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A Comparative Framework for Evaluating Classification Algorithms

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Abstract—**Data mining methods have been widely used for extracting precious knowledge from large amounts of data. Classification algorithms are the most popular models. The model is selected with respect to its classification accuracy; therefore, the performance of each classifier plays a very crucial role. This paper discusses the application of some classification models on multiple datasets and compares the accuracy of the results. The relationship between dataset characteristics and accuracy is also debated, and finally, a regression model is introduced for predicting the classifier accuracy on a given dataset.**

Index Terms—**Data mining, classification, model assessment**

I. INTRODUCTION

As data volume increases in real life, making precious and meaningful decisions based on this data becomes more difficult. In such cases, Data Mining, a method that is used to extract the hidden knowledge from large amounts of data, is commonly used [6].

Classification or prediction is the most widely used data mining task. Classification algorithms are supervised methods that uncover the hidden relationship between the target class and the independent variables [11]. Supervised learning algorithms allow labels to be assigned to the observations so that new data can be classified based on the training data [6]. Each algorithm consists of a task, a model structure, a score function, a search method and a data management method [2]. Examples of classification tasks are image and pattern recognition, medical diagnosis, loan approval, detecting faults or financial trends [10].

Once a classification algorithm produces a model, it is evaluated with respect to certain criteria and is then selected for usage. It is likely that a model will result in some errors, which is the basic concern of the data miner in selecting that model [8]. Accuracy, which is the percentage of instances that are correctly classified by the model, is the most commonly used decision criteria for model assessments [6].

The predictive power of the data mining classification algorithms has been interesting for many years. Many studies are focused on proposing a new classification model, comparing the models or important factors affecting the model's performance.

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Quinlan states that it is not an easy task to claim that one algorithm is always superior to others, and links the abilities of models to task dependency. The study compares the decision tree with network algorithms and concludes that parallel type problems are not common for decision trees and sequential type problems are not suited to back-propagation [7]. Additionally, the researchers propose another study where some algorithms like LARCKDNF, IEKDNF, LARC, BPRC and IE are compared on three tasks, and different results are stated for each task [9]. Another crucial point is introduced about the danger of using a single dataset for performance comparison, and tests are carried out for dynamic modifications of penalty and network architectures [15]. Hacker and Ahn have done a study on eliciting user preferences, and compare many methods and propose a new classifier called relative SVM, which outperforms others where another comparative experiment is observed [13]. The decision tree and regression methods are applied on a study of breastfeeding survey data and the importance of feature selection is emphasised [5]. Naïve Bayesian, decision tree, KNN, NN and M5 are implemented to predict the lifetime prediction of metallic components, and it is stated that methods which can directly deal with continuous variables are performing better [4]. Putten, Meng and Kok compare the AIRS algorithm to other algorithms, and no significant evidence that it consistently outperforms the others has been found [12]. On the other hand, the performance results of learning algorithms are expected to deviate across different datasets; data and implementation bias is discussed on time series datasets [3]. As seen in the literature review, the data mining community is very interested in comparing different classification algorithms and this study is concerned with classification performance and other factors affecting the accuracy, with new perspectives.

II. RESEARCH QUESTIONS

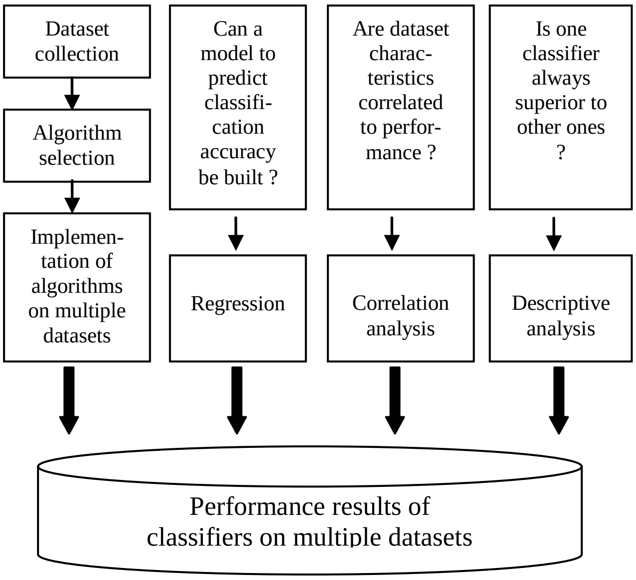
This study aims to find differences or similarities among the data mining classification algorithm performances. The research questions of this study are as follows:

1. Does an algorithm always outperform the others? In other words, does implementing the same classification algorithm on multiple datasets result in different performance indicators?
2. Are the characteristics of datasets correlated to the performance results of the classification algorithms?
3. Can a model to predict the performance of the classification algorithm be built?

III. METHOD

The methodological framework maintained during the research study is shown in Figure 1. Since research study is interested in multiple datasets, in the implementation phase sample datasets have been used. On the experimental datasets, the selected classification algorithms have been implemented. WEKA has been utilised as the tool to run Naïve Bayesian, AIRS, Logistics and MLP algorithms. SPSS has been utilised as the tool to run the Chaid algorithm since it is available in SPSS. The results of the implementations have been tabulated. Afterwards, a descriptive analysis has been conducted to find answers to the first research question. Correlation analysis has been studied to answer the second research question and lastly, a regression model has been built to deal with the third research question.

Figure 1: Methodological Framework



A. *Data collection*

Sample datasets have been collected from internet repositories, mainly from the UCI Machine Learning Repository. The experimental datasets are Acute, Breast Cancer, Cars, Chess, Credits, Iris, Letters, Red wine, White wine and Wine. Table I summarises the attributes of each dataset.

B. *Algorithms*

Although many classification models exist, only some have been selected within the scope of this study. The selected algorithms are Naïve Bayesian algorithm, Chaid decision tree algorithm, Multilayer perceptron (MLP), Artificial Immune Recognition Systems (AIRS) and Logistics Regression.

The Naïve Bayesian model defines the classification problem with respect to probabilistic idioms, and supplies statistical methods to classify the instances based on probabilities [8].

In decision tree algorithms, the classification process is summarised by a tree. After the model is built, it is applied to the database [10]. The Chaid algorithm grows the tree by finding the optimal split until the stopping criteria is met with respect to the chi-squares [1]. It can handle missing values and the target function has discrete outputs [14].

Multilayer perceptron is a type of artificial neural network algorithm which regards the human brain as the modelling tool [8]. It provides a generic model for learning real, discrete and vector target values. The ability to understand the hidden model is hard and training times may be long [14].

As the human natural immune system distinguishes and remembers the intruders, the AIRS algorithm is a cluster-based approach that learns the structure of the data and performs a k-nearest neighbour search [12].

Logistic regression makes use of independent variables to predict the probability of events by fitting the data to a logistic curve [2].

Each algorithm can make use of both numerical and categorical variables as inputs. They can handle target classes with more than two class types. Algorithms can also be referred to as classifiers or models.

Table I: Dataset characteristics

Dataset Name	Number of Variables	Number of Nominal Variables	Number of Numerical Variables	Target Class Types	Number of Instances
acute	7	6	1	2	120
breast cancer	9	0	9	2	684
cars	6	4	2	4	1727
chess	6	3	3	18	28056
credits	15	9	6	2	653
iris	4	0	4	3	150
letters	16	0	16	26	20000
wineall	11	0	11	7	6497
wine red	11	0	11	6	1599
wine white	11	0	11	7	4898

C. *Implementation*

First, data cleaning was applied on the datasets selected. According to the missing data analysis, missing data have been removed from the datasets. Other than missing data analysis, datasets were also cleaned to remove noisy data. Unnecessary space characters or other spelling mistakes were also cleaned in the datasets.

Another usual step in data pre-processing is data discretisation. Although some algorithms are said to perform better when the numerical input variables are discretised [4], in this study numerical variables have not been put into binned intervals in order to maintain the same conditions for all algorithms.

Once the data pre-processing steps have been completed, all 10 datasets (Acute, Breast Cancer, Cars, Chess, Credits, Iris, Letters, Red wine, White wine and Wine) have been used to run the 5 classification algorithms (Naïve Bayesian, Chaid, MLP, AIRS and Logistics algorithms). For all algorithms, splitting the data into train and test splits has been selected as the validation method. 66% of the data has been set as the training part and the rest has been set as the testing part. Then 10-fold cross validation has been implemented on the same

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datasets for the selected algorithms. In other words, both splitting and 10-fold cross validation methods have been applied.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section the performance results of each algorithm on each dataset will be discussed and research questions will be answered accordingly.

When pointing at the performance results of the classifier, its classification accuracy is actually measured. Accuracy is calculated by determining the percentage of instances correctly classified [10]. Costs for wrong assignment can also be applied in classification problems; however, misclassification costs are not within the scope of this study.

The accuracy values of the multiple dataset implementations according to each classifier can be seen in Tables II and III.

Table II: Accuracy results / 10-fold cross validation

	Airs	Chaid	Logistics	Mlp	Naive Bayes
acute	100.0	91.7	100.0	100.0	95.8
breast cancer	96.2	93.0	96.8	96.0	96.3
cars	94.6	81.9	93.4	99.6	85.2
chess	38.0	39.9	30.8	54.1	34.1
credits	82.5	86.4	86.1	82.7	78.3
iris	95.3	66.7	96.0	97.3	96.0
letters	86.5	53.8	77.4	82.2	64.0
wineall	86.5	53.8	77.4	54.9	64.0
winered	51.3	59.4	59.8	60.7	55.0
winewhite	48.3	54.6	53.7	55.2	44.3

Table III: Accuracy results / 66% train-test split

	Airs	Chaid	Logistics	Mlp	Naive Bayes
acute	100.0	61.9	100.0	100.0	95.1
breast cancer	96.1	93.2	97.0	96.6	96.1
cars	92.9	81.3	90.5	98.8	87.6
chess	36.6	37.0	32.6	53.8	33.6
credits	78.5	88.1	83.0	79.7	75.3
iris	98.0	23.5	92.2	98.0	94.1
letters	83.6	54.5	77.0	82.8	64.4
wineall	83.6	54.5	77.0	56.3	64.4
winered	51.8	57.7	57.9	62.5	52.0
winewhite	46.0	53.9	52.3	51.2	43.2

A. Research question 1: Does one classifier always outperform the others?

Based on the findings of the empirical study, it can be seen in Tables II and III that the same classifier is not the best one for all datasets and always outperforms the other classifiers. For each dataset the best predictive classifier has been defined. So we can conclude that a classifier cannot be said to outperform the others in every dataset.

According to Table IV, the overall best accuracy is obtained as 100% in the "acute" dataset. The classifiers producing that rate of accuracy are Logistics, AIRS and MLP.

Table IV: Overall best accuracy results

Dataset Name	Algorithm Name	Validation Method	Performance
acute	logistics	10fold	100
acute	airs	10fold	100
acute	mlp	10fold	100
acute	logistics	traintestsplit	100
acute	airs	traintestsplit	100
acute	mlp	traintestsplit	100

Table V displays the detailed accuracy results for the best result cases of each dataset. Logistics has the best performance for 'acute' and 'breast cancer' datasets; AIRS has the best accuracy for 'acute', 'iris', 'letters' and 'wine all' datasets and lastly, MLP has the best accuracy for 'acute', 'cars', 'wine red', 'wine white' and 'chess' datasets. Chaid produces better performance only for the 'credits' dataset. Interestingly, Naïve Bayesian has never produced the best result for a dataset from those classifiers.

Table V: Best accuracy results for each dataset

Dataset Name	Algorithm Name	Validation Method	Performance
acute	logistics	10fold	100.0
acute	airs	10fold	100.0
acute	mlp	10fold	100.0
acute	logistics	traintestsplit	100.0
acute	airs	traintestsplit	100.0
acute	mlp	traintestsplit	100.0
cars	mlp	10fold	99.6
Iris	airs	traintestsplit	98.0
breastcancer	logistics	traintestsplit	97.0
credits	chaid	traintestsplit	88.1
letters	airs	10fold	86.5
wineall	airs	10fold	86.5
winered	mlp	traintestsplit	62.5
winewhite	mlp	10fold	55.2
chess	mlp	10fold	54.1

Based on the empirical findings, firstly MLP, secondly AIRS and lastly Logistics can be said to perform better with respect to Bayesian or Chaid classifiers. The performance variable has been binned into intervals as LOW, MIDDLE, GOOD and VERY GOOD. Table VI shows the distribution of each classifier across those performance intervals.

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Table VI: Distribution of classifiers across performance intervals

		Performance (Binned)				
		Low	Middle	Good	Very Good	Total
Algorithm Name	Airs	6	0	8	6	20
	Chaid	3	10	7	0	20
	Logistics	2	4	9	5	20
	Mlp	1	7	4	8	20
	Naïve Bayes	4	6	5	5	20
Total		16	27	33	24	100

B. Research question 2: Are dataset characteristics correlated to the performance of classifiers?

Once all of the iterations have been completed in the implementation step, a dataset of 100 rows including the combinations of the datasets, the algorithms and the validation methods with 9 columns for the variables have been obtained.

The first eight columns in Table VII have been set as input variables, which are dataset name, algorithm name, validation method, number of variables, number of nominal variables, number of numerical variables, number of target class types and number of instances. The last column in Table VII shows the performance variable, which is set as the dependent variable. Since the second research question is interested in dataset characteristics, independent variables have been defined based on dataset attributes such as number of variables, number of nominal variables, number of numerical variables, number of target class types and number of instances.

Table VII: An excerpt from the Results dataset

Dataset specific characteristics

Dataset Name	Algorithm Name	Validation Method	No Of Variables	No Of Nominal Var	No Of Numerical Var	No Of Target Class	No Of Instances	Performance
acute	naivebayes	10fold	7	6	1	2	120	95.8
breastcancer	naivebayes	10fold	9	0	9	2	684	96.3
cars	naivebayes	10fold	6	4	2	4	1727	85.2
chess	naivebayes	10fold	6	3	3	18	28056	34.1
credits	naivebayes	10fold	15	9	6	2	653	78.3
iris	naivebayes	10fold	4	0	4	3	150	96.0
letters	naivebayes	10fold	16	0	16	26	20000	64.0
acute	logistics	10fold	7	6	1	2	120	100.0
breastcancer	logistics	10fold	9	0	9	2	684	96.8
cars	logistics	10fold	6	4	2	4	1727	93.4
credits	logistics	10fold	6	3	3	18	653	86.1
chess	logistics	10fold	15	9	6	2	28056	30.8
iris	logistics	10fold	4	0	4	3	150	96.0
letters	logistics	10fold	16	0	16	26	20000	77.4
acute	chaid	10fold	7	6	1	2	120	91.7
breastcancer	chaid	10fold	9	0	9	2	684	93.0
cars	chaid	10fold	6	4	2	4	1727	81.9
credits	chaid	10fold	6	3	3	18	653	86.4
chess	chaid	10fold	15	9	6	2	28056	39.9
iris	chaid	10fold	4	0	4	3	150	66.7
letters	chaid	10fold	16	0	16	26	20000	53.8
acute	airs	10fold	7	6	1	2	120	100.0

On the newly created dataset, which is referred to as the Results dataset, some kind of correlation analysis can be conducted in order to determine if any of the input variables affect the performance results significantly.

Firstly, in order to conduct the correlation analysis, all variables have been coded into numerical variables, and Z-score normalisations have been applied to them. SPSS has been used for implementation.

Table VIII: Correlation between accuracy and number of variables

		Performance	**Number of Variables**
Performance	Pearson Correlation	1	-.509**
	Sig. (2-tailed)		.000
	N	100	100
Number Of Variables	Pearson Correlation	-.509**	1
	Sig. (2-tailed)	.000	
	N	100	100

Table IX: Correlation between accuracy and number of nominal variables

		Performance	**Number of Nominal Variables**
Performance	Pearson Correlation	1	-.058
	Sig. (2-tailed)		.566
	N	100	100
Number Of Nominal Variables	Pearson Correlation	-.058	1
	Sig. (2-tailed)	.566	
	N	100	100

Table X: Correlation between accuracy and number of numerical variables

		Performance	**Number of Numerical Variables**
Performance	Pearson Correlation	1	-.370**
	Sig. (2-tailed)		.000
	N	100	100
Number of Numerical Variables	Pearson Correlation	-.370**	1
	Sig. (2-tailed)	.000	
	N	100	100

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Table XI: Correlation between accuracy and number of target class types

		Performance	Number of Target Class Types
Performance	Pearson Correlation	1	-.115
	Sig. (2-tailed)		.255
	N	100	100
Number Of Target Class Types	Pearson Correlation	-.115	1
	Sig. (2-tailed)	.255	
	N	100	100

Table XII: Correlation between accuracy and number of instances

		Performance	Number of Instances
Performance	Pearson Correlation	1	-.564**
	Sig. (2-tailed)		.000
	N	100	100
Number of Instances	Pearson Correlation	-.564**	1
	Sig. (2-tailed)	.000	
	N	100	100

Table XIII: Correlation between accuracy and algorithm type

		Performance	Algoritm Type
Performance	Pearson Correlation	1	.007
	Sig. (2-tailed)		.947
	N	100	100
Algorithm Type	Pearson Correlation	.007	1
	Sig. (2-tailed)	.947	
	N	100	100

Table XIV: Correlation between accuracy and validation methods

		Performance	Validation Method
Performance	Pearson Correlation	1	-.051
	Sig. (2-tailed)		.611
	N	100	100
Validation Method	Pearson Correlation	-.051	1
	Sig. (2-tailed)	.611	
	N	100	100

According to Tables VIII to XIV, some of the input variables have been found to be significantly correlated to the dependent variable, which is the performance of the classifier. Based on these results, the number of variables in the dataset (-0.509 Pearson value), the number of numerical variables in the dataset (-0.370 Pearson value) and the number of instances in the dataset (- 0.564 Pearson value) have been found to go hand in hand with the classifier performance. On the other hand, the number of nominal variables in a dataset, the number of target class types, algorithm name and validation method have been found not to be significantly correlated to classifier accuracy. As a result, the answer to the second question can be concluded in such a way that some of the dataset characteristics can affect the classifier performance.

C. Research question 3: Can a model to predict the classifier performance be built?

A regression model has been developed to answer the last research question. Due to finding the correlations between the selected independent and dependent performance variable in the previous stage, it is important to design a regression model.

Since there is a Results dataset containing the algorithm and dataset specific attributes in Table XV, it is possible to use these in a regression model and see their causal effects on the dependent performance variable.

According to the regression results, it is possible to build a model to predict the performance result. Figure 2 shows the regression function for predicting the performance.

Performance =
-0.210 * Number of Variables
+0.218 * Number of Nominal Variables
+0.261 * Number of Target Class
-0.591 * Number of Instance
-0.007 * Algorithm Type
-0.051 * Validation Method

Figure 2: Regression function

The aim of running a regression is to figure out whether the coefficients on the independent variables are really different from 0; in other words, whether the independent variables are having an observable effect on the dependent variable. If coefficients are different than 0, this means the null hypothesis (the dependent not affected by the

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independents) can be rejected. Based on the regression equation in Figure 2, some of the independent variables have been found to affect the dependent variable's performance. As a result, the number of variables, number of instances, algorithm type and validation method have a negative effect on performance. On the other hand, the number of nominal variables and number of target classes have a positive effect on the performance.

Within a 95% confidence interval, p values in Table XV should be close to or lower than 0.05 in order to be accepted as significant enough. With respect to p values (sig. column), the effect of the number of nominal variables, number of target class types and number of instances on performance is said to be more certain.

Table XV: Regression results

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.00	.08		.00	1.00
	Number of Variables	-.21	.11	-.21	-1.84	.07
	Number of Nominal Variables	.22	.10	.22	2.22	.03
	Number of Target Class Types	.26	.10	.26	2.61	.01
	Number of Instances	-.59	.13	-.59	-4.53	.00
	Algorithm Type	.01	.08	.01	.08	.93
	Validation Method	-.05	.08	-.05	-.64	.52

V. CONCLUSION

In this study, CHAID, MLP, Logistics, AIRS and Naïve Bayesian classification algorithms have been implemented on 10 datasets.

According to the accuracy results, AIRS, MLP and Logistic Function algorithms proved to have the best performances. However, none of the algorithms can outperform the others in every case.

Another interest has been to find out the correlations between the accuracy results of classifiers and the dataset attributes. Based on the correlation analysis, the number of variables, number of numerical variables and number of instances in the dataset have been found to be significantly correlated with performance.

Based on the findings of this study, it can also be said that a regression model can be built to predict the performance of a classifier on a given dataset.

In this study, the factors affecting the classification algorithm performance have been underlined based on the empirical results of correlation and regression studies. The fact that dataset characteristics influence the accuracy of the algorithm cannot be denied. The deviation of algorithm accuracies across different datasets is observable. The business and academic community should take these results into consideration, since establishing a knowledge discovery process on the same algorithm may not always be certain. The model assessment and selection phase should be paid the utmost attention in an iterative manner, because any difference in dataset characteristics can change the model's accuracy, and switching to another classifier may be a better decision. The regression model also gives some hints about the importance of a dataset, and that the accuracy can be predicted based on the instances or the field attributes of the dataset.

It is not an easy task to decide which classifier to use in a data mining problem; thus this study shows the importance of model selection and explains that an algorithm is not the best choice for all datasets.

Certainly, conclusions are based on the scope of this study; therefore, increasing the scope may help to develop an extended framework for predicting the accuracy of classifiers. Obviously, there may be other factors influencing the accuracy of a model, thus input variables of the regression function should be increased in the future.

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