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| 1 | Comparative Analysis of Random Forest and J48 Classifiers for |
|---|--|
| 2 | "IRIS" Variety Prediction |
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7 Abstract

⁸ Data mining may be a computerized technology that uses complicated algorithms to seek out

⁹ relationships and trends in large databases, real or perceived, previously unknown to the

¹⁰ retailer, to market decision support. Data mining is predicted to be one of the widespread

¹¹ recognition of the potential for analysis of past transaction data to enhance the standard of

¹² future business decisions. The aim is to arrange a set of knowledge items and classify them.In

this paper, we apply two classifier algorithms: J48 (c4.5) and Random Forest on the IRIS

¹⁴ dataset, and we compare their performance based on different measures.

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16 Index terms— IRIS, J48 classifier, proficiency comparison, random forest classifier

17 **1** Introduction

eople are often susceptible to making mistakes during analyses or, possibly, when trying to determine relationships
between multiple features. This fact, makes it difficult for them to seek out solutions to certain problems. Data
mining involves the utilization of sophisticated data analysis tools to get previously unknown, valid patterns,
and relationships in the datasets [1]. These tools can include statistical models, mathematical algorithms, and

22 machine learning methods [2].

Consequently, data processing consists of quite a collection and managing data, it also includes analysis and prediction [1].

The classification technique is capable of processing a sort of data than regression and is growing in popularity [3].

27 **2** II.

28 3 Dataset Used

In this research work, we use the IRIS plant data set, one of the most popular databases for the classification
problems, it is obtained from UCI Machine Learning Repository and created by R.A. Fisher while donated by
Michael Marshall (MARSHALL%PLU @io.arc.nasa.gov) on ??uly 1988[4].

The IRIS dataset contains three different classes of IRIS plants depending on their pattern ??5, ??]. Each class of IRIS plant contain fifty objects. The attributes that already predicted belongs to a category of IRIS

plant. The list of attributes presents within the IRIS is often described as categorical, nominal, and continuous. The experts have mentioned that the info set is complete i.e. there isn't any missing value found in any attribute

of this data set ??6].

37 This research makes use of the documented IRIS dataset, which contains three classes of fifty instances

each. The 150 instances, which are equally divided between the three classes, hold the subsequent four numeric

39 attributes:

Classifiers Used 4 40

In this paper, we compared the proficiency assessment of IRIS variety for two tree based classifiers: Random 41 Forest and J48 Classifiers. 42

a) Random Forest Classifier 5 43

Random Forest [7] is considered one of the best "off-the-shelf" classifiers for high-dimensional data. Random 44 forest is a mix of tree predictors sampled autonomously count on the values of a random vector following an 45 equivalent distribution for all trees of the forest. The generalization error of random forest classifier depends on 46 the association between the individual trees inside the forest and the strength of them. The dataset divided into 47 a training dataset to learn each tree, and the remaining of the data set is used to estimate error and variable 48 importance. Class assignment is formed according to the number of votes for any of the trees, to apply the model 49 of the results. it's almost like bagged decision trees with hardly some key differences as given below:

50 For every split point, the search isn't overall p variables but just over m (number of tested) variables (where, 51 e.g,m = [p/3])52

No pruning necessary. Trees are often grown until each node contains just only a few observations. The 53 Random Forest gave better prediction, and almost no parameter adjustment is necessary. 54

b) J48 Classifier 6 55

The J48 classifier is an extension of the decision tree C4.5 algorithm for classification ??8], which creates a 56 binary tree. It's the foremost useful decision tree approach for classification problems. This system constructs 57

a tree to model the classification process. After the tree is made, the algorithm is applied to every tuple within 58

the database and leads to classification for that tuple ?? The absent values are ignored by J48 while building a 59

decision tree, i.e. the known information about the attribute values for the other records is helpful to predict the 60

value for that item. The idea is to divide the data into a range based on the attribute values for that element 61 which are identified in the training sample ??10]. 62

63 IV.

Performance Measures Used 7 64

Various scales are wont to gauge the performance of the classifiers. 65

8 a) Classification Accuracy (CA) 66

Classification accuracy presents the percent of correctly classified instance in the test dataset. We calculate it by 67 dividing the correctly classified instances by the total number of instance multiplied by 100. 68

9 b) Mean Absolute Error (MAE) 69

Mean absolute error is that the average of the variance between predicted and actual value altogether test cases. 70

It's an honest measure to measure performance. 71

c) Root Mean Square Error (RMSE) 1072

Root mean squared error is employed to scale dissimilarities between values. It's determined by taking the root 73 of the mean square error. 74

d) Confusion Matrix (CM) 11 75

A confusion matrix is a tool checking in particular how often the predictions are correct compared to reality in 76 classification problems. 77 V.

78

12**Results and Discussion** 79

In this work, to evaluate the performance of the different Tree-based Classifiers (Random Forest and J48), we 80 used a well-known open-source tool in the machine learning field called "WEKA". The performance is tested 81 using two methods, first by splitting the dataset into training (70%) and testing (30%) datasets, as well as using 82

different Cross-Validation methods. 83

a) Performance of Random Forest Classifier 1384

Table 1 show the global evaluation summary of Random Forest Classifier using both of the test modes: splitting 85 and different cross-validation methods. Fig. ?? and Fig. 2 display the performance of Random Forest Classifier 86

in terms of Classification Accuracy and time taken to build the model. From Table ?? to Table VI we gave the 87 confusion matrix for different test modes. 88

By applying these test modes using Random Forest Classifier, we got 95.55% accuracy, spending 0.17s on 89 building the model for the split. Using different cross-validation methods to check their performance, we obtained 90

- around 94.99% accuracy, spending 0.06s on building the model. By applying these test modes using J48classifier
- we got 95.55% accuracy, spending 0.05s on building the model for the split mode. Using different cross-validation
- ⁹³ methods to check their performance, on average we obtained around 95.83% accuracy, spending 0.025s to build
- $_{\rm 94}$ $\,$ the model. Comparison of Random Forest and j48 Classifiers

95 14 Conclusion

- $_{\rm 96}$ $\,$ This research work compares the efficiency of Random Forest and J48 Classifiers for IRIS variety prediction. The
- test is accomplished using WEKA 3.9in a machine with a processor i5-2430M 2.40 GHz and 4.00GB in RAM.
 Also, we compare the performance of both of the classifiers in terms of different scales of effectiveness evaluation.
- Ariso, we compare the performance of both of the classifiers in terms of university scales of electiveness evaluation. 99 At last, we observed that J48classifier performs best than Random Forest classifier for IRIS variety prediction
- by taking different measures, including classification accuracy, Mean Absolute Error, and Time Taken to Build the Model.



Figure 1: Figure 2 :

101



Figure 2: Figure 3 :







Figure 4: Fig. 5







Figure 6: Figure 6 :

| | Correctly | Incorrectly | y | Mean | Root Mean | Time Taken |
|-------------|------------|-------------|--------------|----------|-----------|-------------------|
| Test Mede | Cleasified | Classified | 1.000000.000 | Abgoluto | Coursed | to Duild Model |
| Test Mode | Instances | Instances | Accuracy | Error | Squared | (Sec) |
| Split (70%) | 43 | 2 | 95.55% | 0.0363 | 0.1532 | 0.17 |
| 5 Fold CV | 143 | 7 | 95.33% | 0.037 | 0.1531 | 0.05 |
| 10Fold CV | 142 | 8 | 94.66% | 0.0408 | 0.1624 | 0.03 |
| 15Fold CV | 142 | 8 | 94.66% | 0.0385 | 0.1613 | 0.14 |
| 20Fold CV | 143 | 7 | 95.33% | 0.0379 | 0.1558 | 0.03 |

Figure 7: Table 1 :

 $\mathbf{2}$

| | Setosa | Versicolor | Virginica | Actual (Total) |
|-------------------|--------|------------|-----------|----------------|
| Setosa | 14 | 0 | 0 | 14 |
| Versicolor | 0 | 16 | 0 | 16 |
| Virginica | 0 | 2 | 13 | 15 |
| Predicted (Total) | 14 | 18 | 13 | 45 |

Figure 8: Table 2 :

3

| | Setosa | Versicolor | Virginica | Actual (Total) |
|-------------------|--------|------------|-----------|----------------|
| Setosa | 50 | 0 | 0 | 50 |
| Versicolor | 0 | 47 | 3 | 50 |
| Virginica | 0 | 4 | 46 | 50 |
| Predicted (Total) | 50 | 51 | 49 | 150 |

Figure 9: Table 3 :

 $\mathbf{4}$

| | Setosa | Versicolor | Virginica | Actual (Total) |
|-------------------|--------|------------|-----------|----------------|
| Setosa | 50 | 0 | 0 | 50 |
| Versicolor | 0 | 47 | 3 | 50 |
| Virginica | 0 | 4 | 46 | 50 |
| Predicted (Total) | 50 | 51 | 49 | 150 |

Figure 10: Table 4 :

 $\mathbf{5}$

| | Setosa | Versicolor | Virginica | Actual (Total) |
|-------------------|--------|------------|-----------|----------------|
| Setosa | 50 | 0 | 0 | 50 |
| Versicolor | 0 | 47 | 3 | 50 |
| Virginica | 0 | 5 | 45 | 50 |
| Predicted (Total) | 50 | 52 | 48 | 150 |

Figure 11: Table 5 :

| 6 | | | | |
|---------------------------------|----|------------|-----------|-------------------|
| Setosa | | Versicolor | Virginica | Actual (Total) |
| Setosa | 50 | 0 | 0 | 50 |
| Versicolor | 0 | 47 | 3 | 50 |
| Virginica | 0 | 4 | 46 | 50 |
| Predicted (Total) | 50 | 51 | 49 | 150 |
| b) Performance of J48Classifier | | | | |

Figure 12: Table 6 :

 $\mathbf{7}$

| | Correctly | Incorrectly | | Mean | Root Mean | Time Taken |
|-------------|------------|-------------|----------|----------|-----------|-------------|
| | | | | | | to |
| Test Mode | Classified | Classified | Accuracy | Absolute | Squared | Build Model |
| | Instances | Instances | | Error | Error | (Sec) |
| Split (70%) | 43 | 2 | 95.55% | 0.0416 | 0.1682 | 0.05 |
| 5Fold CV | 144 | 6 | 96% | 0.035 | 0.1582 | 0.02 |
| 10Fold CV | 144 | 6 | 96% | 0.035 | 0.1586 | 0.02 |
| 15Fold CV | 143 | 7 | 95.33% | 0.0395 | 0.1758 | 0.03 |
| 20Fold CV | 144 | 6 | 96% | 0.0354 | 0.1586 | 0.03 |

Figure 13: Table 7 :

| | - | | |
|---|---|---|---|
| | | J | , |
| | | ٠ | ٠ |
| • | | 2 | , |

| | Setosa | Versicolor | Virginica | Actual (Total) |
|-------------------|--------|------------|-----------|----------------|
| Setosa | 14 | 0 | 0 | 14 |
| Versicolor | 0 | 16 | 0 | 16 |
| Virginica | 0 | 2 | 13 | 15 |
| Predicted (Total) | 14 | 18 | 13 | |

Figure 14: Table 8 :

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