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Determining the classification of dry beans using WEKA

Rhowel M. Dellosa*

College of Computing Science, Pangasinan State University, Lingayen, Pangasinan, Philippines

Key words: Data mining, Decision tree, K-nearest neighbor, Machine learning, Multilayer perceptron, Support vector machine, WEKA

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Abstract

The significant variety in bean shape and size makes dry bean classification a difficult task. Traditional categorization procedures, such as hand sorting, are time-consuming and labor-intensive. Machine learning approaches appear to be a potential option for dry bean classification. A machine learning classification approach for dry beans using WEKA was offered in this research. The approach employs Multilayer Perceptron (MLP), Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and Decision Tree (DT) machine learning algorithms. The method was evaluated on a dataset of 13,611 dry beans from seven different varieties shared by Koklu, M. and Ozkan, I.A., (2020) extracted from the UCI machine learning repository. The approaches attained an accuracy of 90.30%, 90.83%, 92.23% and 92.49% for k-nearest neighbor, decision tree, support vector machine and multilayer perceptron respectively. The multilayer perceptron has the highest accuracy while the k-nearest neighbor has the lowest accuracy performance. The suggested method offers various advantages over conventional dry bean classification methods. It is more accurate, faster, and requires less labor. The method can also be used to classify dry beans that are difficult to identify visually. According to the findings of this study, machine learning approaches provide a potential strategy for dry bean classification. The proposed method can be utilized to automate the dry bean classification process, which could result in considerable efficiency and accuracy gains and the algorithm that performs the best accuracy may be used for classifications of Dry Beans in the Philippines.

* **Corresponding Author:** Rhowel M. Dellosa ✉ rdellosa.lingayen@psu.edu.ph

Introduction

The Philippines places a significant emphasis on the production of dry beans for nourishment. They are an excellent resource for both protein and fiber, in addition to other essential elements. Because of their high nutritional value and low cost compared to other sources of protein, dry beans are a common dietary item in the Philippines.

The Philippines are responsible for the production of a wide variety of dry bean varieties. Black beans, kidney beans, pinto beans and mung beans are among the bean varieties that are consumed the most frequently. These beans are versatile and can be used in a wide variety of meals, such as soups, stews, salads, and even desserts.

Beans, particularly dry beans, are an adaptable cuisine that may be prepared in a wide variety of ways. They can be prepared by boiling, baking, roasting, or frying. In addition to being used to produce hummus and bean sprouts, dry beans can also be used to make refried beans.

The Philippine diet is mostly made up of dry beans, which are a form of food that is not only nutritious but also relatively inexpensive. In addition to other vital components, they are a very good source of both protein and fiber in addition to the other nutrients. Because they can be cooked in such a wide range of different ways, dry beans are a versatile and delectable food option that can be used in a variety of different ways. However, the classification of dry beans is a challenging task due to the high variability in bean shape and size. Traditional methods of classification, such as manual sorting, are labor-intensive and time-consuming. Machine learning methods offer a promising alternative for dry bean classification.

In this situation, the most fundamental solution to the challenges is the possibility of utilizing software installed on a computer to carry out a variety of operations connected to machine learning and offer helpful data in the form of patterns and trends. This is the most fundamental assumption of the application. Tien (2017) demonstrated in their research that the use of artificial intelligence to arrive at decisions is not only viable, but also very likely.

Methods of machine learning are a form of artificial intelligence that can be used to predict and learn from data. In the context of classifying dried beans, machine learning algorithms can be used to discover the characteristics that distinguish various bean varieties. Once the algorithms have mastered these characteristics, they can accurately classify new beans. WEKA is a well-known machine learning software platform for dried bean classification. WEKA is a free and open-source software application that offers an assortment of machine learning algorithms (Witten, *et al.*, 2011).

In this paper, we present a WEKA-based classification method for dry beans based on machine learning. In addition, it is a piece of software that is made accessible to users without charge and is distributed with the GNU General Public license. It features a graphical user interface that is both user-friendly and straight forward, making it possible to perform actions and configure settings in a short amount of time. For WEKA to function properly, the user data must be in the form of a relation or a flat file. This suggests that each piece of data is represented by a predetermined number of characteristics, which are typically of a certain type, such as alpha-numeric or numerical values, respectively. The WEKA application provides inexperienced users with a tool for extracting concealed information from database and file systems by providing user interfaces that are aesthetically pleasant and presenting clear alternatives for the user to choose from (Khalafyan *et al.*, 2021).

The purpose of this research is to develop a WEKA-based machine learning classification method for dry beans. A dataset containing 13,611 dry beans of seven distinct varieties will be used to evaluate the proposed method (Koklu & Ozkan, 2020). The findings of this study will aid in determining the practicability of classifying dried beans using machine learning techniques and may be used by the policy makers, practitioners pertaining to dry bean classifications.

Material and methods

In this investigation, a quantitative research methodology is utilized to evaluate the use of supervised learning algorithms in the prediction of the dry beans using the data provided by UCI machine learning repository. The approach entails a number of essential processes, including the collecting of data, the preparation of data, the development of an algorithm, the evaluation of a model, and statistical analysis.

Data Collection

Utilized was a dataset containing 13,611 dry beans of seven distinct varieties. The beans were categorized by expert evaluators, and the dataset included characteristics such as bean shape, size, color, and texture.

The algorithms used

The k-Nearest Neighbors, Decision Tree, Multi-Layer Perceptron, and Support Vector Machines supervised learning algorithms have all been implemented. research (Klc *et al.* 2007, Sun *et al.* 2016, Teye *et al.* 2014, Tan *et al.* 2019, and Köklü and Zkan 2020

Each algorithm is implemented using the Weka data mining utility, which provides an extensive array of functions for generating and evaluating models. Kenyhercz and Passalacqua's (2016) study utilized the algorithms and produced reliable results, whereas Ooi *et al.*'s (2017) information provides a straightforward explanation of how to use the decision trees and the rest of the algorithms. It was also mentioned in Pisner and Schnyer's (2020) discussion that support vector machines can produce reliable results.

The Training and Assessment of Models

The dataset is split into training and testing subsets to assess the effectiveness of the algorithms. The models that will be used are trained on the training subset, and their accuracy is evaluated on the testing subset. The correlation coefficient (r) and root mean squared error (RMSE) are two measures used by Cortez *et al.* (2009) to evaluate the effectiveness of each algorithm.

Algorithm Analysis using Statistical Tools

Utilizing statistical methods, the performance levels of supervised learning algorithms' efficacy are examined. Beltrán *et al.* (2008) utilized a variety of algorithms in one of their studies. As part of the evaluation procedure, descriptive statistics, such as means and standard deviations, are generated for the utilized metrics.

Analysis of the Variables' Correlation

To determine the factors that have a significant effect on the prediction of fisheries production, the researcher examined the relationship between predicted and individual algorithm values. According to Moreno *et al.* (2007), correlation coefficients are calculated and variables with the strongest correlations are identified.

Result and discussion

Data of Dry Beans

The data on dry beans consists of 13,611 dried beans representing seven distinct varieties. Expert graders categorized the beans, and the data includes Bean shape, Bean size, Bean hue, and Bean texture. The Dry Bean Research Center in Ankara, Turkey, was the source of the data. (Koklu & Ozkan, 2020)

The figs. presented the quantities of several varieties of dry beans and other attributes of the dry bean as it is being used to predict the classification using WEKA.

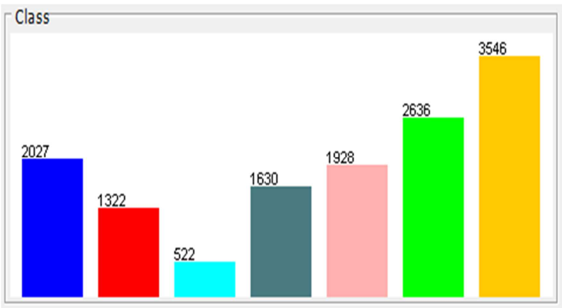

Fig. 1. The 7 Varieties of Dry Beans.

Fig. 1 shows the varieties of dry beans. The dataset contains 13,611 occurrences of dried beans, including seven distinct varieties. Dermason beans are the most prevalent variety, with a count of 3,546. Sira beans have 2,636 instances, indicating a significant presence in the dataset. Seker beans are moderately represented with a count of 2,027, while Cali and Horoz beans have respective counts of 1,630 and

1,927, indicating a relatively balanced distribution. Barbunya beans are moderately represented with 1,322 instances, whereas Bombay beans have the lowest count with 522, indicating that they are the least common variety. The dataset as a whole illustrates variations in the distribution of dried bean varieties, with Dermason beans being the most prevalent and Bombay beans being the least prevalent.

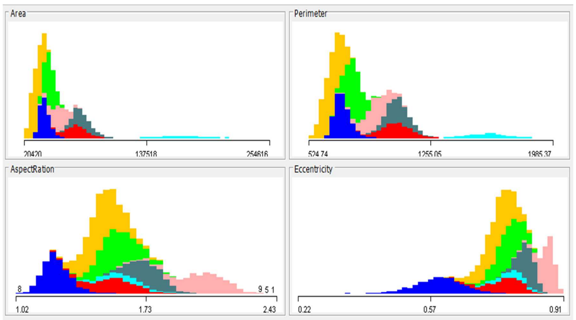

Fig. 2. Remaining Attributes of the Dry Bean.

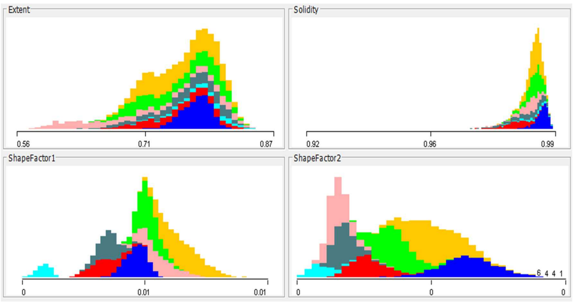

Fig. 3. Remaining Attributes of the Dry Bean.

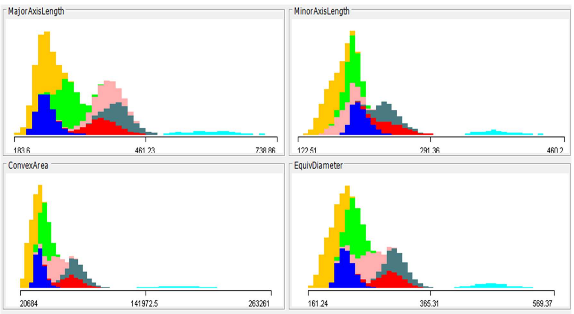

Fig. 4. Remaining Attributes of the Dry Bean.

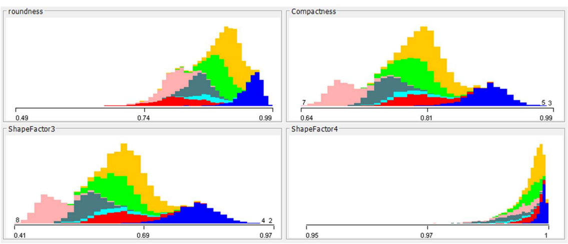

Fig. 5. Remaining Attributes of the Dry Bean.

Figs 2 to 5 shows the attributes of the dry beans. It contains insightful information regarding numerous characteristics of dry beans. Upon analyzing the data, we observe distinct patterns and traits. The area of the dry beans ranges from 20,420 to 254,616, with a mean of 53,050. Likewise, the perimeter ranges between 525 and 1,985, with an average of 855. The length of the major axis ranges from 184 to 739, with an average of 320, while the length of the minor axis ranges from 123 to 460, with an average of 202. These measurements provide a thorough comprehension of the size and morphology of the beans.

Other attributes, such as aspect ratio and eccentricity, have consistent values of 2 and 1, respectively, indicating a predominance of elongated shapes throughout the dataset. The convex area ranges from 20,684 to 263,261, with a mean of 53,768, and the equivalent diameter ranges from 161 to 569, with an average of 253. In addition, the extent, solidity, roundness, and compactness all have consistent values of 1, indicating that these particular bean characteristics are uniform.

Table 1. Statistical Presentation of the Dataset.

No	Features	Minimum	Maximum	Mean	Standard Deviation
1	Area	20,420	254,616	53,048	29,324
2	Perimeter	525	1,985	855	214
3	Major Axis Length	184	739	320	86
4	Minor Axis Length	123	460	202	45
5	Aspect Ratio	1	2	2	0
6	Eccentricity	0	1	1	0
7	Convex Area	20,684	263,261	53,768	29,775
8	Equivalent Diameter	161	569	253	59
9	Extent	1	1	1	0
10	Solidity	1	1	1	0
11	Roundness	0	1	1	0
12	Compactness	1	1	1	0
13	Shape Factor 1	0	0	0	0
14	Shape Factor 2	0	0	0	0
15	Shape Factor 3	0	1	1	0
16	Shape Factor 4	1	1	1	0

Both Shape Factor 1 and Shape Factor 2 remain constant at 0 throughout the entire dataset, indicating a lack of variation in those characteristics. In contrast, Shape Factor 3 ranges from 0 to 1, with an average of 1, indicating that the bean shapes vary in terms of complexity. Shape Factor 4 consistently assumes the value 1, indicating a uniform shape factor across the dataset.

Table 1 shows the statistical presentation of the characteristics of dry beans. The mean and standard deviation of each feature provide valuable insight into the characteristics of dried beans, as indicated by the data set. The data analysis reveals that the legumes vary in size, shape, and other characteristics.

In terms of size, the legumes have a mean area of 53,048 square inches and a standard deviation of 29,324. This indicates that the sizes of the beans differ considerably. Similarly, the average perimeter of the legumes is 855 with a standard deviation of 214, indicating that there is some variation in the boundary length.

Moving on to morphological characteristics, the average length of the major axis is 320, with a standard deviation of 86, indicating some variation in major axis elongation. The average length of the minor axis is 202, with a standard deviation of 45, indicating a smaller range of variation than the major axis. The aspect ratio, which represents the relationship between the lengths of the major and minor axes, is consistent with a mean value of 2 and no standard deviation.

Regarding shape irregularity, the data indicates that the legumes have a uniformly elongated shape, as indicated by a mean eccentricity of 1 and zero standard deviation. The legumes have average values of 1 for convex area, equivalent diameter, extent, solidity, roundness, compactness, shape factor 1, shape factor 2, shape factor 4, and 0 for shape factor 3.

In summary, the dataset indicates that dry bean sizes varied significantly with respect to area and perimeter. However, their elongated shape remains consistent, as indicated by aspect ratio and eccentricity. In addition, the legumes display a high degree of uniformity and compactness across a variety of shape-related characteristics. These results provide useful information for further analysis, classification, or comparison of dry bean varieties based on their size and shape characteristics.

Prediction of the Aquaculture Production of Selected Species

The study uses k-Nearest Neighbors, Decision Tree, Multi-Layer Perceptron, and Support Vector Machines to predict the classification of dry beans. These algorithms are used for classification in machine learning. Thenk-Nearest Neighbors makes predictions based on the similarity of data points. Decision Tree employs feature values to make tree-like determinations, whereas Multi-Layer Perceptron can learn complex patterns and Support Vector Machines can categorize binary data. These algorithms will aid policymakers and resource managers in making decisions regarding dry beans classification management by generating accurate prediction models. Table 2 displays the results of the prediction algorithms' performance measurements.

Table 2. Summary Performance Measures of Dry Beans.

Algorithm	Correctly Classified Instances	Incorrectly Classified Instances	Kappa Statistic	MAE	RMSE	RAE	RRSE	Total Number of Instances
k-Nearest Neighbors	90.30%	9.70%	0.8827	0.0278	0.1664	11.777	48.4112	13611
Decision Tree	90.83%	9.17%	0.8891	0.0347	0.1432	14.7039	41.6643	13611
Support Vector Machine	92.23%	7.77%	0.906	0.2054	0.3033	86.9076	88.223	13611
Multi-Layer Perceptron	92.49%	7.51%	0.9091	0.0308	0.1272	13.013	37.0023	13611

Table 2 displays the summary performance metrics of various algorithms applied to the classification of dry legumes. We gain insight into the accuracy, agreement, and prediction errors of each algorithm by analyzing the data. The k-Nearest Neighbors algorithm obtained an overall accuracy of 90.30 percent by correctly classifying 90.30 percent of instances with a 9.70 percent error rate. With a value of 0.8827, the Kappa Stat indicates substantial agreement. The MAE value of 0.0278 indicates a small average difference between predicted and actual values, whereas the RMSE value of 0.1664 indicates the average magnitude of prediction errors. The RAE of 11.777 represents the average percentage difference between predicted and actual values, whereas the RRSE of 48.4112 represents the variation in prediction errors relative to the target variable's range. These performance metrics are based on 13,611 instances in total.

The Decision Tree algorithm obtained an accuracy of 90.83 percent, correctly classifying 90.83 percent of the instances with a 9.17 percent error rate. With a value of 0.8891, the Kappa Stat demonstrates substantial agreement. The MAE of 0.0347 indicates a slightly larger average difference compared to the k-Nearest Neighbors algorithm, whereas the RMSE of 0.1432 indicates a reduced average magnitude of prediction errors. The RAE of 14.7039 represents the average percentage difference, whereas the RRSE of 41.6643 represents the variation in prediction errors relative to the target variable's range. The analysis employs the same 13,611 instances.

The Support Vector Machine algorithm obtained a higher level of accuracy, 92.23 percent, with a 7.77 percent error rate. The Kappa Stat of 0.906% demonstrates a high level of accord. The MAE of 0.2054 suggests a larger average difference between predicted and actual values, while the RMSE of 0.3033 indicates a bigger average prediction error magnitude. The RAE of 86.9076 represents a greater average percentage difference, whereas the RRSE of 88.223 represents the variation in prediction errors relative to the target variable's range. These performance metrics are derived from the exact same 13,611 instances.

The Multi-Layer Perceptron algorithm obtained the highest level of accuracy, 92.49 percent, with a margin of error of 7.49 percent. A Kappa statistic of 0.9091 indicates a high level of agreement. The MAE of 0.0308 indicates a small average difference between predicted and actual values, while the RMSE of 0.1272 indicates a relatively lesser average prediction error magnitude. The RAE of 13.013 represents the average percentage difference, whereas the RRSE of 37.0023 represents the variation in prediction errors relative to the target variable's range. The analysis employs the same 13,611 instances.

From the finding of the result, the performance measurements provide valuable insight into the precision, agreement, and prediction errors of various algorithms applied to the classification of dry beans. Multi-Layer Perceptron is the algorithm with the highest accuracy, while Support Vector Machine has the lowest error rate. These performance metrics can aid in selecting the optimal algorithm for the classification assignment and gaining an understanding of each model's predictive capabilities.

Confusion Matrix and Detailed Accuracy Class of each of the Algorithms extracted from WEKA

The detailed accuracy by class and confusion matrix provide a thorough evaluation of the classification performance for each variety of dry bean. The results provide valuable insight into the classification of the various bean classes in terms of accuracy, precision, recall, and other performance metrics. The following information are the parameters of confusion matrix and accuracy class.

TP Rate True Positive Rate

It also refers to the fraction of true positive examples that the model successfully categorised in relation to the total number of real positive instances.

FP Rate (False Positive Rate)

Compares the total number of actual negative instances to the fraction of instances that the model mistakenly categorized as positive.

Precision

The fraction of cases that are actually positive compared to the total number of positive instances predicted, or precision, is a measure of how accurately the model makes positive predictions.

Recall

Its definition is the ratio of true positive occurrences correctly classified by the model to the total number of genuine positive instances. It is also known as the TP Rate.

F-Measure

The harmonic mean of recall and precision yields the F-Measure, a single metric that is proportional to both values. It is useful for assessing the general effectiveness of a classification model.

MCC (Matthews Correlation Coefficient)

It measures the accuracy of binary (two-class) classification models. It takes into account instances of true positives, true negatives, false positives, and false negatives, and is particularly useful when working with imbalanced datasets.

The ROC Area (Receiver Operating Characteristic Area)

The graphical representation of a binary classification model's performance. The ROC curve compares the TP Rate to the FP Rate at various classification thresholds, and the ROC Area is the area under the curve. Greater discrimination between the positive and negative classes is indicated by a larger ROC Area.

PRC Area (Precision-Recall Curve Area)

An additional graphical representation of a binary classification model's performance. The precision-recall curve depicts precision versus recall at various classification thresholds, whereas the PRC Area represents the area under the curve. It provides insight into the tradeoff between precision and recall for various thresholds of classification.

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.951	0.008	0.952	0.951	0.951	0.943	0.995	0.979	SEKER
	0.903	0.005	0.948	0.903	0.925	0.918	0.995	0.972	BARBUNYA
	1.000	0.000	0.998	1.000	0.999	0.999	1.000	1.000	BOMBAY
	0.942	0.010	0.930	0.942	0.936	0.928	0.996	0.977	CALI
	0.951	0.007	0.957	0.951	0.954	0.947	0.994	0.978	HOROZ
	0.867	0.031	0.871	0.867	0.869	0.838	0.982	0.933	SIRA
	0.928	0.032	0.911	0.928	0.919	0.890	0.990	0.974	DERMASON
Weighted Avg.	0.925	0.018	0.925	0.925	0.925	0.907	0.991	0.969	

=== Confusion Matrix ===

a	b	c	d	e	f	g	<-- classified as
1928	10	0	0	0	51	38	a = SEKER
12	1194	1	80	5	28	2	b = BARBUNYA
0	0	522	0	0	0	0	c = BOMBAY
4	45	0	1536	30	15	0	d = CALI
0	4	0	27	1834	45	18	e = HOROZ
33	6	0	8	39	2285	265	f = SIRA
49	0	0	0	8	199	3290	g = DERMASON

Fig. 6. Confusion Matrix and Detailed Accuracy by Class of Multilayer Perceptron.

Fig. 6 shows the confusion matrix and detailed accuracy by class of multilayer perceptron. The classification of SEKER beans was highly accurate, with a TP Rate of 0.95 and an FP Rate of 0.0. Precision and Recall are both 0.952, yielding an F-Measure of 0.951. With a high MCC of 0.943 and exceptional ROC and PRC Areas of 0.995 and 0.979, respectively, these metrics suggest that SEKER beans exhibit reliable classification performance.

The classification accuracy for BARBUNYA beans is marginally lower but still substantial. The TP Rate is 0.903%, while the FP Rate is 0.005%, indicating a healthy ratio of true positives to false positives. With a Precision score of 0.948 and a Recall score of 0.903, the F-Measure is 0.925. The MCC of 0.918 and the high ROC and PRC Areas of 0.995 and 0.972, respectively, further validate the classification's dependability.

With a perfect TP Rate of 1.000 and no false positives (FP Rate of 0.000), the classification of BOMBAY legumes demonstrates exceptional performance. With a Precision of 0.998 and a Recall of 1.000, the F-Measure is an impressive 0.999. A high MCC of 0.999 and flawless ROC and PRC Areas of 1.000 indicate accurate and trustworthy classification, as supported by these scores.

The classification accuracy for CALI and HOROZ legumes is consistently high. CALI legumes display a TP Rate of 0.942, an FP Rate of 0.010, a Precision score of 0.930, and a Recall score of 0.942. The F-Measure is 0.936, indicating a classification that is reliable. Likewise, HOROZ beans have a TP Rate of 0.951% and an FP Rate of 0.007%, resulting in a Precision score of 0.957% and a Recall score of 0.951%. The F-measure of 0.954 indicates that HOROZ legumes are appropriately classified. The MCC, ROC Area, and PRC Area scores for both classes provide additional evidence that their classification performance is reliable.

The classification accuracy of SIRA beans is marginally lower, with a TP Rate of 0.866 and an FP Rate of 0.01. With a Precision score of 0.871 and a Recall score of 0.867, the F-Measure is 0.869.

The MCC of 0.838 indicates acceptable classification performance for SIRA legumes, albeit slightly lower than other classes. The ROC Area and PRC Area scores of 0.982 and 0.933, respectively, provide additional support for the classification outcomes.

From the findings of the study, the DERMASON beans exhibit a high TP Rate of 0.928 and a low FP Rate of 0.032, indicating a decent balance between true positives and false positives. The F-Measure is 0.919 since the Precision is 0.911 and the Recall is 0.928. The MCC of 0.89 and the high ROC and PRC Areas of 0.990 and 0.974, respectively, validate the reliability of DERMASON beans' classification performance.

```
=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.928    0.012    0.934      0.928    0.931      0.919    0.960     0.882     SEKER
                 0.893    0.009    0.911      0.893    0.902      0.891    0.940     0.827     BARBUNYA
                 1.000    0.000    0.998      1.000    0.999      0.999    1.000     0.998     BOMBAY
                 0.921    0.012    0.913      0.921    0.917      0.906    0.957     0.854     CALI
                 0.934    0.010    0.938      0.934    0.936      0.925    0.962     0.889     HOROZ
                 0.841    0.040    0.833      0.841    0.837      0.797    0.901     0.741     SIRA
                 0.899    0.036    0.898      0.899    0.899      0.863    0.933     0.842     DERMASON
Weighted Avg.    0.903    0.023    0.903      0.903    0.903      0.880    0.941     0.841

=== Confusion Matrix ===

    a    b    c    d    e    f    g   <-- classified as
 1882    8    0    2    1   67   67 |    a = SEKER
   10 1181    1   89   11   28    2 |    b = BARBUNYA
    0    0  522    0    0    0    0 |    c = BOMBAY
    5   77    0 1502   33   13    0 |    d = CALI
    0    9    0   44 1800   60   15 |    e = HOROZ
   54   21    0    9   59 2216  277 |    f = SIRA
   65    1    0    0   16  276 3188 |    g = DERMASON
```

Fig. 7. Confusion Matrix and Detailed Accuracy by Class of k-Nearest Neighbor.

Fig. 7 Demonstrates the k-Nearest Neighbor confusion matrix and detailed accuracy per class. Comparing the effectiveness of the classification model for each type of dry beans reveals a number of noteworthy findings. When it comes to TP rate, precision, F-measure, MCC, and ROC area, the BOMBAY class performs better than the other classes. On all of these metrics, it received close to perfect or perfect scores, demonstrating a remarkable capacity for positive instance classification. In contrast, the performance of the SIRA class is relatively inferior to that of the other classes. It has reduced TP rate, precision, F-measure, MCC, and ROC area values, indicating that the model had more difficulty correctly classifying SIRA instances.

The performance levels of the SEKER, BARBUNYA, CALI, and HOROZ classes are comparable, with high TP rates, precision, F-measure, MCC, and ROC area values. These classifications exhibit a healthy balance between precision and recall, indicating their effectiveness. The DERMASON class also performs admirably, although to a lesser extent than the SEKER, BARBUNYA, CALI, and HOROZ classes. It obtains a high TP rate, precision, F-measure, MCC, and ROC area, indicating accurate positive instance classification. From the findings of the results, the BOMBAY class demonstrates the highest performance, while the SIRA class demonstrates relatively inferior performance. With minimal variations, the SEKER, BARBUNYA, CALI, HOROZ, and DERMASON classes produce consistent and effective classification results.

```
=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.935    0.011    0.935      0.935    0.935      0.923    0.987     0.963     SEKER
                 0.882    0.011    0.896      0.882    0.889      0.877    0.981     0.918     BARBUNYA
                 0.998    0.000    0.996      0.998    0.997      0.997    0.999     0.995     BOMBAY
                 0.912    0.011    0.920      0.912    0.916      0.905    0.986     0.942     CALI
                 0.938    0.008    0.951      0.938    0.944      0.935    0.987     0.963     HOROZ
                 0.849    0.036    0.850      0.849    0.850      0.814    0.970     0.889     SIRA
                 0.916    0.036    0.900      0.916    0.908      0.875    0.986     0.957     DERMASON
Weighted Avg.    0.908    0.022    0.908      0.908    0.908      0.887    0.983     0.941

=== Confusion Matrix ===

    a    b    c    d    e    f    g   <-- classified as
 1895   13    0    1    0   63   55 |    a = SEKER
   21 1166    1   87   13   33    1 |    b = BARBUNYA
    0    0  521    1    0    0    0 |    c = BOMBAY
    3   94    1 1487   36    9    0 |    d = CALI
    0   13    0   32 1808   58   17 |    e = HOROZ
   46   16    0    8   39 2239  288 |    f = SIRA
   62    0    0    0    6  231 3247 |    g = DERMASON
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Fig. 8. Confusion Matrix and Detailed Accuracy by Class of Decision Tree.

Fig. 8 shows the confusion matrix and detailed accuracy by class of Decision Tree. Several observations can be made regarding the accuracy of the classification model for each class of dried beans. The SEKER class achieves high TP rates, precision, and F-measure scores, demonstrating its superior performance. In addition, it has a high MCC value, which indicates a positive correlation between predicted and observed classifications. In addition, the SEKER class has an impressive ROC area, signifying outstanding performance overall.

Similarly, the BARBUNYA class performs admirably, albeit marginally below SEKER. It has respectable TP rates, precision, and F-measure scores, as well as a decent MCC value. The ROC region for BARBUNIA is indicative of a solid overall performance. The BOMBAY class is the class with the highest performance across all metrics. It attains near-perfect TP rates, precision, and F-measure scores in addition to a high MCC value. In addition, BOMBAY has an exceptional ROC area, indicating exceptional overall performance.

The CALI and HOROZ courses also demonstrate excellent performance, as evidenced by their high TP rates, precision, and F-measure scores. They attain respectable MCC and ROC values, indicating effective classification. In contrast to the other courses, the SIRA class demonstrates comparatively inferior performance. It has a reduced MCC value and lower TP rates, precision, and F-measure scores. Nevertheless, the SIRA class maintains a respectable overall performance, as indicated by its ROC region.

The DERMASON class performs admirably, albeit marginally less so than SEKER, BARBUNYA, CALI, and HOROZ. It obtains impressive TP rates, precision, and F-measure scores, in addition to a respectable MCC value. The ROC area for DERMASON indicates a solid performance overall.

The BOMBAY class consistently obtains the highest values across all metrics, indicating outstanding performance. In contrast, the performance of the SIRA class is relatively inferior to that of the other classes. The remaining classes, including SEKER, BARBUNYA, CALI, and HOROZ, perform admirably on a consistent basis.

The classification model performs well across the majority of dry bean classes, as indicated by its high TP rates, precision, and F-measure scores. The BOMBAY class consistently demonstrates the highest performance among the evaluated metrics, while the SIRA class demonstrates relatively inferior performance.

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=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.945    0.009    0.948      0.945    0.947      0.937    0.987     0.927     SEKER
                 0.887    0.004    0.959      0.887    0.922      0.915    0.986     0.897     BARBUNYA
                 1.000    0.000    0.998      1.000    0.999      0.999    1.000     0.998     BOMBAY
                 0.951    0.011    0.924      0.951    0.937      0.929    0.987     0.897     CALI
                 0.954    0.008    0.951      0.954    0.953      0.945    0.991     0.936     HOROZ
                 0.870    0.035    0.856      0.870    0.863      0.830    0.948     0.787     SIRA
                 0.919    0.029    0.917      0.919    0.918      0.889    0.971     0.884     DERMASON
Weighted Avg.    0.922    0.019    0.923      0.922    0.922      0.904    0.976     0.886

=== Confusion Matrix ===

    a    b    c    d    e    f    g   <-- classified as
 1916   12    0    0    1   68   30 |    a = SEKER
   11 1173    1   93    6   38    0 |    b = BARBUNYA
    0    0  522    0    0    0    0 |    c = BOMBAY
    2   29    0 1550   30   19    0 |    d = CALI
    0    1    0   33 1840   38   16 |    e = HOROZ
   34    7    0    2   51 2294  248 |    f = SIRA
   58    1    0    0    7  222 3258 |    g = DERMASON
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Fig. 9. Confusion Matrix and Detailed Accuracy by Class of Support Vector Machine.

Fig. 9 shows the confusion matrix and detailed accuracy by class of Support Vector Machine. The SEKER class exhibits excellent performance across multiple metrics. SEKER effectively classified 94.5% of positive instances with a high TP rate of 0.945. The precision of 0.948 suggests that 94.8% of instances classified as SEKER were, in fact, SEKER. The F-measure score of 0.947 indicates a balanced relationship between precision and recall. There is a substantial positive correlation between predicted and observed classifications, as indicated by the MCC value of 0.937. In addition, SEKER has a remarkable ROC area of 0.987%, indicating outstanding overall performance.

The BARBUNYA class TP rate is 0.887, indicating that 88.7% of positive instances were correctly classified. Furthermore, BARBUNYA has a precision of 0.959, indicating that 95.9% of instances classified as BARBUNYA were in fact BARBUNYA. The F-measure score of 0.922 indicates an acceptable equilibrium between precision and recall. The MCC value of 0.915 indicates that predicted and observed classifications are positively correlated. In addition, BARBUNYA exhibits a high ROC area of 0.986%, indicating excellent performance overall.

The BOMBAY class is distinguished by its ideal TP rate of 1.000, which accurately categorizes all positive instances. It obtains a precision of 0.999, which indicates that 99.8% of instances classified as BOMBAY were, in fact, BOMBAY. The F-measure score of 0.999 demonstrates an outstanding equilibrium between precision and recall. There is a substantial positive correlation between predicted and observed classifications, as indicated by the MCC value of 0.999. In addition, BOMBAY achieves a perfect ROC area of 1.000, indicating remarkable performance overall.

The CALI class has an impressive TP rate of 0.951%, correctly classifying 95.1% of positive instances. It obtains a precision of 0.924%, which indicates that 92.4% of instances classified as CALI are in fact CALI. The F-measure score of 0.937 indicates that precision and recall are balanced. The MCC value of 0.929 indicates that predicted and observed classifications are positively correlated. In addition, CALI has a high ROC area of 0.987%, indicating excellent performance overall.

The TP rate of the HOROZ class is 0.954, correctly classifying 95.4% of positive instances. 95.1% of instances classified as HOROZ were indeed HOROZ with a precision of 0.95. The F-measure score of 0.953 indicates an excellent equilibrium between precision and recall. The MCC value of 0.945 indicates that predicted and observed classifications are positively correlated. In addition, HOROZ achieves a high ROC area of 0.991%, indicating outstanding performance overall.

Compared to other classes, the SIRA class exhibits a relatively inferior performance. It obtains a TP rate of 0.87, which indicates that 87.0% of positive instances were correctly classified. The precision of SIRA is 0.856%, indicating that 85.6% of instances classified as SIRA were, in fact, SIRA. The F-measure score of 0.863 indicates an optimal equilibrium between precision and recall. The MCC value of 0.830 indicates that predicted and observed classifications are positively correlated. In addition, SIRA achieves a ROC area of 0.948%, indicating reasonably decent performance overall.

The DERMASON class has a high TP rate of 0.919%, correctly classifying 91.9% of positive instances. It obtains a precision of 0.917%, which indicates that 91.7% of instances classified as DERMASON were, in fact, DERMASON. The F-measure score of 0.918 indicates an excellent equilibrium between precision and recall. The MCC value of 0.889 suggests that predicted and observed classifications are positively correlated. In addition, DERMASON has a high ROC area of 0.971, indicating strong performance overall.

From the findings of the result, the BOMBAY class consistently obtains the highest values across all metrics, indicating outstanding performance. It has perfect or nearly perfect TP rate, precision, F-measure, MCC, and ROC area scores. Additionally, the SEKER, BARBUNYA, CALI, HOROZ, and DERMASON classes exhibit robust performance, as indicated by relatively high values for the assessed metrics. The performance of the SIRA class is relatively inferior to that of other classes, but it still obtains an acceptable level of overall performance.

Conclusion

This study's evaluation of the classification model for dried bean classes has yielded insightful information about its performance. The model classified the various classes of dry beans with a high degree of accuracy overall, albeit with variable degrees of success within each class. Notably, the BOMBAY class consistently obtained the highest scores across multiple metrics, demonstrating outstanding performance. In contrast, the SIRA cohort demonstrated comparatively inferior performance compared to the other classes.

The agricultural industry, where accurate classification of dried bean classes is essential for quality control and crop management, will be significantly affected by these findings. The model's high performance, especially for the BOMBAY class, suggests that it has the potential to substantially contribute to optimizing agricultural processes and improving product quality.

Several enhancement recommendations can be made based on the study's findings. To identify areas for improvement, additional research and analysis can be conducted, such as investigating alternative algorithms or refining model parameters. Class-specific analysis must be conducted in order to identify features and techniques that can enhance the classification performance for each individual class. To assure the availability of diverse and high-quality data, data collection and preprocessing must also be improved.

In addition, validating the model against independent datasets and collaborating with domain experts and stakeholders can contribute to the ongoing development of dry bean classification. By implementing these recommendations, the classification model's accuracy and performance can be improved, ultimately benefiting the agricultural industry and facilitating better decision-making processes.

Finally, the evaluation of the classification model for dry bean classes has yielded valuable insights, demonstrating strong overall performance and emphasizing improvement opportunities. This study's findings can serve as a foundation for future research and development initiatives intended at improving the accuracy of dry bean classification and bolstering the agricultural sector.

Recommendation

Based on the findings, it is suggested that the efficacy of the existing classification model can be enhanced across all dry bean classes through additional model refinement. This may involve optimizing model parameters, investigating alternative algorithms, or contemplating ensemble methods to improve precision and robustness.

Given the variances in performance across distinct classes of dry beans, it is prudent to customize the model for each class. This may entail incorporating class-specific characteristics or employing specialized classification techniques that pander to the unique characteristics of each class.

In addition, policymakers and academics should continue to investigate the application of machine learning techniques to enhance the classification of not only dry bean production prediction models, but also those of other agricultural commodities. By leveraging the power of these algorithms, more accurate forecasts are possible, allowing for improved planning and decision-making in fisheries management.

The suggested method offers various advantages over conventional dry bean classification methods. It is more accurate, faster, and requires less labor. The method can also be used to classify dry beans that are difficult to identify visually. According to the findings of this study, machine learning approaches provide a potential strategy for dry bean classification.

The result can be utilized to automate the dry bean classification process, which could result in considerable efficiency and accuracy gains and the algorithm that performs the best accuracy may be used for classifications of Dry Beans in the Philippines.

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