Literature Review, Data Description, and Approach

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GitHub link: [***https://github.com/Ta2299/CIND-820#cind-820***](https://github.com/Ta2299/CIND-820#cind-820)

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# Project Abstract

There are many different types of rice grown globally and determining which type of rice a grain falls under is vital as there are many different rice varieties. The dataset chosen will look at rice variants grown in Turkey, specifically the Osmancik and Cammeo variants. Classifying grains manually would not be feasible, so being able to do this using imagery and models would be much more efficient. These images of rice grains were processed, resulting in a dataset with features for each grain of rice and a class variable that classified the grain as either Cammeo or Osmancik varieties. Assuming we have a program that detects the values for the seven attributes, we will be using classification and regression modeling to predict if the grain is Cammeo or Osmancik.

Some of the issues that will be addressed are: which variables impact whether a grain is Cammeo or Osmancik and which ones have the most significant impact? Given the conditions, how accurately can a grain be classified as Cammeo instead of Osmancik?

The data being used is the Rice Dataset (Cammeo and Osmancik) found in the UCI Machine Learning Repository. This dataset looks at the independent variables: Area, Perimeter, Major Axis Length, Minor Axis Length, Eccentricity, Convex Area, and the Extent of each grain of rice. The dataset contains 3810 rows and eight columns, including the class attribute column, the dependent variable. The class attribute is ‘Class’, classifying each instance as either ‘Cammeo’ or ‘Osmancik.’

The techniques that will be used for this analysis include K-fold cross-validation to improve the effectiveness of the models, and given that the class variable contains two classes, multiple logistic regression modeling, as well as Naïve Bayes classification and decision tree classifier, will also be performed. Multiple logistic regression modeling and Naïve Bayes classification will give us the probability of the grain variations given the variables, which can then be used on a new instance. The decision tree classifier will classify grains based on the conditions of the various attributes. After these models are developed, they will be compared using a confusion matrix. The accuracy, precision, sensitivity (recall), specificity, PPV, NPV and error rate will be calculated to determine how effective and reliable the models are.

# Literature Review

**Introduction**

Rice is one of the most widely eaten foods worldwide, with global consumption of 509.87 million metric tons in the 2021/2022 crop year (Shahbandeh 2022). With more than 120,000 different varieties of rice in the world, the classification of grains is significant. Being able to distinguish between types is important but manually doing so is inefficient and costly.

With the growth in technology, people and industries adapt to make processes more efficient. Using image processing, grains can be processed and have their features extracted from the images, which can then be used to classify the types of grains based on the features. Using machine learning algorithms on the extracted data would allow large amounts of data to be analyzed quickly and efficiently without having manual labourers identifying grains individually, which can be prone to error and time-consuming. The extracted features of grains of rice are typically geometric parameters such as length, width, perimeter, area, etc.; after pulling the features, classification algorithms are performed. Many different types of classification algorithms have been used to classify agricultural produce, such as LR (Koklu et al., 2021), KNN (Ozkan et al., 2021), CNN (Dheir et al., 2019; Singh et al., 2022), NB (Cinar & Koklu, 2019), ANN (Koklu et al., 2021), MLP (Cinar & Koklu, 2019), DT (Cinar & Koklu, 2019) and more.

**Related works**

Many researchers have completed research on classifying agricultural products based on the variants. Below we look at some research related to the classification of rice, pistachios, nuts, dates, wheat, and apples. All works below have processed images and extracted features to develop a dataset for classification models or used the processed images directly for classification.

In the study by Cinar & Koklu (2019), they obtained 3810 images of Cammeo and Osmancik rice grains and processed them to get seven features. They performed cross-validation using a k-value of 4 with the data divided into a 25% test set and 75% train set. They developed the following models to classify grains as either Cammeo or Osmancik with the following accuracy levels: Logistic Regression (LR) 93.02%, Multiplayer Perceptron (MLP) 92.86%, Support Vector Machine (SVM) 92.83%, Decision Tree (DT) 92.49%, Random Forest (RF) 92.39%, Naïve Bayes (NB) 91.71%, and K-Nearest Neighbor (KNN) 88.58%. This study found that LR had the highest accuracy at 93.02%, and all of the classifiers had an accuracy of 90%+ besides the KNN classifier.

Another study on rice was done by Koklu, Cinar, and Taspinar (2021), where five rice varieties were classified using deep learning methods. The varieties included Arborio, Basmati, Ipsala, Jasmine, and Karacadag. The dataset had 75k images with 15k of each rice type. After processing the photos, the dataset had 12 morphological, four shape, and 90 colour features. K-fold cross-validation was used with k equal to 10. The deep learning methods used were ANN, CNN, and DNN. The average accuracy achieved for each of the methods was 99.87% (ANN), 99.95% (DNN), and 100% (CNN). Thus, concluding the most accurate classifier was the CNN model.

Ibrahim et al. (2019) suggest using a multi-class support vector machine (SVM) for rice grain classification. They classified Basmati, Ponni, and Brown rice using 90 images. Using a multi-class SVM, they could classify more classes than a normal SVM. The One-against-One (OAO) technique was used and achieved an accuracy of 90% for basmati, 93.33% for Ponni and Brown rice, and overall accuracy of 92.22%.

A contrastive study was done by Ibrahim et al. (2020) where rice grains were classified using a multi-class support vector machine (SVM) vs. artificial neural network (ANN). The same data was used in this study as in Ibrahim et al. (2019) with Basmati, Ponni, and Brown rice. The data was partitioned into a train, test, and validation set twice, with the values being 80%, 10%, 10%, and 70%, 15%, and 15%, respectively. For ANN, the first data partitioned set (80/10/10) had an overall correct classification rate (OCCR) of 92.25%, and the second partitioned set (70/15/15) had an OCCR of 93.34%. For the multi-class SVM, the OCCR was 92.22%, as observed in the study by Ibrahim et al. (2019). This study determined that using an ANN model can provide more accurate and precise results.

Singh et al. (2022) completed a study on classifying pistachios where they aimed to classify pistachios using a total of 2148 images, 1232 of Kirmizi type and 916 of Siirt type. They created three different CNN models using the transfer learning method, with AlexNet, VGG16, and VGG19. The three models had a classification success of 94.42%, 98.84%, and 98.14%, respectively.

A study on pistachio classification by Ozkan et al. (2021) used an improved KNN classifier. They performed principal component analysis (PCA) on the image data to reduce the feature vector size. Dimensionality reduction was used to prevent overfitting by eliminating the high dimensional data disadvantage. They developed a weighted and non-weighted KNN model using Euclidean distance, and the accuracy was 83.38% and 87.38% for the weighted model. Implementing PCA, they achieved better results; for the PCA weighted KNN model, they reached an accuracy of 94.18%. This study showed that PCA reduces the amount of noise in data and provides a higher accuracy model showing an increase in 10% accuracy for the weighted KNN model.

Dheir et al. (2019) conducted a study that classified five nuts: hazelnut, chestnut, nut forest, nut pecan, and walnut. The dataset contained 2868 images, 1390 training images, 550 validation images, and 910 test images. The features extraction had four convolutional layers: Relu activation function followed by max-pooling layer, two dense layers, and a layer with Softmax activation. After training the data and achieving an accuracy of 81.28%, it was found that the data was being overfitted, so they applied an augmentation to rescale the data and reached a validation accuracy of 94%. The overall accuracy achieved from the model was 98%.

Koklu et al. (2021) classified date fruits by variety after obtaining images, processing the photos, and extracting features from the pictures. There were seven types of dates: Barhee, Deglet Nour, Sukkary, Rotab Mozafati, Ruthana, Sawafi, and Sagai. The three classification models were LR, ANN, and stacking LR and ANN. Cross-validation was performed using k folds where k was equal to 10. KNN had an accuracy of 92.2%, LR had an accuracy of 91%, and stacking the two had an accuracy of 92.8%. From the confusion matrix developed, it was evident that the classification success of the Safawi variant was the highest, and the success of the Barhee variant was the lowest.

In a classification study on apple varieties, Sabanci et al. (2016) used KNN and MLP algorithms to classify 90 apples: Golden Delicious (30), Granny Smith (30), and Starking Delicious (30) apples. Images were captured of these apples, and the properties used for image processing were the diameter, area, perimeter, and fullness, as well as the colour properties red, green, and blue. The image processing results extracted seven features: radius, perimeter, area, volume, mass, and eccentricity. An open-source software, WEKA, was used to perform the classification. The best results for KNN were achieved using KNN, where k was 3 with a success of 97.77%. The highest accuracy for MLP was using MLP with five neurons in the hidden layer to achieve an accuracy of 98.88%. Therefore, classification using the MLP model provided better results.

6400 images of 40 different wheat grains were classified by Olgun et al. (2016) using dense SIFT features with an SVM classifier. After obtaining the DSIFT vector size, the dimensions were reduced using a k-means clustering algorithm to get k clusters where k equals 1000. A Bag of Words (BoW) model was created to reduce the features, and then 10-fold cross-validation was performed on the data before an SVM model was created. The resulting SVM model classified wheat grains with an overall accuracy of 88.33%.

Although very similar research has already been done in Classification of Rice Varieties Using Artificial Intelligence Methods (Cinar & Koklu, 2019), where they compared LR, MLP, SVM, DT, RF, NB, and KNN on the same set of data (Cammeo and Osmancik), this research will replicate and apply k-fold cross-validation using a different k-value to see if it helps improve the classifiers chosen. This classification results of DT, NB, and LR models after applying the k-fold cross-validation will be compared with the results achieved by Cinar and Koklu (2019), who used a k value of 4.

A lot of the classification studies that have been done used KNN, MLP, SVM, ANN, and CNN but hardly any have used Naïve Bayes, Decision Tree, and Logistic Regression. It would be interesting to compare the accuracy of the SVM and ANN classifiers by Ibrahim et al. (2020) as their study was also on the classification of grains of rice. Although they were classifying different variants from Cammeo and Osmancik, the process would be similar.

Regarding similar studies, Koklu et al. (2021) used LR to classify dates that are different from rice. Still, the study is similar to the research that will be completed as they also used k-fold cross-validation with k being ten, and the research that will be done will have a k-value other than 4.

Koklu, Cinar, and Taspinar (2021) did a related study on classifying five types of rice with CNN, ANN, and DNN, which are three different methods from the ones chosen for this research. So, the accuracy results will be compared with those achieved from DT, NB, and LR models.

It’s also important to note that the image collection, processing, and feature extraction have already been done to create the Cammeo and Osmancik dataset, which will be used in this research. The dataset was created based on the collection, processing, and feature extraction done by Cinar & Koklu (2019).

**Methodology**

The following methodology chart outlines the steps that will be taken in this research.

Diagram

Description automatically generated

Feature selection was done using different methods such as the Boruta method and looking at the correlation of the variables and removing the ones with very high correlation and low variance. After the variables are selected, four models were trained with the train control being cross validation, more specifically, a 10-fold cross validation. For the naïve bayes diagram, the data was normalized because naïve bayes assumes the data is normalized. Two models were created for each type of model, one using PCA for pre-processing and the other without. This is done to compare the results and see if PCA improves our models. For the decision tree model training, two decision tree methods will be used, the CART method using rpart and conditional inference tree using ctree. Once the models are developed, a confusion matrix will be generated based on the model which had the higher accuracy and then the other performance metric will be evaluated such as sensitivity, specificity, prevalence, PPV, NPV, and error rate. The performance metrics of each of the selected models will be compared with each other and with existing models from past research to choose the best model created and see how the best model compares to past models.

# Data Description

**Univariate Analysis**

**Data Dictionary**

**Attribute Information:**

1. Area: Returns the number of pixels within the boundaries of the rice grain.

2. Perimeter: Calculates the circumference by calculating the distance between pixels around the boundaries of the rice grain.

3. Major Axis Length: The longest line that can be drawn on the rice grain, i.e., the main axis distance, gives.

4. Minor Axis Length: The shortest line that can be drawn on the rice grain, i.e., the small axis distance, gives.

5. Eccentricity: Measures how round the ellipse, which has the same moments as the rice grain, is.

6. Convex Area: Returns the pixel count of the smallest convex shell of the region formed by the rice grain.

7. Extent: Returns the ratio of the region formed by the rice grain to the bounding box pixels

8. Class: Cammeo and Osmancik.

*Data Dictionary obtained from Cinar and Koklu(2019) pp.188-194.*

**Data Distribution**

The dependent variable is the binary variable ‘Class’, which is not too imbalanced. The data for the independent variables are distributed normally, as seen by the histograms below.

Chart, histogram

Description automatically generated

**Bivariate Analysis**

**Correlation Analysis**

The correlation between the independent variables is shown in the graph below. As we can see, the Area, Convex Area, Perimeter, and Major Axis Length are all very highly correlated. The Area and the Convex Area have the exact correlation with the Perimeter and Major Axis Length, so we can safely remove the feature with the lower variance, Area.

There is also a high correlation between Perimeter, Major Axis Length, and the Convex Area. After checking the variance of these three attributes, the conclusion was made to remove the Major Axis Length variable as it had the lowest variance.

Table

Description automatically generated with low confidence

After removing the very highly correlated variables, we are left with the following correlations.

Table

Description automatically generated with medium confidence

**Pairwise Relations**

The pairwise relations chart shows the relations between the independent variables. The minor axis length and convex area have a positive relationship, and the minor axis length and eccentricity have a negative relationship. The perimeter and minor axis length have a positively correlated relationship as well.

Arrow

Description automatically generated

Strip plots were used to show the relationship between the chosen quantitative independent variables and the categorical dependent variable.

These graphs show that the minor axis length, eccentricity, perimeter, and convex area of the Osmancik species tend to have a lower minimum and maximum compared to the Cammeo variety. It’s also evident that the variety does not affect the extent distribution.

Graphical user interface, application, Word

Description automatically generated

1: Min Max distribution of each variable by class

# Models

Two models were made for each model type when building models based on the data. One uses PCA, and the other without PCA. PCA was implemented due to the high correlation of the variables, and comparing the two types of each model can determine whether PCA helps increase the accuracy of the models or not.

A Boruta search was used to identify the significant variables and the results concluded that all variables were significant.

Graphical user interface, text, application

Description automatically generated

2: Boruta search results are shown above and below

Chart

Description automatically generated

It’s important to note that the Area and Major\_Axis\_Length variables were ultimately not included in any of the models due to their high correlation with existing variables.

**Regression Analysis**

Two models were created for the regression analysis. PCA algorithm was applied to the dataset to determine the important components which replace the use of variables; instead, the components act as the variables.

Text

Description automatically generated

Components 1 to 3 have a cumulative proportion of 99.7% of the data and should therefore be used for the regression analysis. The graph below also shows the variance of each component and confirms that components 4 and 5 are not significant. Chart, bar chart

Description automatically generated

For the first model (lr\_model), 10-fold cross-validation was used as the train control method, and a binomial general linear model was created.

Text

Description automatically generated

The resulting model (lr\_model) has an accuracy of 93.12%. Minor axis length and Convex area are the two significant variables.

The second model (lr\_model2) was the same as model 1 but with the pre-processing of PCA.

Text

Description automatically generated

The accuracy of this model (lr\_model2) is 92.7%, and all three components are significant.

After comparing the accuracies of the models and the AIC values where lr\_model is 1387.3 and lr\_model2 is 1403.9, lr\_model is the better model as the higher accuracy and lower AIC determines it is slightly better.

**Confusion Matrix:**

Graphical user interface, text

Description automatically generated

Using the values from the confusion matrix, sensitivity, specificity, prevalence, PPV, NPV & error rate were calculated.

|  |  |
| --- | --- |
| Regression Model Results (lr\_model) | |
| Accuracy | 0.9312 |
| Sensitivity | 0.9159 |
| Specificity | 0.9441 |
| Prevalence | 0.428 |
| PPV | 0.9245 |
| NPV | 0.9095 |
| Error Rate | 0.0688 |

The variable importance was also calculated for each of the variables of the model.

Chart

Description automatically generated

From this, we can see that convex area and minor axis length are the most important variables, andeccentricity, perimeter, and extent are the least important variables of the model.

**Naïve Bayes Analysis**

When performing the Naïve Bayes analysis, the numeric data was normalized first using a min-max function.

Text, letter

Description automatically generated

From the results of nb\_rice, the accuracy of predicting the probability of Osmancik rice variety is 91.65%, and the accuracy of predicting the probability of Cammeo rice is 91.57%.

The second model (nb\_rice2) had PCA pre-processing, and the resulting model has a lower accuracy in predicting each rice variety’s probability than the first model (nb\_rice).

Text, letter

Description automatically generated

The first model also has higher kappa values meaning the model has higher reliability.

The accuracy of each fold was also calculated to see how good the 10-fold cross-validation is by graphing the accuracy of each of the ten folds. The average accuracy lies around 0.913.Chart

Description automatically generated

The confusion matrix was created based on the first model, and the values for sensitivity, specificity, prevalence, PPV, and NPV were calculated.

Text

Description automatically generated

|  |  |
| --- | --- |
| Naïve Bayes Model Results (nb\_rice) | |
| Accuracy | 0.9165 |
| Sensitivity | 0.8902 |
| Specificity | 0.9370 |
| Prevalence | 0.428 |
| PPV | 0.9137 |
| NPV | 0.8734 |
| Error Rate | 0.0835 |

The variable importance was then calculated for each variable in the nb\_rice model.

Chart

Description automatically generated

Perimeter, Convex Area and Eccentricity seem to be the most important variables, and Extent is the least important variable.

**Decision Tree Analysis**

The decision tree analysis was done twice using two different decision tree methods. One was using rpart and the other using ctree. For each method, two models were made, one using PCA and the other without.

**RPart Model 1**

RPart uses the CART method for analysis which builds a binary tree, and the results were as follows:

Text

Description automatically generated

From looking at model one (dt\_rice), a cp value of 0.004601227 is used as it yields the highest accuracy at 0.9186.

**RPart Model 2**

Using PCA, the results indicated that similarly to model 1, the cp value of 0.004601227 is the best choice. The cp value indicates the best value that should be used for pruning the tree to prevent overfitting the model. The highest accuracy achieved was 0.9178.

Text, letter

Description automatically generated

**Confusion Matrix and Results**

RPart model 1 was determined to be the better model because it had a higher accuracy at the chosen cp value. RPart model 1 was then visualized, and we can see the decision tree created:

Graphical user interface, diagram

Description automatically generated

The decision tree classifies instances as either 1 – Cammeo or 0 – Osmancik by looking at the Perimeter and Eccentricity variables.

**Confusion Matrix:**

Text

Description automatically generated

|  |  |
| --- | --- |
| RPart Decision Tree Model Results (dt\_rice) | |
| Accuracy | 0.9186 |
| Sensitivity | 0.9089 |
| Specificity | 0.9250 |
| Prevalence | 0.428 |
| PPV | 0.9005 |
| NPV | 0.9153 |
| Error Rate | 0.0814 |

The variable importance for each of the variables used by model 1 (dt\_rice) were calculated.

Chart

Description automatically generated

The Perimeter, Convex Area and Eccentricity are the most important variables, and the Extent and Minor Axis Length were the least important.

**CTree Model 1**

Ctree models use conditional inference to create a decision tree. The first models’ results were:

Text

Description automatically generated

According to the output, the min criterion should be 0.99 as it yielded the highest accuracy at 0.9199 and the highest kappa at 0.8363.

**CTree Model 2**

Ctree model 2 uses PCA for pre-processing and the results were:

Text

Description automatically generated

The mincriterion selected for this model was 0.5 as it has the highest accuracy at 0.9152 and the highest kappa at 0.8266.

**Confusion Matrix and Results**

The results of the models suggested that model one is the better model due to its higher accuracy and kappa. We can plot the ctree resulting from model 1 and the resulting diagram is presented below. Link to view the image clearly:

<https://raw.githubusercontent.com/Ta2299/CIND-820/main/rice_ctree.png>

Diagram

Description automatically generatedFrom looking at this decision tree, the variables used to classify an instance as Cammeo or Osmancik are Perimeter, Eccentricity and Convex area.

**Confusion Matrix:**

Text

Description automatically generated

|  |  |
| --- | --- |
| CTree Decision Tree Model Results (ctree\_Rice) | |
| Accuracy | 0.9199 |
| Sensitivity | 0.9040 |
| Specificity | 0.9319 |
| Prevalence | 0.427 |
| PPV | 0.9082 |
| NPV | 0.9008 |
| Error Rate | 0.0801 |

The variable importance was then calculated for the ctree model variables. Chart

Description automatically generated

From the results, we see the Perimeter, Convex area and Eccentricity were the most important variables and the variables that were used in the decision tree model to classify instances.

# Conclusions

**Comparisons**

The results of each of the models will be compared with the models previously created by Cinar and Koklu (2019). The results of the models created have the confusion matrix based off of the average results of the ten folds during the cross validation. This average may result in the values not being an exact representation of the models.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | LR | NB | RPart DT | CTree DT |
| Accuracy | 93,12 | 91,65 | 91,86 | 91,99 |
| Sensitivity | 91,59 | 89,02 | 90,89 | 90,40 |
| Specificity | 94,41 | 93,71 | 92,50 | 93,19 |
| Precision | 92,24 | 91,37 | 90,05 | 90,82 |
| NPV | 90,95 | 87,34 | 91,53 | 90,08 |
| FPR | 5,77 | 6,29 | 7,50 | 6,81 |
| FDR | 7,76 | 8,63 | 9,95 | 9,18 |
| FNR | 8,41 | 10,98 | 9,11 | 9,60 |

The results of this table clearly indicate that the LR model has the highest accuracy, the lowest false positives and false negatives, and has the highest precision amongst all the models. We can conclude that the LR model is the best model amongst the four models. If we were to rank the rest of the models in order from best to worst, CTree DT, RPart DT and then NB would be the order. The NB model has a significantly higher false negative rate, meaning it falsely detects Osmancik rice variety 10.98% of the time. The two decision tree models were very close in their results but the CTree was slightly better due to its higher accuracy and false detection rate.

Graphical user interface, table

Description automatically generated

The table above indicates results achieved by Cinar and Koklu (2019) while working on the same dataset to classify Osmancik and Cammeo rice varieties. The best model they created was the LR model which had an accuracy of 93.02%. When comparing the LR model they achieved to the LR model achieved in this study, it is evident that our LR model has a slightly higher accuracy at 93.12%. Cinar and Koklus model has a lower rate at falsely detecting Osmancik variety whereas our LR model has a lower rate at falsely detecting the Cammeo variety. Overall, our model has a lower false discovery rate, but the Cinar and Koklu model is more balanced when it comes to false detections of each type.

**Final Thoughts**

Overall, the research was successful in creating a model that gives a higher accuracy than models that have been created in the past. It was also evident that not using PCA and using a 10-fold cross validation yielded better results for each model type. Another interesting takeaway from this study was that certain variables are more important in certain types of models. For example, when using a Naïve Bayes model or a Decision Tree model, the most important variables were Perimeter, Convex Area, and Eccentricity. The Minor Axis Length had a greater importance in the CTree Decision Tree model and Naïve Bayes model opposed to the RPart Decision Tree model. For the LR model, the Convex Area and Minor Axis Length were very important to the model and the Perimeter, Eccentricity and Extent were not very important. Moving forward, next steps would be to work towards building a more balanced model which can detect either rice variety since the chosen model from this research (LR model) had a notable bias towards detecting Cammeo as opposed to Osmancik rice varieties.

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