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Comparative study of Jrip j48 and naive bayes algorithm in Flower specie prediction

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Abstract: Artificial intelligence and Deep learning techniques propose and provide effective mechanism for classification among several commodities like gender classification on basis of ridge count, spam mail classification and detection etc. Here we have proposed a hybrid module on basis of available AI and ML techniques by which we can achieve more than 90% accuracy for any provided test dataset. We have included over 50423 samples, out of which we use 66 percentage of data for training purpose of our model and 34% remaining sample we use as test dataset, with 8 fold we have achieve approximately 96% accuracy. For collection of dataset and processing of dataset we gone through several phases which include extraction of feature (EoF) using feature extraction technique, for cleaning of dataset we have use dimension reduction technique factor analysis(FA). In next phase for classification of flowers we have used classification techniques in which we found the accuracy score of j48 classifier is higher than Naïve Bayes and Jrip algorithm. Hence the choice of j48 classifier for classification is right.

Keywords: Bayes-classifier, Naïve-Bayes, Bayes-Net, Flower-Classifications, J48, EoF

1. Introduction:

Now a day's image classification is rapidly increasing its area of being in interest of data analyst and data scientists and the classification results and accuracy of results is giving effective mode of



prediction in various fields like healthcare, traffic monitoring, agriculture etc. When we talk about Google photos, it can be considered as best example of image processing and classification as it correctly classify and group photos of person with higher accuracy along with that it take suggestion from user about similar images. With Google photos we can easily check our images with additional search (Triguero & Vens, 2016, p. 171) (Mukane, 2013, p. 83).

In this world over millions of species of flower exist if we wanted to make a model by which we can classify the species of flower with accuracy then AI and ML algorithms comes into picture, as the algorithm with its ability to classify a class or specie of flower with provided details about that flower leads to produce results of higher accuracy.

Bloom order frameworks (Abdul Aziz et al., 2019a, p. 25) (Liu, 2014, p. 285) have a place with a shape coordinating issue, which is a major issue in PC vision and example acknowledgment. It characterized as the foundation of a similitude measure among shapes and its utilization for shape examination (Mukane, 2013, p. 83) (Abdul Aziz et al., 2019b, p. 30). The significant hypothetical fascinating inspiration for picture grouping comes from that shape coordinating is instinctively precise for people and need an associate which isn't fathomed at this point in its full consensus. Shape coordinating framework incorporates object acknowledgment and location, picture attachment, and substance based recovery of pictures (Mukane, 2013, p. 83).

2. Algorithm Used:

2.1 J48: J48 algorithm comes under Weka platform in a inbuilt manner which is basically implementation of C4.5 algorithm which generally used for making decision in a hierarchical manner, are known as decision trees, and when we combine two or more algorithm to make decisions then that combination is known as random forest (Koul & Singhanian, 2020, p. 1726). C4.5 algorithm was a advancement of original ID.3 algorithm whose limitations later on overcome in C4.5 algorithm. Whatever decisions made by these algorithms (in a hierarchy) (Mukane, 2013, p. 83) (Koul & Singhanian, 2020, p. 1726) are generally used for classification purpose. Here in our proposed model we want to classify the species of provided bunch of dataset of flowers so choosing this algorithm was wise option [28 - 35].

2.2 Naïve Bayes: Another algorithm which is popular in term of statistics and widely used for classification purpose is Naïve Bayes Koul, S., & Singhanian, U. (2020).. This algorithm is a implementation of original Bayes' theorem (S.Sarkate & B. Khanale, 2014, p. 16) with assuming assumption among features of provided or selected dataset. In statistics Naïve Bayes classifier known as 'probabilistic classifier'. The assumptions which are made while implementations of naïve bayes (S.Sarkate & B. Khanale, 2014, p. 16) consider the independency among features that mean the presence of a feature in class is not related to presence of other feature Patel, I., Patel, S., & Patel, A. (2018). (Wäldchen et al., 2018). Naïve bayes is popular because of easy implementation and ability to perform well and give considerable accuracy level on high sophisticated datasets as well (Chitra et al., 2016, p. 18) (Pornpanomchai et al., 2011, p. 350)

2.3 Jrip: JRIP once in a while called as RIPPER is one of well-known classifier calculation (Pornpanomchai et al., 2011, p. 350) (Sai Kumar et al., 2011, p. 49). In JRIP examples of the dataset are assessed in expanding request, for given dataset of danger a bunch of rules are produced. JRIP (RIPPER) (Mohanty & Bag, 2017, p. 520) calculation treats each dataset of given information base and produces a bunch of rules including all the qualities of the class. At that point next class will get assessed and does likewise measure as past class, this cycle proceeds until all the classes have been covered (Najjar & Zagrouba, 2016, p. 53023).

3. Related work:

Saitoh and Kaneko proposed a programmed acknowledgment framework (Wäldchen et al., 2018) for wild blossoms. They utilize both the bloom and leaves picture to perceive the blossom name. To begin with, the bloom and leaves are divided. At that point, their highlights are separated to speak to the wild utilizing a bunching strategy. Their acknowledgment is accomplished utilizing a piecewise direct discriminant work (Pornpanomchai et al., 2011, p. 350)(Sai Kumar et al., 2011, p. 49). Nilsback and Zisserman mean to upgrade characterization execution on a comparable class's enormous dataset by removing blends(Zaitoun & Aqel, 2015, p. 801) of highlights. Such blends of highlights can improve arrangement execution on an enormous dataset of comparable classes. These highlights are shading, SIFT for both the frontal area district and limit, and Histogram of Gradients. Their framework fragments blossoms picture, at that point extricates the highlights blends which are utilized as contribution to Support Vector Machine (SVM) classifier to arrange bloom picture (Abdul Aziz et al., 2019a, p. 25). Another perceiving rose framework is introduced in (Abdul Aziz et al., 2019a, p. 25)(Walowe Mwadulo, 2016, p. 396). For bloom division, a client chooses the fitting bouncing window that holds the blossom area through an intuitive interface. At that point, the blossom is portioned from the chose windows. They separate tone and shape highlights of the entire blossom district and the pistil/stamen zone to speak to the bloom highlights. At that point, they perceive blossom by looking at the distances between the info bloom picture and all bloom pictures existing in the information base to come to the most like the info blossom picture (Inthiyaz et al., 2017, p. 1323572)(Patel et al., 2018, p. 1112). A Division Phase A significant issue in a bloom order framework is the manner by which to remove the blossom locale from a characteristic complex foundation with great accuracy(Wäldchen et al., 2018) (Dutt, 2018, p. 116). Blossom locale can be divided dependent on utilizing shading highlights, since its pictures comprise of a huge green territory and bloom zone. The green region speaks to the leaves encompassing the bloom and blossom territory speaks to the bloom area which is portrayed by its tone ((Jain, 2017, p. 89). Shading fragmented can be accomplished utilizing the distinction/distance between two tones. In this work, the pictures are changed to Lab shading space. At that point, a casing which incorporates the bloom is chosen by client. The Delta E is utilized to compute the distance between each pixel in the chose outline and the normal LAB tone (Jain, 2017, p. 49). From that point forward, OTSU limit is applied on every Lab tone to fragmented bloom. OTSU calculation attempts to locate an ideal division between classes by registering a worldwide edge for a picture (Sharma, 2017, p. 83)

4. Experimental Results

Our experimental approach has been carried out to evaluate the proposed Hybrid module of 2 types of classifiers to have comparative analysis of two kinds. The proposed system was implemented using WEKA 3.8.3 on Windows 8.1 operation system.

4.1 Dataset



Figure 1: Some sample images for setosa specie



Figure 2: Some sample image sfor versicolor specie



Figure 3: Some sample image sfor versicolor specie

The hybrid combination is evaluated using around 50423 samples which represented 3 species. The used dataset in this experiment has been taken from Git hub in which we have add additional entries via extraction of feature f each and every specie and created around 50423 sample after that we have use 66 present of data as training data for our proposed model and remaining data which was chosen at complete random as test data.

The features which we have considered in this dataset are:

Saple-width: We have taken basic measurement in which flower of each species may have

Saple-Height: We have taken basic measurement in which flower of each species may have

Petal-width: We have taken basic measurement in which flower of each species may have

Petal Height: We have taken basic measurement in which flower of each specie may have

Specie: Specie is our class variable or we and say target variable. Target variable is always a dependant variable which depends on independent variable which are our other features which we consider as variable which play significant role in prediction of target variable

TPR	FPR	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	<u>setosa</u> -flower
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	<u>versicolor</u> -flower
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	<u>virginica</u> -flower
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Weighted Avg.

Table 1: Jrip Classifier class accuracy:

TPR	FPR	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	setosa-flower
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	versicolor-flower
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	virginica-flower
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Weighted Avg.

Table 2: J48 Classifier class accuracy:

TPR	FPR	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	setosa-flower
0.973	0.033	0.965	0.973	0.969	0.939	0.997	0.996	versicolor-flower
0.928	0.017	0.943	0.928	0.936	0.916	0.995	0.987	virginica-flower
0.970	0.020	0.970	0.970	0.970	0.951	0.997	0.995	Weighted Avg.

Table 3: Naïve Bayes Classifier class accuracy:

```

=== Classifier model (full training set) ===

J48 pruned tree
-----
petal_width <= 0.6: setosa-flower (13955.0)
petal_width > 0.6
|   petal_width <= 1.7
|   |   sepal_length <= 4.9
|   |   |   sepal_width <= 2.4: versicolor-flower (60.0)
|   |   |   sepal_width > 2.4: virginica-flower (387.0)
|   |   |   sepal_length > 4.9
|   |   |   |   sepal_width <= 2.2
|   |   |   |   |   petal_length <= 4.7: versicolor-flower (180.0)
|   |   |   |   |   petal_length > 4.7: virginica-flower (353.0)
|   |   |   |   |   sepal_width > 2.2
|   |   |   |   |   |   petal_length <= 5.3
|   |   |   |   |   |   |   petal_length <= 5: versicolor-flower (23598.0)
|   |   |   |   |   |   |   petal_length > 5
|   |   |   |   |   |   |   |   sepal_length <= 6.1: versicolor-flower (626.0)
|   |   |   |   |   |   |   |   sepal_length > 6.1: virginica-flower (60.0)
|   |   |   |   |   |   |   |   petal_length > 5.3: virginica-flower (120.0)
|   |   petal_width > 1.7
|   |   |   petal_length <= 4.8
|   |   |   |   sepal_length <= 5.9: versicolor-flower (60.0)
|   |   |   |   sepal_length > 5.9: virginica-flower (120.0)
|   |   |   |   petal_length > 4.8: virginica-flower (10904.0)
Number of Leaves :    12

```

Figure 4: J48 tree Classification output-I

```

Size of the tree :      23

Time taken to build model: 0.64 seconds

=== Evaluation on test split ===

Time taken to test model on test split: 0.16 seconds

=== Summary ===

Correctly Classified Instances      17144      100      %
Incorrectly Classified Instances      0          0      %
Kappa statistic                      1
Mean absolute error                  0
Root mean squared error              0
Relative absolute error              0      %
Root relative squared error          0      %
Total Number of Instances          17144

=== Detailed Accuracy By Class ===

```

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	setosa-flower
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	versicolor-flower
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	virginica-flower
Weighted Avg.	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	

Figure 5: J48 tree Classification output-II

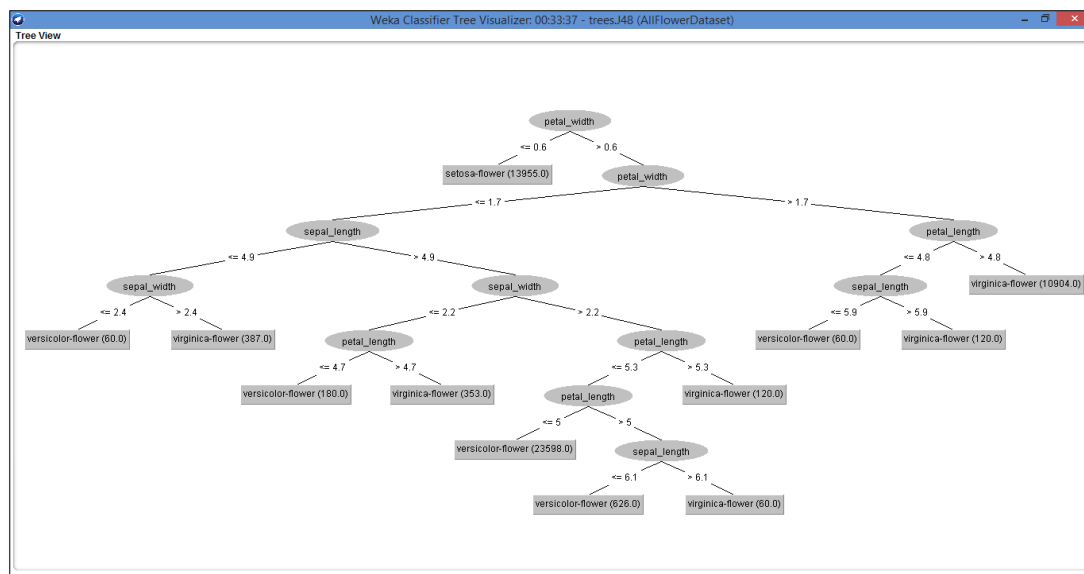


Figure 6: J48 decision Tree

```

Test mode:      split 66.0% train, remainder test

=== Classifier model (full training set) ===

JRIP rules:
=====

(petal_width >= 1.8) and (petal_length >= 4.9) => species=virginica-flower (10904.0/0.0)
(petal_width >= 1.5) and (sepal_width <= 2.5) and (sepal_length <= 6) => species=virginica-flower (740.0/0.0)
(petal_length >= 5.6) => species=virginica-flower (120.0/0.0)
(petal_width >= 1.8) and (sepal_length >= 6) => species=virginica-flower (120.0/0.0)
(petal_length >= 5.1) and (sepal_length >= 6.3) => species=virginica-flower (60.0/0.0)
(petal_length <= 1.9) => species=setosa-flower (13955.0/0.0)
=> species=versicolor-flower (24524.0/0.0)

Number of Rules : 7

Time taken to build model: 2.19 seconds

=== Evaluation on test split ===

Time taken to test model on test split: 0.19 seconds

```

Figure 7: Jrip Classification output-I

```

=== Summary ===

Correctly Classified Instances      17144          100    %
Incorrectly Classified Instances      0             0    %
Kappa statistic                      1
Mean absolute error                  0
Root mean squared error              0
Relative absolute error              0    %
Root relative squared error          0    %
Total Number of Instances          17144

=== Detailed Accuracy By Class ===

          TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
          1.000    0.000    1.000     1.000    1.000     1.000    1.000    1.000    setosa-flower
          1.000    0.000    1.000     1.000    1.000     1.000    1.000    1.000    versicolor-flower
          1.000    0.000    1.000     1.000    1.000     1.000    1.000    1.000    virginica-flower
Weighted Avg.   1.000    0.000    1.000     1.000    1.000     1.000    1.000    1.000

=== Confusion Matrix ===

  a    b    c  <-- classified as
4770   0    0 |  a = setosa-flower
  0 8292   0 |  b = versicolor-flower
  0   0 4082 |  c = virginica-flower

```

Figure 8: Jrip Classification output-II


```

=== Classifier model (full training set) ===

Naive Bayes Classifier

```

Attribute	Class		
	setosa-flower (0.28)	versicolor-flower (0.49)	virginica-flower (0.24)
=====			
sepal_length			
mean	4.981	5.8489	6.5333
std. dev.	0.3334	0.4619	0.677
weight sum	13955	24524	11944
precision	0.1059	0.1059	0.1059
sepal_width			
mean	3.3881	2.7603	2.9593
std. dev.	0.3868	0.2556	0.3345
weight sum	13955	24524	11944
precision	0.1091	0.1091	0.1091
petal_length			
mean	1.4736	4.1744	5.6414
std. dev.	0.1856	0.489	0.5928
weight sum	13955	24524	11944
precision	0.1405	0.1405	0.1405
petal_width			
mean	0.276	1.2686	2.0964
std. dev.	0.1116	0.1675	0.2679
weight sum	13955	24524	11944
precision	0.1143	0.1143	0.1143

Figure 9: Naïve Bayes Classification output-I

```

std. dev.      0.1856      0.489      0.5928
weight sum     13955      24524      11944
precision      0.1405      0.1405      0.1405

petal_width
mean           0.276       1.2686      2.0964
std. dev.      0.1116      0.1675      0.2679
weight sum     13955      24524      11944
precision      0.1143      0.1143      0.1143

Time taken to build model: 0.13 seconds

=== Evaluation on test split ===

Time taken to test model on test split: 0.31 seconds

=== Summary ===

```

Correctly Classified Instances	16622	96.9552 %
Incorrectly Classified Instances	522	3.0448 %
Kappa statistic	0.9517	
Mean absolute error	0.0247	
Root mean squared error	0.1384	
Relative absolute error	5.8776 %	
Root relative squared error	30.1521 %	
Total Number of Instances	17144	

Figure 10 : Naïve Bayes Classification output-II

```

Time taken to test model on test split: 0.31 seconds

=== Summary ===

Correctly Classified Instances      16622          96.9552 %
Incorrectly Classified Instances    522            3.0448 %
Kappa statistic                    0.9517
Mean absolute error                0.0247
Root mean squared error            0.1384
Relative absolute error            5.8776 %
Root relative squared error        30.1521 %
Total Number of Instances          17144

=== Detailed Accuracy By Class ===

      TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
      1.000    0.000    1.000    1.000    1.000    1.000    1.000    1.000    setosa-flower
      0.975    0.035    0.963    0.975    0.969    0.939    0.996    0.996    versicolor-flower
      0.923    0.016    0.948    0.923    0.935    0.915    0.995    0.986    virginica-flower
Weighted Avg.  0.970    0.021    0.969    0.970    0.969    0.950    0.997    0.995

=== Confusion Matrix ===

  a    b    c  <-- classified as
4770   0   0 |  a = setosa-flower
  8084 208 |  b = versicolor-flower
  314 3768 |  c = virginica-flower

```

Figure 11: Naïve Bayes Classification output-III

5 Conclusions And Future Work

A hybrid approach is proposed which is capable to identify the species of flower which is provided as data to be tested with approx. 96 percent accuracy.

The proposed approach incorporates three stages: division, highlight extraction, and arrangement stages. Division stage plans to improve the exactness by isolating the blossom shape from the picture normal foundation. After that with chosen classification algorithm we have applied each algorithm on prepared dataset and with the comparative analysis we have found that The tree classifier and rule based classification algorithm shows best accuracy measure in prediction of correct specie i.e. Setosa, Veriginica, vericolor with the accuracy of 100%, whereas selected Naïve Bayes algorithm shows good results but in comparison of rule based and tree classifier it shows 96% accuracy. This hybrid model of combination of three algorithms will be suitable of any kind of flower specie and with some modification it can exceed its limitation to category other than flower also. This hybrid model shows nearly maximum possible accuracy on such a large dataset and with number of folds it won't take much time in calculation of correct specie, with these characteristics of hybrid module we are proposing this Hybrid combination of algorithm for data analysis and prediction purpose for future also.

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