Ripple Down Rule learner (RIDOR) Classifier for IRIS Dataset

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Abstract

In this paper compares the rule classifiers based on the evaluation metrics. The classification is a step by step procedure for designating a given piece of input data into any one of the given categories. Analyzing the performance of 3 Rules classifiers algorithms namely JRIP, RIDOR, Decision Table. The Iris datasets are used for calculating the performance by using the cross validation parameter. And finally find out the comparative analysis based on the performance factors such as the classification accuracy and execution time is performed on all the algorithms. The goal of this paper is to specify the best technique from the rules classification technique under the Iris datasets and also provide a comparison result which can be used for further analysis.

Keywords: - Rule classifiers, JRIP, RIDOR, Decision Table, cross validation, and Iris dataset**.**

I. INTRODUCTION

The aim of our work is to investigate the performance of different classification methods using WEKA for Iris dataset. WEKA is a data mining system developed by the University of Waikato in New Zealand that implements data mining algorithms using the JAVA language. WEKA implements algorithms for data preprocessing, classification, regression, and clustering and association rules. It also includes visualization tools [1].

In our work the classification is done based on rule classifier. It is used to automatically classify the variable. The rule classifier is generated for predict the best value. The characteristics of rule based classifier are mutually exclusive rules and exhaustive rules. In the mutual exclusive and each rule are independent. In exhaustive rules it has a combination of attribute values. It has small independent chunks of knowledge and it can be easier to explain.

In this paper comparison is made to find out the optimal result for Rules classifier algorithm such as JRIP, RIDOR and Decision Table. In the test option there are four kinds of parameter like training set, supplied test set, cross validation and percentage spilt. In this paper the cross validation parameter is used to calculate the data set values. The Iris dataset is using for comparison of those algorithms. And our paper described the following sections, Section 2 describes the literature review, Section 3 describes the methodology and Section 4 describes our experimental result and discussion. And finally Section 5 gives the Conclusion.

II. LITERATURE REVIEW

Lakshmi Devasena C., proposed the rule based classifier algorithm namely, RIDOR, ZeroR and PART Classifiers for credit risk prediction. using the open source machine learning tool the test is completed. RIDOR Classifier performs best, followed by PART Classifier and then by ZeroR Classifier for credit risk prediction by taking various measures [3].

C. Lakshmi Devasena et., studied Rule based classifiers are used to estimate classification accuracy of that classifier in a classification problem using Iris dataset. Among these classifiers (Conjunctive Rule Classifier, Decision Table Classifier, DTNB Classifier, OneR Classifier, JRIP Classifier, NNGE Classifier, PART Classifier, RIDOR Classifier and ZeroR Classifier) NNGE classifier performs well in classification problem [4].

M. Thangaraj et al., presented rule based classifier across multiple database relations using tuple-id propagation technique. The overall position is done based on the number of relations, number of tuples, number of attributes, number of foreign keys, classification accuracy and runtime. Based on the results, PART Classifier appears to be superior to Decision tree, RIPPER and RIDOR [5].

Mohd Fauzi bin Othman et al., investigated the performance of different classification or clustering methods for a set of large data. The breast cancer dataset are used and tested based on Bayes Network, Radial

Basis Function, Rule based classifier, Pruned Tree, Single Conjunctive Rule Learner and Nearest Neighbors Algorithm. Bayes network classifier has significantly improved the conventional classification methods for use in medical or bioinformatics field [6].

III. METHODOLOGY

A. *Dataset*

The Iris dataset is collected from the UCI machine learning repository. IRIS dataset consists of 149 instances from Iris setosa, Iris virginica and Iris versicolor. Length and width of sepal and petals is measured from each sample of three selected species of Iris flower. It has four features such as sepal length, sepal width, petal length and petal width. The weka tool is used for analysis the performance of the rule classifier algorithms.

B. *Classification*

The classification is similar to the clustering technique. In order to predict the outcome of the datasets, the algorithm processes cross validation of the 10 folds containing a set of attributes and the respective outcome, usually called target or prediction attribute. In this paper the rule classification algorithms are used to predict which of the algorithm is most suitable for the Iris dataset. The flow diagram for the comparative analysis is shown in Fig 1.

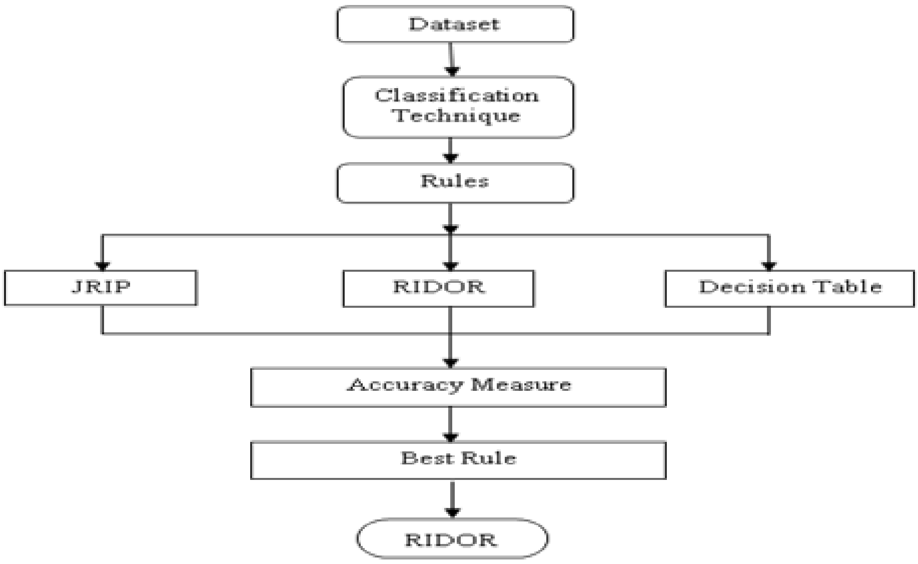

Fig 1: Flow diagram for comparative analysis.

In the study, the WEKA open-source software was used to implement the three rule-based classifier methods. To compare the three classifiers namely JRIP Classifier, RIDOR, Decision Table and find out which one produce the effective result. In WEKA, the RIPPER algorithm is implemented and named as JRIP.

1. Rule Classifier

Rule based classifier is one of the classification techniques. Different rule classifiers are used in this work and produce the better results for Iris dataset. The flow diagram is shown in Fig 1. Some of the classifiers are

JRIP Classifier

RIDOR

Decision Table

a) *JRIP Classifier*

JRIP implements a propositional rule learner. William W. JRip proposed a Repeated Incremental Pruning to Produce Error Reduction (RIPPER). It is an inference and rules-based learner (RIPPER) that can be used to classify elements with propositional rules. The RIPPER algorithm is a direct method used to extracts the rules directly from the data. The algorithm progresses through four phases: i) growth, ii) pruning, iii) optimization and iv) selection [4] [5]. The pseudo code is describes in Fig 2.

```
Procedure BUILDRULESET (P,N)
P=positive examples
N=negative examples
RuleSet={}
DL=DescriptionLength (RuleSet, P, N)
        while P not equal to {}
        // Grow and prune a new rule
        split (P,N) into (GrowPos, GrowNeg) and (PrunePos, PruneNeg)
        Rule := GrowRule (GrowPos, GrowNeg)
        Rule := PruneRule (Rule, PrunePos, PruneNeg)
        add Rule to RuleSet
        if DescriptionLength (RuleSet, P, N) > DL+64 then
                // Prune the whole rule set and exit
                for each rule R in RuleSet
                        if DescriptionLength (RuleSet -> R}, P, N) < DL then
                                delete R from RuleSet
                                DL := DescriptionLength (RuleSet, P, N)
                                endif
                        end for
                return (RuleSet)
                endif
        DL := DescriptionLength (RuleSet, P, N)
        delete from P and N all examples covered by Rule
        end while
end BUILDRULESET

Procedure OPTIMIZERUKESET (RuleSet, P, N)
for each rule R in RuleSet
        delete R from RuleSet
        U Pos := examples in P not covered by RuleSet
        U Neg := examples in N not covered by RuleSet
        spilt (U Pos, U Neg) into (GrowPos, GrowNeg) and (PrunePos, PruneNeg)
        RepRule := GrowRule (GrowPos, GrowNeg)
        RepRule := PruneRule (RepRule, PrunePos, PruneNeg)
        RevRule := GrowRule (GrowPos, GrowNeg, R)
        Rev Rule := PruneRule (RevRule, PrunePos, PruneNeg)
        choose better of RepRule and RevRule and add to RuleSet
        end for
end OPTIMIZERULESET

Procedure RIPPER (P,N, k)
RuleSet := BUILDRULESET (P,N)
repeat k times RuleSet := OPTIMIZERULESET (RuleSet, P, N)
return (RuleSet)
end RIPPER
```

Fig 2 Pseudo code for JRIP Classifier [2] *b) RIDOR*

Ripple Down Rule learner (RIDOR) is also a direct classification method. It constructs the default rule. An incremental reduced error pruning is used to find exceptions with the smallest error rate, finding the best exceptions for each exception, and iterating. The most excellent exceptions are created by each exceptions produces the tree-like expansion of exceptions. The exceptions are a set of rules that predict classes other than the default. IREP is used to create exceptions [7]. The pseudo code is describes in Fig 3.

```
Algorithm: Ridor (D,Rt)
Imput       : A relational database D with target
                          Relation Rt that contains P positive and N negative tuples
Output     : A set of rules for predicting class labels of target tuples
Procedure:
        Rule set R= empty
        If |Rt|< MIN_SUP then return
        Ruler=empty rule
        Set R_r active
Repeat
        Find a rule in active relation
        Learn except branch and if not branch
        Set relation of r to active
        R=R+r
                X=X-r
Until (X=NULL)
Set all active relations into inactive
        Return R
End
```

Fig 3 Pseudo code for Ridor Classifier

c) Decision Table

A decision table specifies only the logical rules. It is used to find out the decision quality. Conditional logic in this context refers to a set of tests, and a set of actions to take as a result of these tests. The classifier rules decision table is described as building and using a simple decision table majority classifier. The decision table classifiers has two variants such as

- DTMaj (Decision Table Majority)
- DTLoc(Decision Table Local)

Decision Table Majority returns the majority of the training set if the decision table cell matching the new instance is empty, that is, it does not contain any training instances.

Decision Table Local is a new variant that searches for a decision table entry with fewer matching attributes (larger cells) if the matching cell is empty. Hence this variant returns an answer from the native region [8] [9]. The pseudo code step is describes in Fig 4.

Input: T-decision table, R_d-a set of deterministic decision rules of T, α ∈ |0.5,1|,

k- upper bound on the number of decision values;
Output: $R_{nd}(\alpha)$- a set of nondeterministic decision rules for T.
$R_{nd} \leftarrow \phi$;
for all r ∈ R_d do
{r: $L \rightarrow (d = v)$; $L = D_1 \wedge \ldots . \wedge D_m$; $v \in V_d$;}
STOP ← false:
$\lambda_L \leftarrow$ norm_supp(L);
repeat
for all condition attributes from r do
$L^i = D_1 \wedge \ldots . \wedge D_{i+1} \wedge \ldots \wedge D_m$;
{L^i is obtained by dropping i- th attribute from the left hand side rule r }
$\|L^i\|\ \tau$; $\theta = \{ v \in V_{d\,;} \exists_x \in v_{L^i}\ d(x) = v \}$;
Sorting in decreasing order θ;
$\theta_i \subset \theta: conf\left(L \rightarrow (d = \theta_i)\right) = \frac{|||L^i||\cap||\theta_i|||}{|||L^i|||} \geq \alpha; \{\theta_i\ greedy\ selection\}$
$\lambda_{L^i} \leftarrow norm_{supp}(L^i \rightarrow \theta_i)$;
end for
$\lambda^i_{max} \leftarrow argmax\,\{\lambda_{L^i}\}$;
If $\lambda_{max} \geq \lambda_L$ then
$L \leftarrow L_i$; $\lambda_L \leftarrow \lambda_{max}; \{\tau_{nd}: L \rightarrow (d = \theta_i); \lambda_L$
else
STOP ← true;
end if
until STOP
If $|\theta_i| \leq$ k then
$R_{nd} \leftarrow R_{nd} \cup \{\leftarrow \tau_{nd}\}$;
end if
end for
return R_{nd};

Fig 4 Pseudo code for Decision Table Classifier

IV. RESULTS AND DISCUSSION

The work is performed using weka tool to predict the effectiveness of the rule-based classifiers. The performance is calculated based on the accuracy measure. From the results the RIDOR classifier algorithm performs well as compare to the JRIP and Decision Table. Table 1 shows the performance of the various algorithms measured in classification accuracy and comparison among these classifiers based on the correctly classified instances are shown in Figure 1

Table 1: Accuracy Measure by Class for Rule Classifiers

Algorithms	Correctly Classified	Incorrectly Classified	Kappa	TP	Precision	Recall	F-Measures	ROC
JRIP	93.28	6.71	0.89	0.9	0.8	0.9	0.88	0.94
RIDOR	95.30	4.69	0.92	0.92	0.93	0.92	0.92	0.94
Decision Table	91.94	8.05	0.87	0.9	0.9	0.9	0.9	0.96

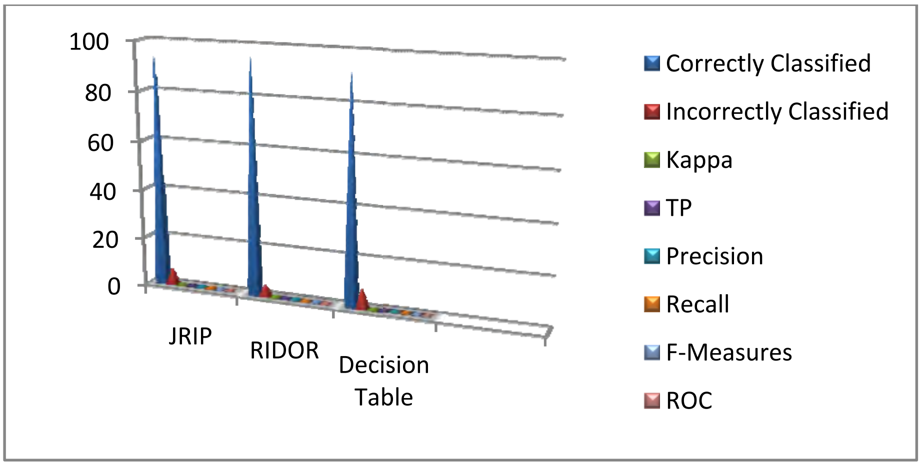

Fig 5: Accuracy Measure for Rule Classifier

From the experimental results it is inferred that the cross validation parameter, for JRIP classifier the Kappa, TP, Precision, Recall, F-Measures are lower than the RIDOR classifier that was shown in Fig 5

For RIDOR classifier the Kappa, TP, Precision, Recall, F-Measures are higher than the JRIP and Decision Table. ROC value is equal to the JRIP and less than the Decision Table. The accuracy measure are shown in Fig 5

Table 2: Error rate measure for Rule classification

Algorithms	MSE	RMSE	RAE	RSE
JRIP	0.05	0.20	12.86	43.02
RIDOR	0.03	0.17	7.04	37.54
Decision Table	0.09	0.21	21.98	45.83

For Decision table it is inferred that the cross validation parameter, the Kappa, TP, Precision, Recall, F-Measure are lower than other classifiers and ROC value is higher than other classifiers that was shown in Fig 5

The experiment was carried out to the Iris dataset by using the cross validation parameters. From the results the RIDOR performs very well compare to the other classifiers. The RIDOR algorithm gives more classified instances than JRIP and Decision Table.

Table 2 shows the comparison of the error rate for rule classifier algorithms such as JRIP, RIDOR, Decision Table. From the results the RIDOR produce the lower error rate than other classifiers. Comparison among classifiers based on MSE, RMSE, RAE, RSE values are shown in Figure 6.

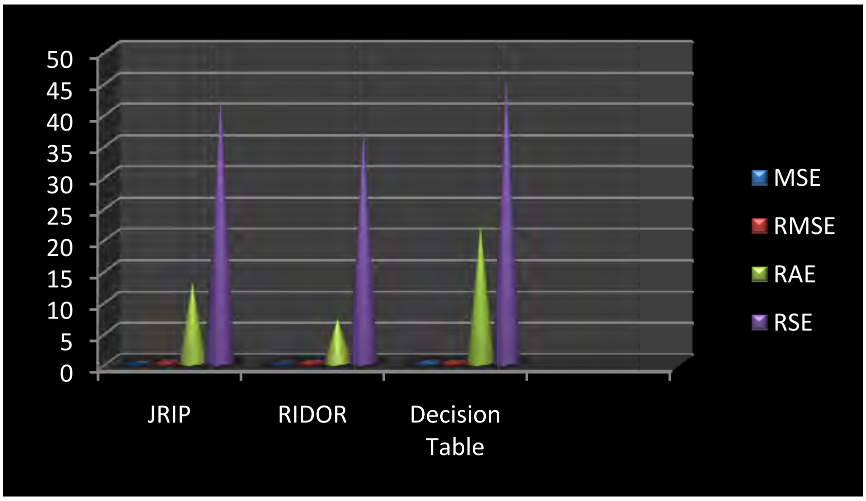

Fig 6: Accuracy error rate measure for Rule classifier

Statistical analysis

Using Iris dataset the classification is done based on the cross validation parameter. In this work the 10 folds cross validation classification are given to the rule classifier algorithms. When increasing the folds 10,15,20,25 to find the accuracy of each classifiers. During the 15 folds the JRIP gives the higher correctly classified accuracy. During the 20 folds the RIDOR and JRIP produces the best solution. During the 25 folds the RIDOR has the higher correctly classification. In this experiment the RIDOR gives the minimum time to obtain the results and the execution time is 0.01 s. In the rule classifier algorithms based on the time and accuracy RIDOR only gives the optimal result.

V. CONCLUSION

In this paper analyzed the performance of 3 Rule classifiers algorithms namely JRIP, RIDOR and Decision Table. By Using the Iris datasets the performance is calculated using the cross validation parameter. And finally we analyzed the algorithms by using the performance factors such as the classification accuracy and execution time. From the results, it is observed that the RIDOR algorithm performs better than other algorithms.

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