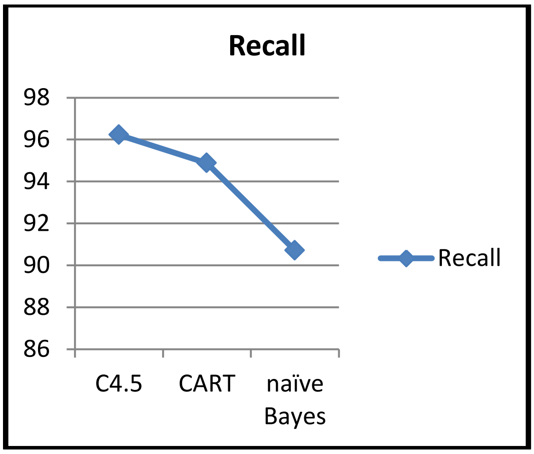

Fig.5. Average Recall value for C4.5, CART and Na ïve Bayes

The average recall value is higher it is 96%, CART is 95% and Na ïve Bayes is 90.80% Here C4.5 is better in comparison to CART and Na ïve Bayes.

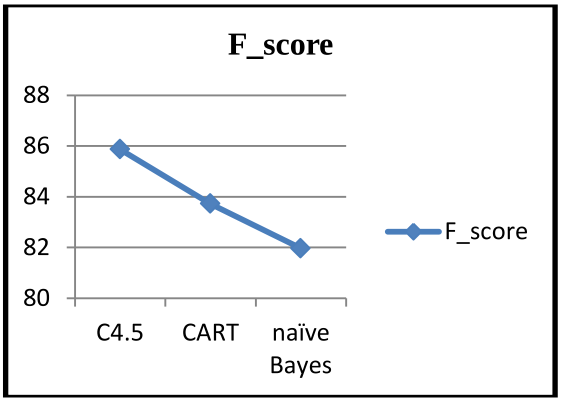

Fig.6. Average F_score value for C4.5, CART and Na ïve Bayes

The average F_score is higher in C4.5 i.e. 86%, CART is 83.80% and that of Na ïve Bayes is 82%. Therefore we can conclude that C4.5 is better.

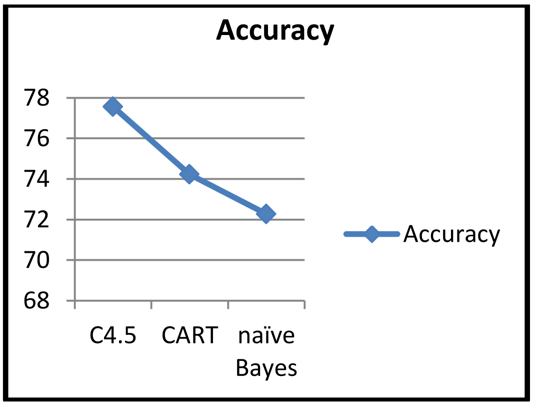

Fig.7. Average F_score value for C4.5, CART and Na ïve Bayes

The average accuracy is higher in comparison to the classifier C4.5 than CART and Na ïve Bayes. The average accuracy for C4.5 is 77.5%, CART is 74% and Na ïve Bayes is 72.1%.

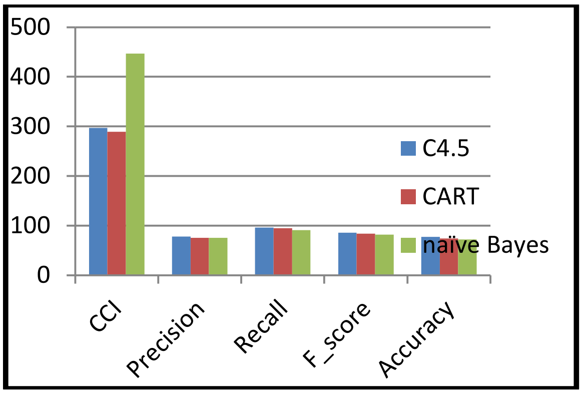

Fig.8. Collective comparison of CCI, Precision, Recall, F_score and Accuracy for C4.5 ,CART and Naïve Bayes

Naïve Bayes predicted higher compared to CART and C4.5 in Correctly classified instances. The average precision, recall, F_score, accuracy is high in C4.5 compared to CART and Naïve Bayes.

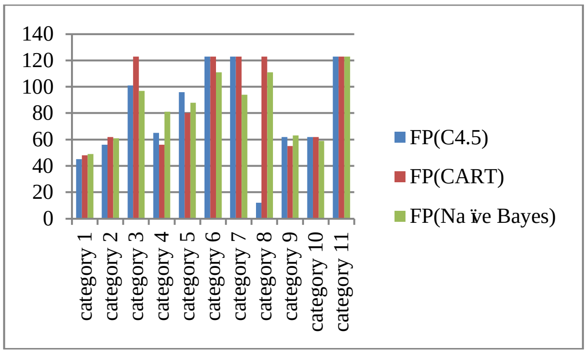

Fig.9. False positive value of Loan data for C4.5, CART and Naïve Bayes

The main focus is on the false positive value as it is the positive count for the bad customers that it the most risk factor for the loan prediction. The categories 1,2,4,8,9,10 contain the lower FP value in which in category 8. C4.5 has the lowest FP. The category 4 is also acceptable as it contains only 4 attributes in which FP is low. The categories 3, 6,7,11 are the worst one.

5. Conclusion and Discussion

If a customer with bad credit is misclassified as a customer with good credit then a bank will suffer. In this research three different classifiers, C4.5, CART and Naïve Bayes have been applied to predict loan grants and the attribute selection in them. More, financial institution is seeking better strategies through the help of credit scoring models. Therefore, it is concluded that categories 4, 8 is the best one and categories 3,6,11 are the worst as it counts false positive value is greater in all the C4.5,CARTand Naïve Bayes testing. Among the classifier C4.5, CART and Naïve Bayes, C4.5 is the best classifier to predict loan.

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