UNIVERSITY OF CANBERRA
AUSTRALIA'S CAPITAL UNIVERSITY

Faculty of Science and Technology

Assignment Coversheet

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Unit number	4483
Unit Tutor	Mr. Pranav Gupta
Assignment name	ST1 Capstone Project – Semester 1 2023
Due date	29 Oct 2023
Date submitted	29 Oct 2023

Student declaration

I certify that the attached assignment is my own work. Material drawn from other sources has been appropriately and fully acknowledged as to author/creator, source, and other bibliographic details.

Signature of student: Yanlong Su **Date: 29/10/2023**

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Introduction

This report is about the capstone project for ST1 unit. It contains the codes that can be run on Python and Google Colab as well as the output from running the code. The structure of the report is organised as follows: firstly, I will introduce the purpose of this report and the pre-process to the provided date set. Secondly, I will perform the exploratory data analysis and predictive data analysis. Then, the project will be set up for deployment of web service via Streamlit. Link to the GitHub repository is also a crucial part of the phase stage, it will be shared in the implement section. The conclusion is presented at last.

Rice MSC data set:

The project uses the data set downloaded from the Kaggle website [1], [2], [3], [4], [5]. It is called Rice MSC data set. The data set contains a CSV file with more than 8 million data cells. It contains 5 classes of rice varieties, they are Arborio, Basmati, Jasmine, Ipsala, and Karacadag. A total of 75,000 pieces of rice grain were obtained from same brand, including 15,000 pieces of each variety of rice. A total of 106 features are identified, including 12 morphological features, 4 shape features and 90 colour features. Roundness, compactness, shape factor 3, aspect ratio and eccentricity are 5 most important features among all 106 features. The purpose of this data set is to develop a model that trains the AI to categorise and differentiate between 5 rice varieties based on their image features.

However, 90 colour features in the data set are seemed to be a noise factor. Since the model should be emphasising on shape attributes rather than colour attributes. Thus, 90 colour features will not be used for model development and training in this report.

Questions:

1. How many rows and columns are used for EDA?
2. what is the sample size for each attribute?
3. How many outliers are in the sample?
4. How many samples left after removal of outlier for each class?
5. What is the correlation between attributes?

Methodology

Exploratory Data Analysis:

The first set for the EDA is to set up the working environment. Google Colab was chosen as it can run the Jupyter notebook and is compatible with Python which is the main language we are using for the coding.

```
# Import Required Python Packages and read data
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno # To visualize missing value
```

```
import plotly.graph_objects as go # To Generate Graphs
import plotly.express as px # To Generate box plot for statistical representation
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

```
# Read dataset
df =
pd.read_csv(r"https://raw.githubusercontent.com/jacklong233/ST1/main/Rice_MSC_Dataset_Trimmed.csv")
```

```
# Checking description: first 5 rows
df.head()
```

5 rows × 17 columns pd.DataFrame

	AREA	PERIMETER	MAJOR_AXIS	MINOR_AXIS	ECCENTRICITY	EQDIASQ	SOLIDITY	CONVEX_AREA	EXTENT	ASPECT_RATIO	ROUNDNESS
0	7805	437.915	209.8215	48.0221	0.9735	99.6877	0.9775	7985	0.3547	4.3693	0.5114
1	7503	340.757	138.3361	69.8417	0.8632	97.7400	0.9660	7767	0.6637	1.9807	0.8120
2	5124	314.617	141.9803	46.5784	0.9447	80.7718	0.9721	5271	0.4760	3.0482	0.6505
3	7990	437.085	201.4386	51.2245	0.9671	100.8622	0.9659	8272	0.6274	3.9325	0.5256
4	7433	342.893	140.3350	68.3927	0.8732	97.2830	0.9831	7561	0.6006	2.0519	0.7944

Continue:

COMPACTNESS	SHAPEFACTOR_1	SHAPEFACTOR_2	SHAPEFACTOR_3	SHAPEFACTOR_4	CLASS
0.4751	0.0269	0.0062	0.2257	0.9863	Basmati
0.7065	0.0184	0.0093	0.4992	0.9888	Arborio
0.5689	0.0277	0.0091	0.3236	0.9865	Jasmine
0.5007	0.0252	0.0064	0.2507	0.9859	Basmati
0.6932	0.0189	0.0092	0.4806	0.9860	Arborio

```
# Checking description: last 5 rows
df.tail()
```

5 rows × 17 columns pd.DataFrame

	AREA	PERIMETER	MAJOR_AXIS	MINOR_AXIS	ECCENTRICITY	EQDIASQ	SOLIDITY	CONVEX_AREA	EXTENT	ASPECT_RATIO	ROUNDNESS
74995	5551	285.911	114.1695	62.9079	0.8345	84.0699	0.9846	5638	0.6418	1.8149	0.8533
74996	7696	322.703	121.3900	81.1375	0.7438	98.9892	0.9868	7799	0.7309	1.4961	0.9287
74997	7579	339.295	136.3125	71.2866	0.8524	98.2338	0.9805	7730	0.6399	1.9122	0.8273
74998	15174	489.502	200.9486	97.6282	0.8740	138.9969	0.9766	15537	0.7903	2.0583	0.7958
74999	12931	452.635	185.5138	90.2651	0.8736	128.3131	0.9760	13249	0.7640	2.0552	0.7931

Continue:

COMPACTNESS	SHAPEFACTOR_1	SHAPEFACTOR_2	SHAPEFACTOR_3	SHAPEFACTOR_4	CLASS
0.7364	0.0206	0.0113	0.5422	0.9841	Arborio
0.8155	0.0158	0.0105	0.6650	0.9949	Karacadag
0.7207	0.0180	0.0094	0.5193	0.9931	Arborio
0.6917	0.0132	0.0064	0.4785	0.9848	Ipsala
0.6917	0.0143	0.0070	0.4784	0.9832	Ipsala

Rows and columns-data shape (attributes & samples)

df.shape

```
(75000, 17)
```

Answer for question 1: there are 75000 rows and 17 columns used for EDA.

Name of the attributes

df.columns

```
Index(['AREA', 'PERIMETER', 'MAJOR_AXIS', 'MINOR_AXIS', 'ECCENTRICITY',
       'EQDIASQ', 'SOLIDITY', 'CONVEX_AREA', 'EXTENT', 'ASPECT_RATIO',
       'ROUNDNESS', 'COMPACTNESS', 'SHAPEFACTOR_1', 'SHAPEFACTOR_2',
       'SHAPEFACTOR_3', 'SHAPEFACTOR_4', 'CLASS'],
      dtype='object')
```

unique values for each attribute

df.nunique()

```
AREA            10793
PERIMETER       57459
MAJOR_AXIS      71629
MINOR_AXIS      67873
ECCENTRICITY     3026
EQDIASQ         10793
SOLIDITY          588
CONVEX_AREA     11069
EXTENT           5464
ASPECT_RATIO    26437
ROUNDNESS        5247
COMPACTNESS      4291
SHAPEFACTOR_1     247
SHAPEFACTOR_2      84
SHAPEFACTOR_3    5411
SHAPEFACTOR_4     544
CLASS               5
dtype: int64
```

Answer to question 2: see above sample numbers for each unique attributes

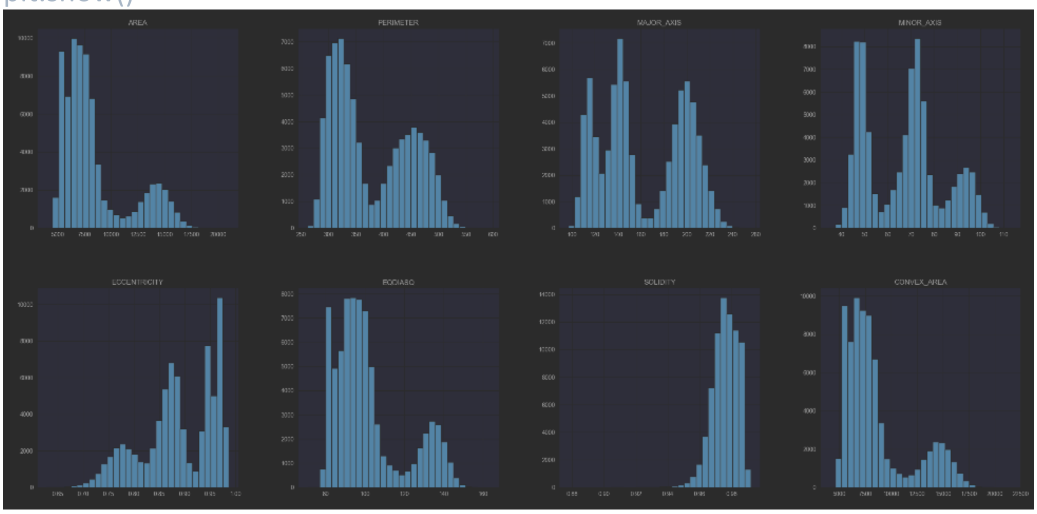
Complete info about data frame

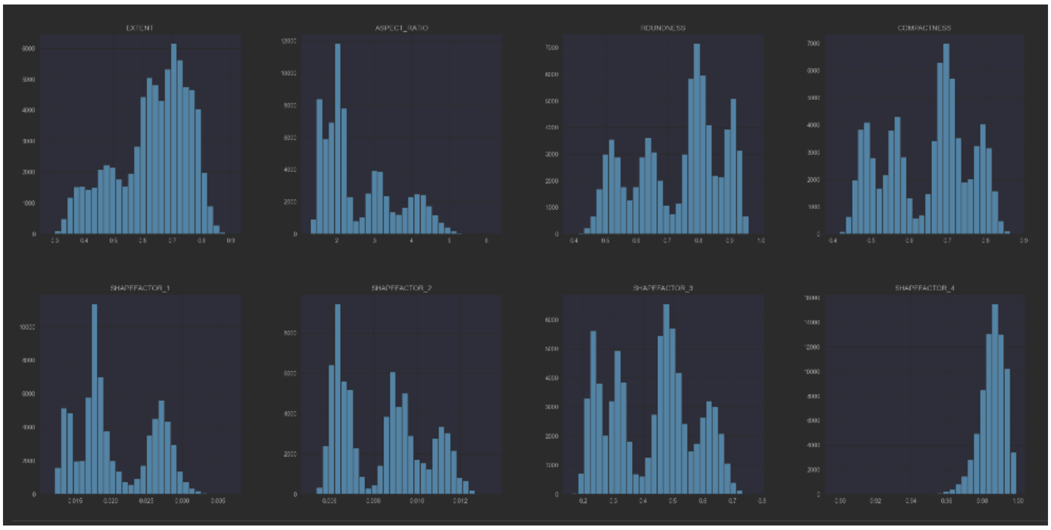
df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 75000 entries, 0 to 74999
```

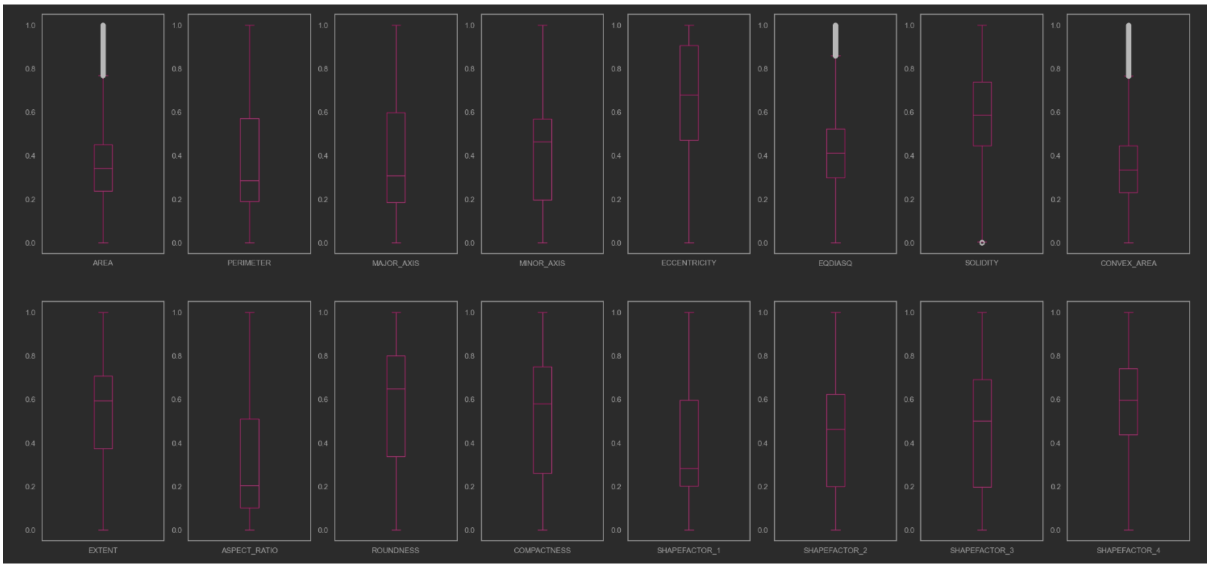
```
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   AREA           75000 non-null  int64
 1   PERIMETER      75000 non-null  float64
 2   MAJOR_AXIS     75000 non-null  float64
 3   MINOR_AXIS     75000 non-null  float64
 4   ECCENTRICITY   75000 non-null  float64
 5   EQDIASQ        75000 non-null  float64
 6   SOLIDITY       75000 non-null  float64
 7   CONVEX_AREA    75000 non-null  int64
 8   EXTENT         75000 non-null  float64
 9   ASPECT_RATIO   75000 non-null  float64
 10  ROUNDNESS      75000 non-null  float64
 11  COMPACTNESS    75000 non-null  float64
 12  SHAPEFACTOR_1  75000 non-null  float64
 13  SHAPEFACTOR_2  75000 non-null  float64
 14  SHAPEFACTOR_3  75000 non-null  float64
 15  SHAPEFACTOR_4  75000 non-null  float64
 16  CLASS          75000 non-null  object
dtypes: float64(14), int64(2), object(1)
memory usage: 9.7+ MB
```

```python
# Visualising data  distribution in detail
fig = plt.figure(figsize =(30,30))
ax=fig.gca()
df.hist(ax=ax,bins =30)
plt.show()
```






```
# Detecting outliers
df.plot(kind='box', subplots=True,
    layout=(20,8),sharex=False,sharey=False, figsize=(30, 150), color='deeppink');
```




```
# Identify the outliers
continous_features = ['AREA', 'PERIMETER', 'MAJOR_AXIS', 'MINOR_AXIS', 'ECCENTRICITY',
'EQDIASQ', 'SOLIDITY', 'CONVEX_AREA', 'EXTENT', 'ASPECT_RATIO', 'ROUNDNESS',
'COMPACTNESS',
'SHAPEFACTOR_1','SHAPEFACTOR_2','SHAPEFACTOR_3','SHAPEFACTOR_4']
def outliers(df_out, drop = False):
  for each_feature in df_out.columns:
    feature_data = df_out[each_feature]
    Q1 = np.percentile(feature_data, 25.) # 25th percentile of the data of the given feature
    Q3 = np.percentile(feature_data, 75.) # 75th percentile of the data of the given feature
    IQR = Q3-Q1 #Interquartile Range
    outlier_step = IQR * 1.5
    outliers = feature_data[~((feature_data >= Q1 - outlier_step) & (feature_data <= Q3 +
```

```python
outlier_step))].index.tolist()
        if not drop:
            print('For the feature {}, No of Outliers is {}'.format(each_feature, len(outliers)))
        if drop:
            df.drop(outliers, inplace = True, errors = 'ignore')
            print('Outliers from {} feature removed'.format(each_feature))

outliers(df[continous_features])
```

```
For the feature AREA, No of Outliers is 11986
For the feature PERIMETER, No of Outliers is 0
For the feature MAJOR_AXIS, No of Outliers is 0
For the feature MINOR_AXIS, No of Outliers is 0
For the feature ECCENTRICITY, No of Outliers is 140
For the feature EQDIASQ, No of Outliers is 9165
For the feature SOLIDITY, No of Outliers is 722
For the feature CONVEX_AREA, No of Outliers is 11569
For the feature EXTENT, No of Outliers is 49
For the feature ASPECT_RATIO, No of Outliers is 113
For the feature ROUNDNESS, No of Outliers is 0
For the feature COMPACTNESS, No of Outliers is 0
For the feature SHAPEFACTOR_1, No of Outliers is 0
For the feature SHAPEFACTOR_2, No of Outliers is 0
For the feature SHAPEFACTOR_3, No of Outliers is 0
For the feature SHAPEFACTOR_4, No of Outliers is 1716
```

Answer to question 3: see above for the outlier amount for each attribute

```python
# Remove outliers:

outliers(df[continous_features], drop = True)
```

```
Outliers from AREA feature removed
Outliers from PERIMETER feature removed
Outliers from MAJOR_AXIS feature removed
Outliers from MINOR_AXIS feature removed
Outliers from ECCENTRICITY feature removed
```

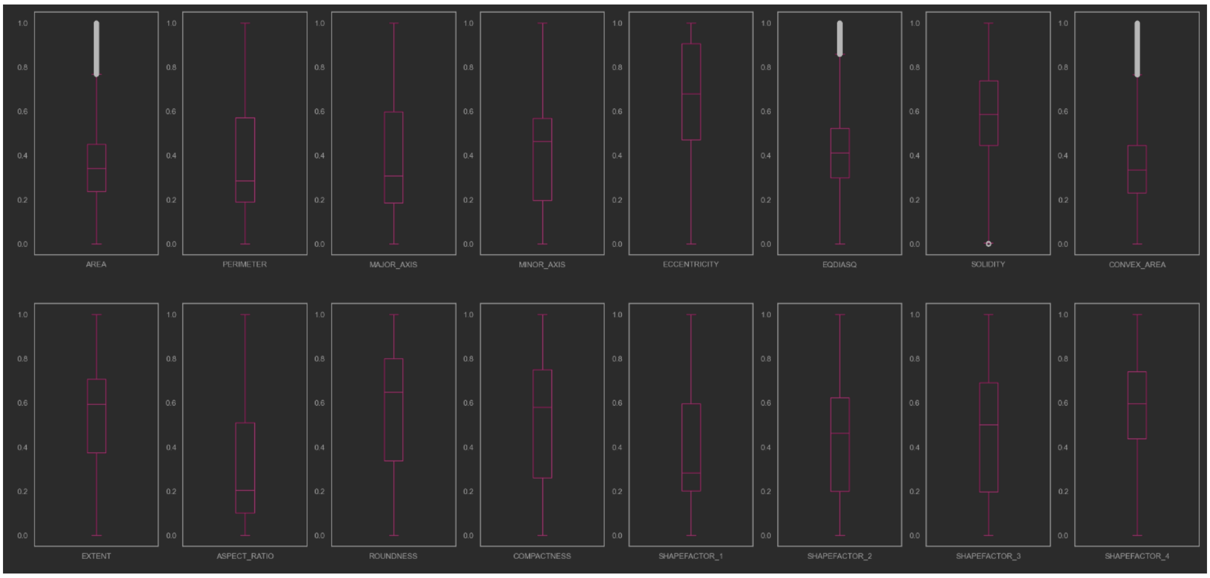
```
Outliers from EQDIASQ feature removed

Outliers from SOLIDITY feature removed

Outliers from CONVEX_AREA feature removed

Outliers from EXTENT feature removed

Outliers from ASPECT_RATIO feature removed

Outliers from ROUNDNESS feature removed

Outliers from COMPACTNESS feature removed

Outliers from SHAPEFACTOR_1 feature removed

Outliers from SHAPEFACTOR_2 feature removed

Outliers from SHAPEFACTOR_3 feature removed

Outliers from SHAPEFACTOR_4 feature removed
```

```
# Rows and columns-data shape after removal of outliers
df.shape
```

```
(60827, 17)
```

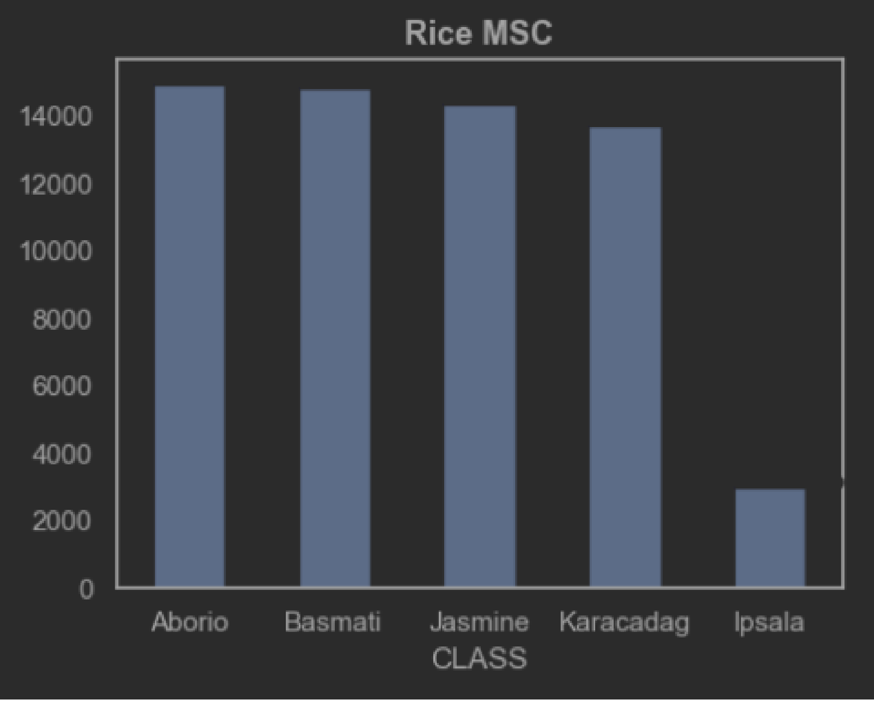
Answer to question 4: only 60,827 samples left.

```
# Check if outliers got removed

df.plot(kind='box', subplots=True,
    layout=(20,8),sharex=False,sharey=False, figsize=(30, 150), color='deeppink');
```



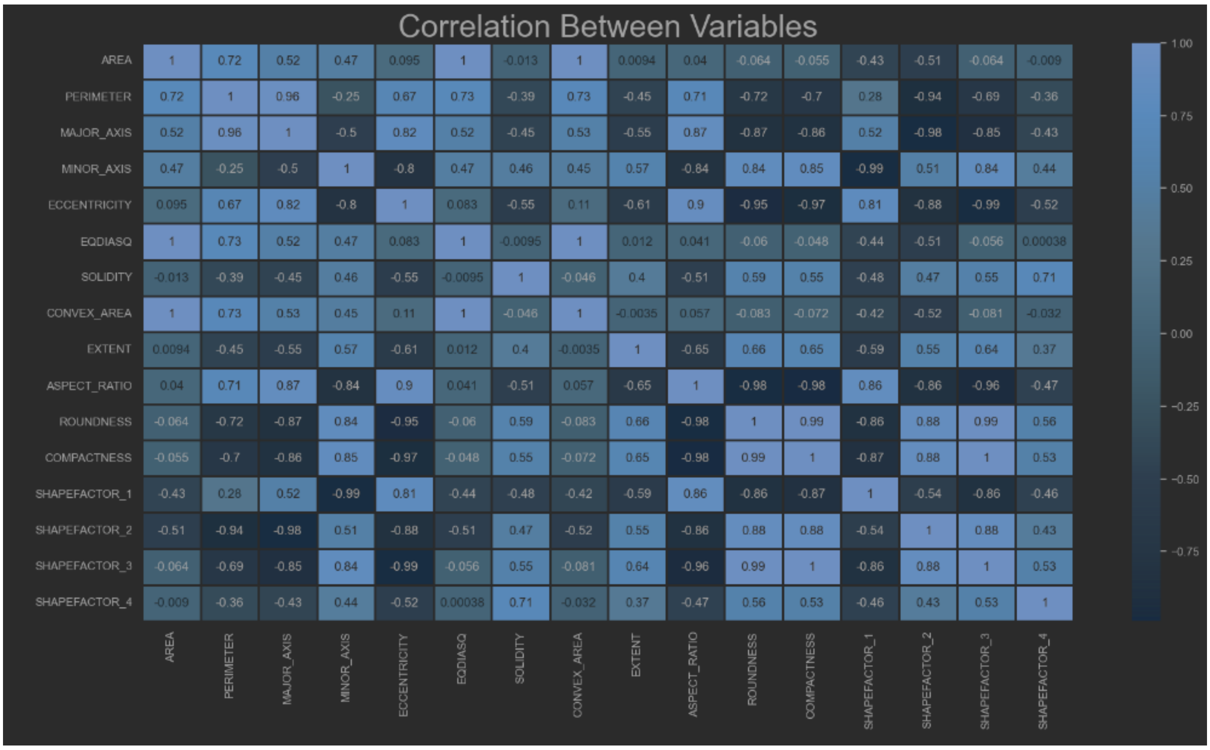
```python
# Checking target value distribution

print(df.CLASS.value_counts())
fig, ax = plt.subplots(figsize=(5,4))
name = ["Aborio", "Basmati", "Jasmine", "Karacadag", "Ipsala"]
ax = df.CLASS.value_counts().plot(kind='bar')
ax.set_title("Rice MSC", fontsize = 13, weight = 'bold')
ax.set_xticklabels (name, rotation = 0)

# To calculate the percentage
totals = []
for i in ax.patches:
    totals.append(i.get_height())
total = sum(totals)
for i in ax.patches:
    ax.text(i.get_x()+.09, i.get_height()-50,
            str(round((i.get_height()/total)*100, 2))+'%', fontsize=14,
                color='white', weight = 'bold')
plt.tight_layout()
```

```
CLASS
0.0    14930
4.0    14859
3.0    14350
1.0    13696
2.0     2992
Name: count, dtype: int64
```



Check correlation between variables

```
sns.set(style="white")
plt.rcParams['figure.figsize'] = (20, 10)
sns.heatmap(df.iloc[:, :-1].corr(), annot = True, linewidths=1, cmap="Blues")
plt.title('Correlation Between Variables', fontsize = 30)
plt.show()
```



Answer to question 5: the correlation is shown in above picture

Obtain full profiler report

```
!pip install https://github.com/pandas-profiling/pandas-profiling/archive/master.zip
```

```
#restart kernel
#re-run import libraries and data
import pandas as pd
import numpy as np
from pandas_profiling import ProfileReport
profile = ProfileReport(df,title="Rice MSC",
                        html={'style':{'full_width':True}})
profile.to_notebook_iframe()
```

Rice MSC

Overview | Variables | Interactions | Correlations | Missing values | Sample | Duplicate rows

Overview

Overview | Alerts 18 | Reproduction

Dataset statistics

Number of variables	17
Number of observations	60827
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	112
Duplicate rows (%)	0.2%
Total size in memory	8.4 MiB
Average record size in memory	144.0 B

Variable types

Numeric	16
Categorical	1

Variables

Predictive Data Analytics:

```
#pre-processing
from sklearn.exceptions import DataDimensionalityWarning
#encode object columns to integers
from sklearn import preprocessing
from sklearn.preprocessing import OrdinalEncoder

for col in df:
 if df[col].dtype =='object':
  df[col]=OrdinalEncoder().fit_transform(df[col].values.reshape(-1,1))
df
```

1-10 60827 rows × 17 columns pd.DataFrame

	AREA	PERIMETER	MAJOR_AXIS	MINOR_AXIS	ECCENTRICITY	EQDIASQ	SOLIDITY
0	7805	437.915	209.8215	48.0221	0.9735	99.6877	0.9775
1	7503	340.757	138.3361	69.8417	0.8632	97.7400	0.9660
2	5124	314.617	141.9803	46.5784	0.9447	80.7718	0.9721
3	7990	437.085	201.4386	51.2245	0.9671	100.8622	0.9659
4	7433	342.893	140.3350	68.3927	0.8732	97.2830	0.9831
5	11648	445.527	178.4659	84.9327	0.8795	121.7813	0.9599
6	7621	450.325	219.0981	45.2301	0.9785	98.5056	0.9718
7	8582	367.338	146.6128	75.5406	0.8570	104.5320	0.9740
8	5450	320.362	139.9963	50.6910	0.9321	83.3016	0.9626
9	6781	307.023	116.2443	74.8093	0.7654	92.9184	0.9819

There are too many rows and columns which can’t be fully written in the report. Please check python file for more details.

```
class_label =df['CLASS']
df = df.drop(['CLASS'], axis =1)
df = (df-df.min())/(df.max()-df.min())
df['CLASS']=class_label
df
```

1-10 60827 rows × 17 columns pd.DataFrame

	AREA	PERIMETER	MAJOR_AXIS	MINOR_AXIS	ECCENTRICITY	EQDIASQ	SOLIDITY
0	0.433800	0.672910	0.748856	0.183046	0.971975	0.505819	0.616798
1	0.400000	0.303278	0.274503	0.524567	0.595010	0.471799	0.314961
2	0.133744	0.203830	0.298684	0.160449	0.873548	0.175419	0.475066
3	0.454505	0.669752	0.693229	0.233170	0.950103	0.526334	0.312336
4	0.392166	0.311405	0.287767	0.501888	0.629187	0.463817	0.763780
5	0.863906	0.701869	0.540790	0.760773	0.650718	0.891723	0.154856
6	0.413206	0.720123	0.810412	0.139345	0.989064	0.485172	0.467192
7	0.520761	0.404404	0.329424	0.613767	0.573821	0.590433	0.524934
8	0.170229	0.225687	0.285519	0.224820	0.830485	0.219606	0.225722
9	0.319194	0.174939	0.127909	0.602321	0.260766	0.387581	0.732283

There are too many rows and columns which can't be fully written in the report. Please check python file for more details.

```
#Data Preprocessing
```

```
import sklearn
from sklearn import linear_model, preprocessing
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import accuracy_score
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier

rice_data = df.copy()
le = preprocessing.LabelEncoder()
area = le.fit_transform(list(rice_data["AREA"]))
perimete = le.fit_transform(list(rice_data["PERIMETER"]))
major_axis = le.fit_transform(list(rice_data["MAJOR_AXIS"]))
minor_axis = le.fit_transform(list(rice_data["MINOR_AXIS"]))
eccentricity = le.fit_transform(list(rice_data["ECCENTRICITY"]))
eqdiasq = le.fit_transform(list(rice_data["EQDIASQ"]))
```

```
solidity = le.fit_transform(list(rice_data["SOLIDITY"]))
convex_area = le.fit_transform(list(rice_data["CONVEX_AREA"]))
extent = le.fit_transform(list(rice_data["EXTENT"]))
aspect_ratio = le.fit_transform(list(rice_data["ASPECT_RATIO"]))
roundness = le.fit_transform(list(rice_data["ROUNDNESS"]))
compactness = le.fit_transform(list(rice_data["COMPACTNESS"]))
shapefactor_1 = le.fit_transform(list(rice_data["SHAPEFACTOR_1"]))
shapefactor_2 = le.fit_transform(list(rice_data["SHAPEFACTOR_2"]))
shapefactor_3 = le.fit_transform(list(rice_data["SHAPEFACTOR_3"]))
shapefactor_4 = le.fit_transform(list(rice_data["SHAPEFACTOR_4"]))
Class = le.fit_transform(list(rice_data["CLASS"]))
```

Model Preparation and Development:

```
x = list(zip(area, perimete, major_axis, minor_axis, eccentricity, eqdiasq, solidity,
convex_area, extent, aspect_ratio, roundness, compactness, shapefactor_1, shapefactor_2,
shapefactor_3, shapefactor_4))
y = list(Class)
# Test options and evaluation metric
num_folds = 5
seed = 7
scoring = 'accuracy'

# Model Test/Train
# Splitting what we are trying to predict into 4 different arrays -
# X train is a section of the x array(attributes) and vise versa for Y(features)
# The test data will test the accuracy of the model created
x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(x, y, test_size =
0.20, random_state=seed)
# Splitting 20% of our data into test samples. If we train the model with higher data it
already has seen that information and knows


# Size of train and test subsets after splitting
np.shape(x_train), np.shape(x_test)
```

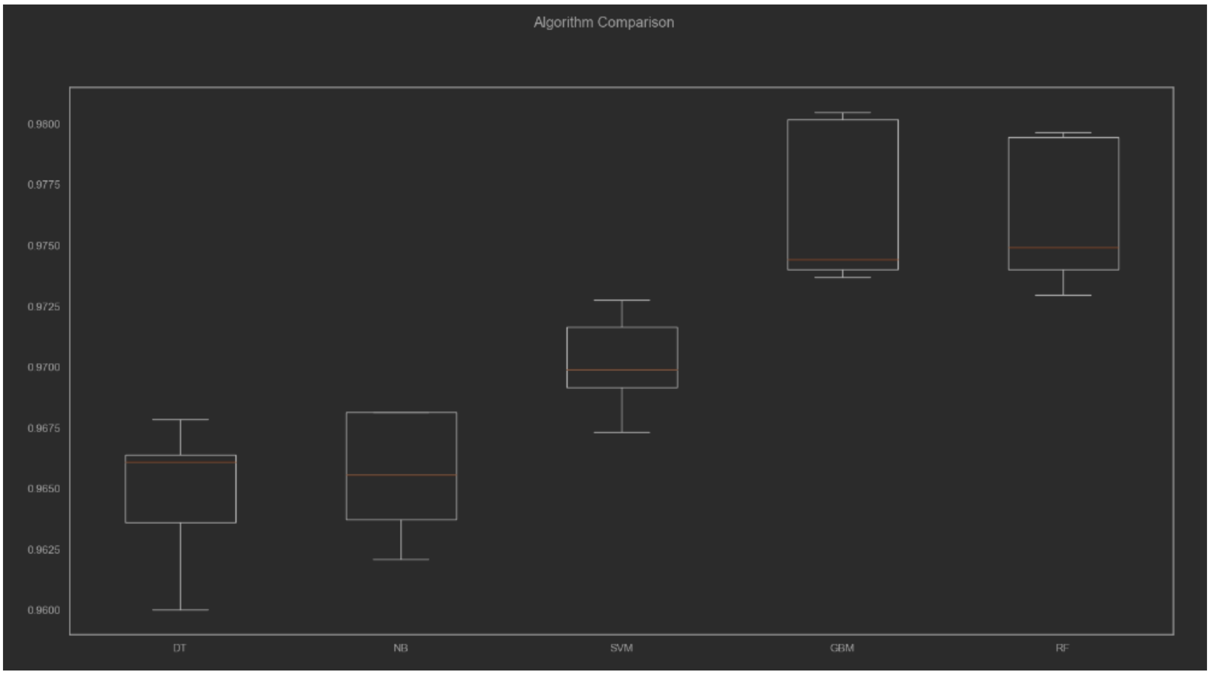
```
((48661, 16), (12166, 16))
```

```
# Predictive analytics model development by comparing different Scikit-learn classification
algorithms

models = []
models.append(('DT', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
```

```python
models.append(('GBM', GradientBoostingClassifier()))
models.append(('RF', RandomForestClassifier()))

# Evaluate each model in turn
results = []
names = []

print("Performance on Training set")

for name, model in models:
   kfold = KFold(n_splits=num_folds,shuffle=True,random_state=seed)
   cv_results = cross_val_score(model, x_train, y_train, cv=kfold, scoring='accuracy')
   results.append(cv_results)
   names.append(name)
   msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
   msg += '\n'
   print(msg)
```

```
Performance on Training set

DT: 0.964797 (0.002743)

NB: 0.965537 (0.002400)

SVM: 0.970161 (0.001902)

GBM: 0.976552 (0.003089)

RF: 0.976203 (0.002804)
```

```python
# Compare Algorithms' Performance
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



Model Evaluation of best performing model, by testing with Independent/external test data set.

Make predictions on validation/test dataset

```
models.append(('DT', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
models.append(('GBM', GradientBoostingClassifier()))
models.append(('RF', RandomForestClassifier()))
dt = DecisionTreeClassifier()
nb = GaussianNB()
gb = GradientBoostingClassifier()
rf = RandomForestClassifier()

best_model = rf
best_model.fit(x_train, y_train)
y_pred = best_model.predict(x_test)
print("Best Model Accuracy Score on Test Set:", accuracy_score(y_test, y_pred))
```

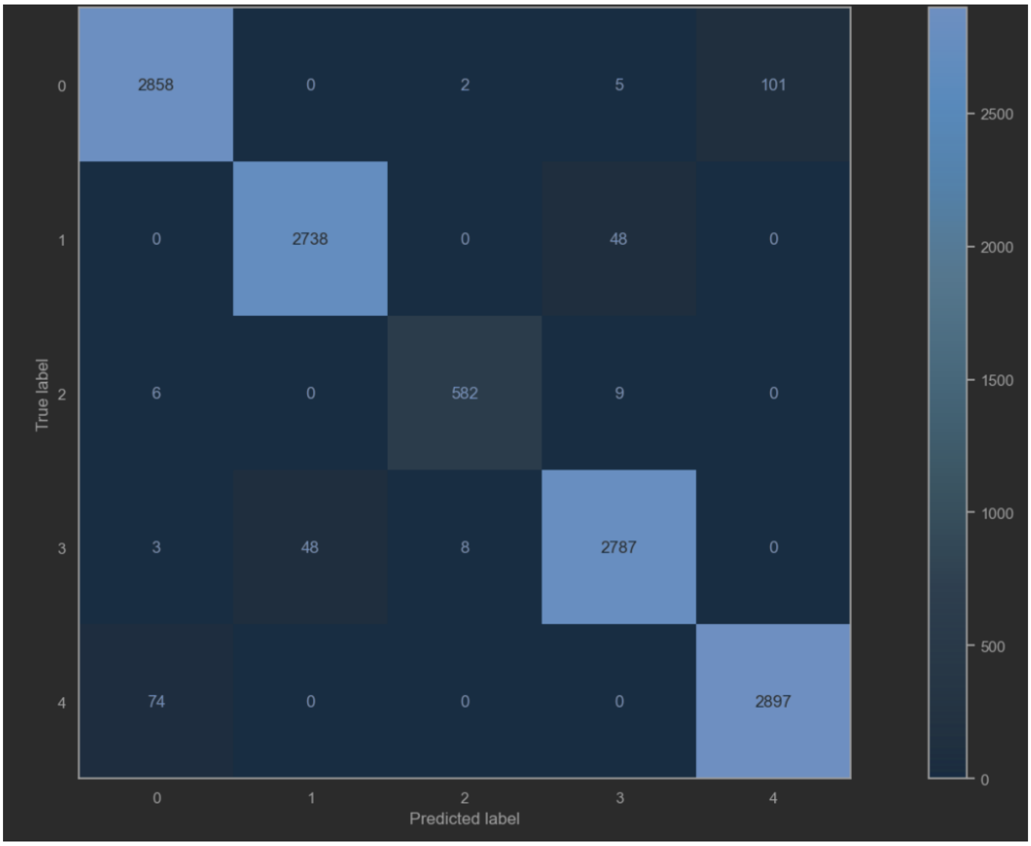
```
Best Model Accuracy Score on Test Set: 0.9750123294427092
```

Model Performance Evaluation Metric 1 - Classification Report

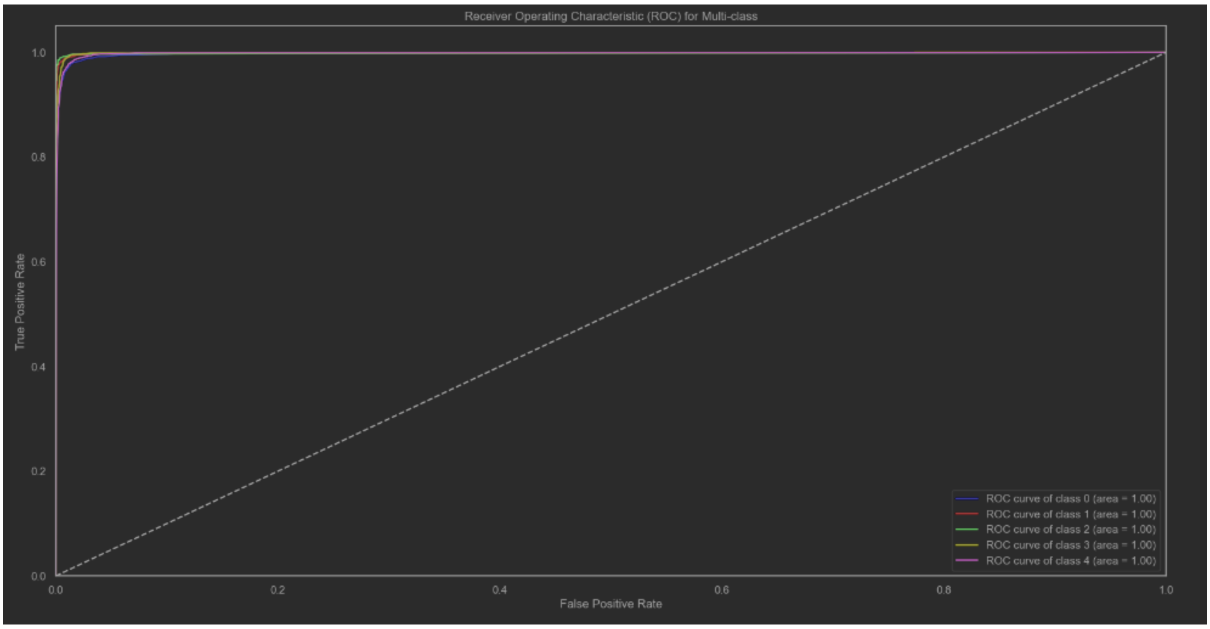
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      0.96      0.97      2966
           1       0.98      0.98      0.98      2786
           2       0.98      0.97      0.98       597
           3       0.98      0.98      0.98      2846
           4       0.97      0.98      0.97      2971

    accuracy                           0.98     12166
   macro avg       0.98      0.98      0.98     12166
weighted avg       0.98      0.98      0.98     12166
```

```
# Model Performance Evaluation Metric 2
# Confusion matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap='Blues')
plt.show()
```



```
# Model Evaluation Metric 3- ROC-AUC curve [6]
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
best_model.fit(x_train, y_train)
n_classes = len(set(y_train))
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
   y_test_bin = pd.Series(y_test).map(lambda x: 1 if x == i else 0)
   y_score_bin = best_model.predict_proba(x_test)[:, i]
   fpr[i], tpr[i], _ = roc_curve(y_test_bin, y_score_bin)
   roc_auc[i] = roc_auc_score(y_test_bin, y_score_bin)
plt.figure()
colors = ['blue', 'red', 'green', 'yellow', 'purple', 'cyan']
for i, color in zip(range(n_classes), colors):
   plt.plot(fpr[i], tpr[i], color=color, label='ROC curve of class {0} (area = {1:0.2f})'.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) for Multi-class')
plt.legend(loc="lower right")
plt.savefig('LOC_ROC')
plt.show()
```



Model Evaluation Metric 4-prediction report

```
for x in range(len(y_pred)):
   print("Predicted: ", y_pred[x], "Actual: ", y_test[x], "Data: ", x_test[x],)
```

There are too many results that can't fit in the report entirely. So only 3 pages of results are shown:

dicted: 0 Actual: 0 Data: (2945, 25072, 27839, 39087, 1691, 2945, 129, 3113, 4330, 5626, 3579, 2688, 47, 38, 3033, 146)

Predicted: 4 Actual: 4 Data: (1713, 7582, 8907, 44632, 782, 1713, 234, 1764, 4544, 1681, 4486, 3563, 41, 58, 4341, 193)

Predicted: 4 Actual: 4 Data: (1966, 8504, 12530, 43104, 1003, 1966, 340, 1947, 3947, 2400, 4681, 3421, 41, 53, 4118, 277)

Predicted: 0 Actual: 0 Data: (3400, 26079, 25204, 50486, 1414, 3400, 242, 3483, 4664, 4034, 3856, 2994, 35, 39, 3473, 150)

Predicted: 4 Actual: 4 Data: (2142, 7473, 5423, 52463, 100, 2142, 325, 2136, 4003, 133, 5072, 4049, 26, 60, 5117, 263)

Predicted: 0 Actual: 0 Data: (2731, 21504, 19064, 45277, 1397, 2731, 267, 2779, 4490, 3953, 3898, 3006, 42, 43, 3490, 138)

Predicted: 0 Actual: 0 Data: (2175, 20887, 17782, 34980, 1536, 2175, 160, 2293, 3115, 4676, 3371, 2832, 53, 46, 3238, 60)

Predicted: 0 Actual: 0 Data: (3116, 26056, 29338, 41276, 1684, 3116, 107, 3309, 3025, 5582, 3578, 2704, 45, 37, 3055, 170)

Predicted: 0 Actual: 0 Data: (3619, 26986, 31434, 48417, 1596, 3619, 256, 3695, 4491, 5029, 3877, 2833, 36, 35, 3238, 244)

Predicted: 3 Actual: 3 Data: (241, 11333, 22659, 13808, 2412, 241, 144, 308, 2288, 10370, 2133, 1552, 133, 41, 1590, 100)

Predicted: 4 Actual: 4 Data: (1558, 5821, 11141, 34726, 1123, 1558, 337, 1536, 3588, 2837, 4567, 3312, 49, 55, 3949, 263)

Predicted: 1 Actual: 1 Data: (3585, 41568, 55743, 18732, 2774, 3585, 176, 3732, 752, 20261, 863, 499, 120, 7, 461, 143)

Predicted: 3 Actual: 3 Data: (4926, 42043, 52768, 24866, 2592, 4926, 219, 5061, 4930, 14598, 1721, 1105, 74, 10, 1083, 97)

Predicted: 3 Actual: 3 Data: (197, 12901, 32274, 5681, 2551, 197, 187, 239, 1352, 13499, 1932, 1212, 150, 36, 1201, 84)

Predicted: 3 Actual: 3 Data: (504, 14733, 32015, 13119, 2486, 504, 221, 535, 1536, 11840, 2138, 1384, 134, 36, 1395, 108)

Predicted: 3 Actual: 3 Data: (387, 18178, 36977, 4724, 2599, 387, 235, 407, 1371, 14772, 1690, 1096, 151, 32, 1073, 138)

Predicted: 3 Actual: 3 Data: (649, 11792, 22701, 20302, 2311, 649, 215, 687, 1850, 9292, 2600, 1777, 113, 41, 1858, 152)

Predicted: 0 Actual: 0 Data: (2479, 20884, 18068, 40561, 1447, 2479, 115, 2642, 4154, 4199, 3705, 2960, 46, 44, 3423, 149)

Predicted: 3 Actual: 3 Data: (61, 9891, 22150, 10732, 2437, 61, 125, 132, 3645, 10822, 2047, 1470, 141, 42, 1493, 12)

Predicted: 0 Actual: 0 Data: (2460, 24850, 32312, 27097, 1999, 2460, 263, 2506, 2755, 7854, 3121, 2294, 64, 35, 2493, 188)

Predicted: 3 Actual: 3 Data: (152, 9953, 25364, 8771, 2479, 152, 205, 183, 3744, 11685, 2158, 1409, 142, 39, 1424, 139)

Predicted: 1 Actual: 1 Data: (1696, 33886, 50584, 1145, 2834, 1696, 175, 1788, 175, 23512, 364, 211, 171, 11, 190, 77)

Predicted: 4 Actual: 4 Data: (1467, 5927, 9200, 36590, 995, 1467, 299, 1469, 4065, 2374, 4424, 3395, 49, 57, 4077, 194)

Predicted: 0 Actual: 0 Data: (2961, 25751, 30690, 35716, 1787, 2961, 216, 3056, 2849, 6303, 3480, 2583, 50, 36, 2886, 183)

Predicted: 1 Actual: 1 Data: (2934, 35936, 49889, 18417, 2732, 2934, 229, 3018, 690, 18222, 1009, 653, 122, 12, 612, 97)

Predicted: 1 Actual: 1 Data: (2818, 39296, 54112, 10975, 2799, 2818, 105, 3001, 563, 21714, 595, 381, 138, 9, 348, 103)

Predicted: 1 Actual: 1 Data: (1709, 31893, 47300, 1980, 2805, 1709, 207, 1779, 2413, 22064, 641, 381, 160, 13, 348, 218)

Predicted: 4 Actual: 4 Data: (1727, 6740, 7989, 45150, 725, 1727, 310, 1726, 3926, 1516, 4638, 3633, 40, 58, 4452, 261)

Predicted: 4 Actual: 4 Data: (1374, 4558, 9244, 33405, 1084, 1374, 320, 1361, 4524, 2693, 4544, 3336, 51, 57, 3986, 235)

Predicted: 1 Actual: 1 Data: (2797, 37967, 52530, 12864, 2781, 2797, 104, 2980, 465, 20653, 705, 466, 134, 10, 428, 129)

Predicted: 1 Actual: 1 Data: (2228, 33522, 47635, 8737, 2767, 2228, 127, 2373, 1449, 19887, 794, 544, 140, 13, 504, 210)

Predicted: 1 Actual: 1 Data: (1384, 32194, 47478, 435, 2836, 1384, 232, 1429, 950, 23577, 347, 256, 176, 12, 232, 305)

Predicted: 4 Actual: 4 Data: (1130, 2882, 8707, 29009, 1218, 1130, 345, 1098, 3684, 3203, 4535, 3222, 58, 57, 3812, 253)

Predicted: 1 Actual: 1 Data: (3390, 40784, 54663, 18749, 2765, 3390, 78, 3619, 718, 19766, 820, 516, 122, 8, 478, 64)

Predicted: 0 Actual: 0 Data: (1958, 17442, 24128, 25216, 1971, 1958, 298, 1969, 4458, 7658, 3555, 2372, 69, 38, 2597, 297)

Predicted: 4 Actual: 4 Data: (1292, 4319, 4650, 39259, 733, 1292, 249, 1324, 3772, 1537, 4472, 3591, 47, 62, 4386, 171)

Predicted: 1 Actual: 1 Data: (1839, 34139, 46733, 3405, 2790, 1839, 129, 1969, 367, 21157, 439, 457, 153, 13, 420, 244)

Predicted: 1 Actual: 1 Data: (2682, 44925, 57594, 1853, 2867, 2682, 142, 2830, 126, 24479, 9, 79, 159, 4, 71, 261)

Predicted: 1 Actual: 1 Data: (3940, 45490, 58221, 16150, 2820, 3940, 180, 4090, 750, 22877, 489, 314, 124, 3, 285, 231)

Predicted: 1 Actual: 1 Data: (2380, 34883, 49976, 10175, 2776, 2380, 158, 2506, 4226, 20373, 743, 470, 141, 12, 433, 61)

Predicted: 4 Actual: 4 Data: (1701, 6808, 8518, 44057, 780, 1701, 263, 1732, 3705, 1677, 4590, 3583, 41, 58, 4373, 240)

Predicted: 4 Actual: 4 Data: (1736, 7090, 10246, 41365, 926, 1736, 339, 1715, 3779, 2136, 4592, 3483, 43, 56, 4215, 273)

Predicted: 4 Actual: 4 Data: (1846, 7445, 7781, 48891, 580, 1846, 285, 1864, 4561, 1117, 4684, 3717, 36, 59, 4587, 209)

Predicted: 4 Actual: 4 Data: (1108, 2272, 946, 42312, 367, 1108, 252, 1134, 4244, 605, 4646, 3856, 43, 67, 4814, 201)

Predicted: 1 Actual: 1 Data: (3422, 40321, 54677, 18629, 2766, 3422, 266, 3485, 4824, 19816, 884, 525, 121, 8, 486, 113)

Predicted: 3 Actual: 3 Data: (411, 21758, 38640, 2704, 2651, 411, 164, 472, 1145, 15953, 1378, 935, 159, 30, 901, 117)

Predicted: 0 Actual: 0 Data: (2641, 21368, 20621, 41024, 1522, 2641, 232, 2715, 4352, 4597, 3818, 2863, 46, 43, 3283, 103)

Predicted: 4 Actual: 4 Data: (863, 1154, 2089, 30805, 857, 863, 278, 868, 4064, 1913, 4605, 3529, 54, 64, 4287, 251)

Predicted: 4 Actual: 4 Data: (1460, 5424, 3991, 45803, 510, 1460, 145, 1566, 4170, 938, 4500, 3745, 41, 63, 4633, 162)

Implementation and deployment

For this project, I've chosen Streamlit for the deployment of the app.

The code shown below will be implemented via Streamlit as a web based tool [6].

```
import streamlit as st
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay, roc_curve
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier, RandomForestClassifier
from sklearn.preprocessing import OrdinalEncoder, LabelEncoder

URL = 'https://raw.githubusercontent.com/jacklong233/ST1/main/Rice_MSC_Dataset_Trimmed.csv'

@st.cache_resource

def load_data():

    df = pd.read_csv(URL)

    for col in df:
        if df[col].dtype == 'object':
            df[col] = OrdinalEncoder().fit_transform(df[col].values.reshape(-1, 1))

    df_normalized = (df - df.min()) / (df.max() - df.min())

    le = LabelEncoder()
    labels = le.fit_transform(df_normalized['CLASS'])
    df_normalized.drop('CLASS', axis=1, inplace=True)
    return df_normalized, labels

def main():
    st.title("Rice Data Classifier")

    data, target = load_data()

    st.sidebar.header("Model Selection")
    model_choice = st.sidebar.selectbox(
        "Choose the Classifier",
        ("DecisionTree", "NaiveBayes", "SVM", "GradientBoosting", "RandomForest"))
```

```
    if st.sidebar.button("Train Model"):
        x_train, x_test, y_train, y_test = train_test_split(data, target, test_size=0.20, random_state=7)

        if model_choice == "DecisionTree":
            model = DecisionTreeClassifier()
        elif model_choice == "NaiveBayes":
            model = GaussianNB()
        elif model_choice == "SVM":
            model = SVC(probability=True)
        elif model_choice == "GradientBoosting":
            model = GradientBoostingClassifier()
        else:
            model = RandomForestClassifier()

        model.fit(x_train, y_train)
        y_pred = model.predict(x_test)

        st.write(f"{model_choice} Accuracy: {accuracy_score(y_test, y_pred)}")
        st.write("Classification Report:")
        st.text(classification_report(y_test, y_pred))


        st.write("Confusion Matrix:")
        cm = confusion_matrix(y_test, y_pred)
        fig, ax = plt.subplots()
        ConfusionMatrixDisplay(confusion_matrix=cm).plot(ax=ax, cmap='Blues')
        st.pyplot(fig)

        y_prob = model.predict_proba(x_test)[:, 0]
        fpr, tpr, _ = roc_curve(y_test, y_prob, pos_label=0)
        fig, ax = plt.subplots()
        ax.plot(fpr, tpr)
        ax.plot([0, 1], [0, 1], linestyle='--')
        ax.set_title('ROC Curve')
        ax.set_xlabel('False Positive Rate')
        ax.set_ylabel('True Positive Rate')
        st.pyplot(fig)


if __name__ == "__main__":
    main()
```

The test run is showing below:

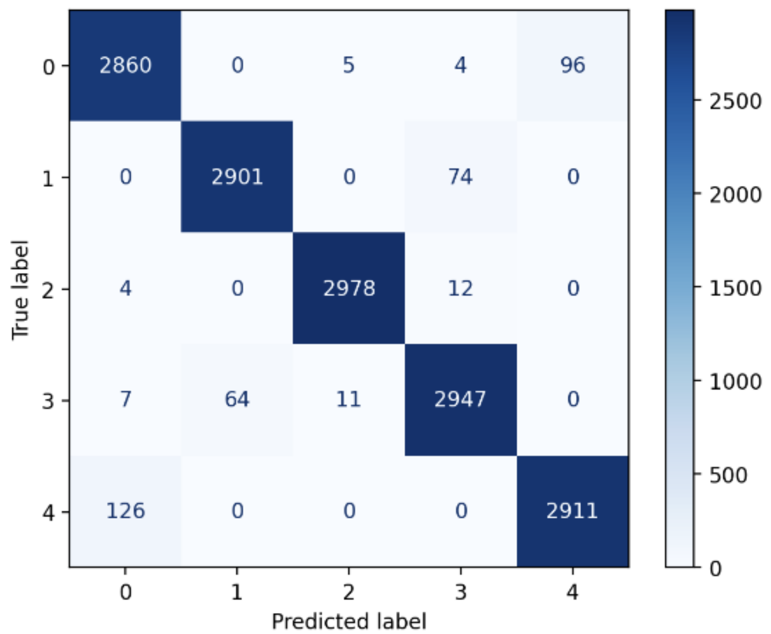
when we choose the DT model and click 'Train Model', the classification report, confusion matrix, and ROC curve will show up:

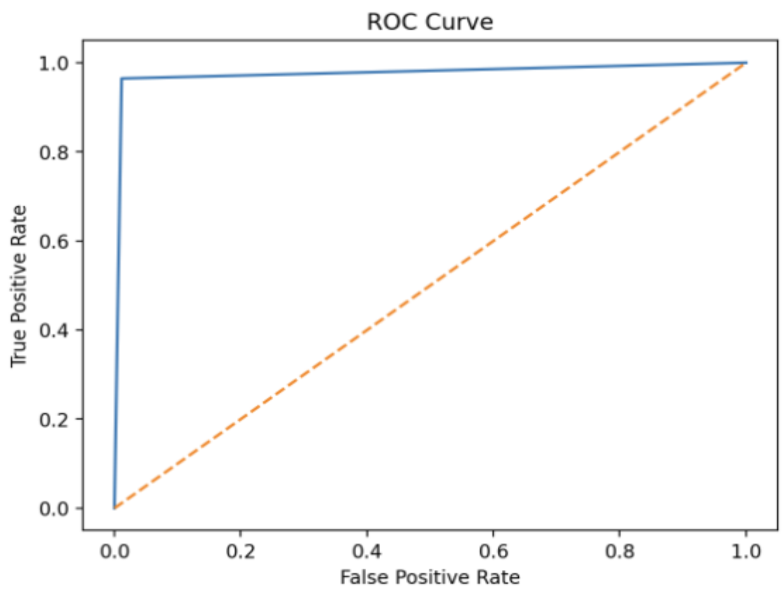
DecisionTree Accuracy: 0.9731333333333333

Classification Report:

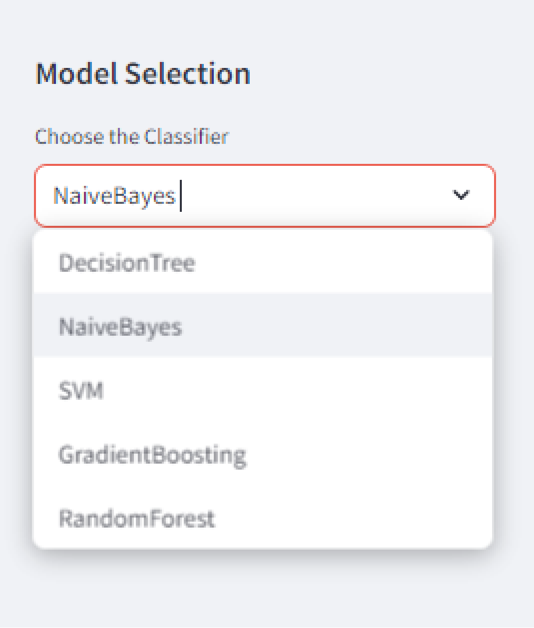
```
precision    recall  f1-score   support

           0       0.95      0.96      0.96      2965
           1       0.98      0.98      0.98      2975
           2       0.99      0.99      0.99      2994
           3       0.97      0.97      0.97      3029
           4       0.97      0.96      0.96      3037

    accuracy                           0.97     15000
   macro avg       0.97      0.97      0.97     15000
weighted avg       0.97      0.97      0.97     15000
```

Confusion Matrix:





On the left side of screen, there are 5 different models for training purpose.



Every trainning model displays the accuracy of the current model, a classification report, the confusion matrix, and ROC curve.

GitHub Link:

The GitHub repositary link is attached below:

https://github.com/jacklong233/ST1

Conlcusions

This report is aiming to develop and deploy a Python based project to catergoise and differentiate 5 different types of rice using the Rice MSC dataset from Kaggle. To enhace the accuracy, I have decided to use 16 attributes instead of 106. Hence 90 colour features are ditched during the pre-processing data phase. With the implementation of Exploratory Data Analysis (EDA) and Predictive Data Analysis (PDA), our model has achieved an accuracy of around 98% in predicting the rice varieties. In order to enahnce the userbility and make the model more accessible, Streamlit is used to deploy the App on the cloud.

However, according to the experiment, the Ipsala type of rice has lost significant amount of samples during the outlier removal phase. There is no evidence on why this happened. Due to the constraint and limitation of this study, we can not identify the cause to the problem.

Implementation of our model can improve the accuracy and efficiency of the rice extraction process significantly. It ensures a higher output and much lower resource wastage, thus give manufactures an advantage in both economic and environmental scale.

References

[1] https://www.kaggle.com/datasets/muratkokludataset/rice-msc-dataset

[2] K. M., C. I., and T. Y.S., “Classification of rice varieties with deep learning methods,” 2021. https://doi.org/10.1016/j.compag.2021.106285

[3] C. I. and K. M., “Determination of Effective and Specific Physical Features of Rice Varieties by Computer Vision In Exterior Quality Inspection,” 2021. https://doi.org/10.15316/SJAFS.2021.252

[4] C. I. and K. M., “Identification of Rice Varieties Using Machine Learning Algorithms,” 2022. https://doi.org/10.15832/ankutbd.862482

[5] C. I and K. M., “Classification of Rice Varieties Using Artificial Intelligence Methods,” 2019. https://doi.org/10.18201/ijisae.2019355381

[6] OpenAI, “ChatGPT,” *chat.openai.com*, Oct. 16, 2023. https://chat.openai.com/

Appendix 1: Log Book

Week	Planned Activities	Tasks Completed	Problems Faced	Further Comments
Week 7	Challenge question 7	Challenge question 7	N/A	
Week 8	Challenge question 9, 10	Challenge question 9, 10	Questions of problem 9b and 10 b are unclear to me, do we store the book name and display it, or shall we input the book name and then let the app display it?	
Week 9	Read materials, familiar with requirement of assignment, challenge 11	Read materials, familiar with requirement of assignment, challenge 11	N/A	
Week 10	EDA, learning the Google Colab platform	EDA, learning the Google Colab platform	Learning the use of Google Colab, Pycharm version out-dated, compatibility of code between Pycharm and Google Colab.	There is not much support materials for data set without images
Week 12	PDA and PPT, prepare for the speech and interview	PDA	Code for Model Evaluation Metric 3-ROC-AUC curve. Both desktop and laptop are too slow to run the model calculations.	The code provided for metric 3 only supports binary class but I have 5 classes, I have to find external support to identify and fix errors.
Week 13	Finalise PPT, interview and speech; Streamlit deployment, final report. GitHub account creation	PPT, speech and interview. Final report. GitHub account creation	Deployment of ROC curve with Streamlit. Integrating algorithm function with Streamlit. Use of GitHub.	As I have never learned coding for machine learning. I have to find external support to fix code as it is well

				beyond my coding skill. Deployment of certain function with Streamlit is much difficult than I expected.