glass-pred

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1 Glass Classification

Assignment submitted by : ***Ritvik Prasad M***

Registration Number : **210801159**

Context

This is a Glass Identification Data Set from UCI. It contains 9 attributes.

The response is glass type(discrete 7 values)

Kaggle Link

UCI dataset Link

Content

Attribute Information - RI: refractive index - Na: Sodium (unit measurement: weight percent in corresponding oxide, as are attributes 4-10) - Mg: Magnesium - Al: Aluminum - Si: Silicon - K: Potassium - Ca: Calcium - Ba: Barium - Fe: Iron - Type of glass: (class attribute)
- 1 building_windows_float_processed - 2 building_windows_non_float_processed - 3 vehicle_windows_float_processed - 4 vehicle_windows_non_float_processed (none in this database) - 5 containers - 6 tableware - 7 headlamps

1.0.1 Data Loading and Analysis

[107]:
```
# importing essential libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[108]:
```
# loading the model
df = pd.read_csv("./glass.csv")
df.head()
```

[108]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.0	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.0	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.0	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.0	0.0	1

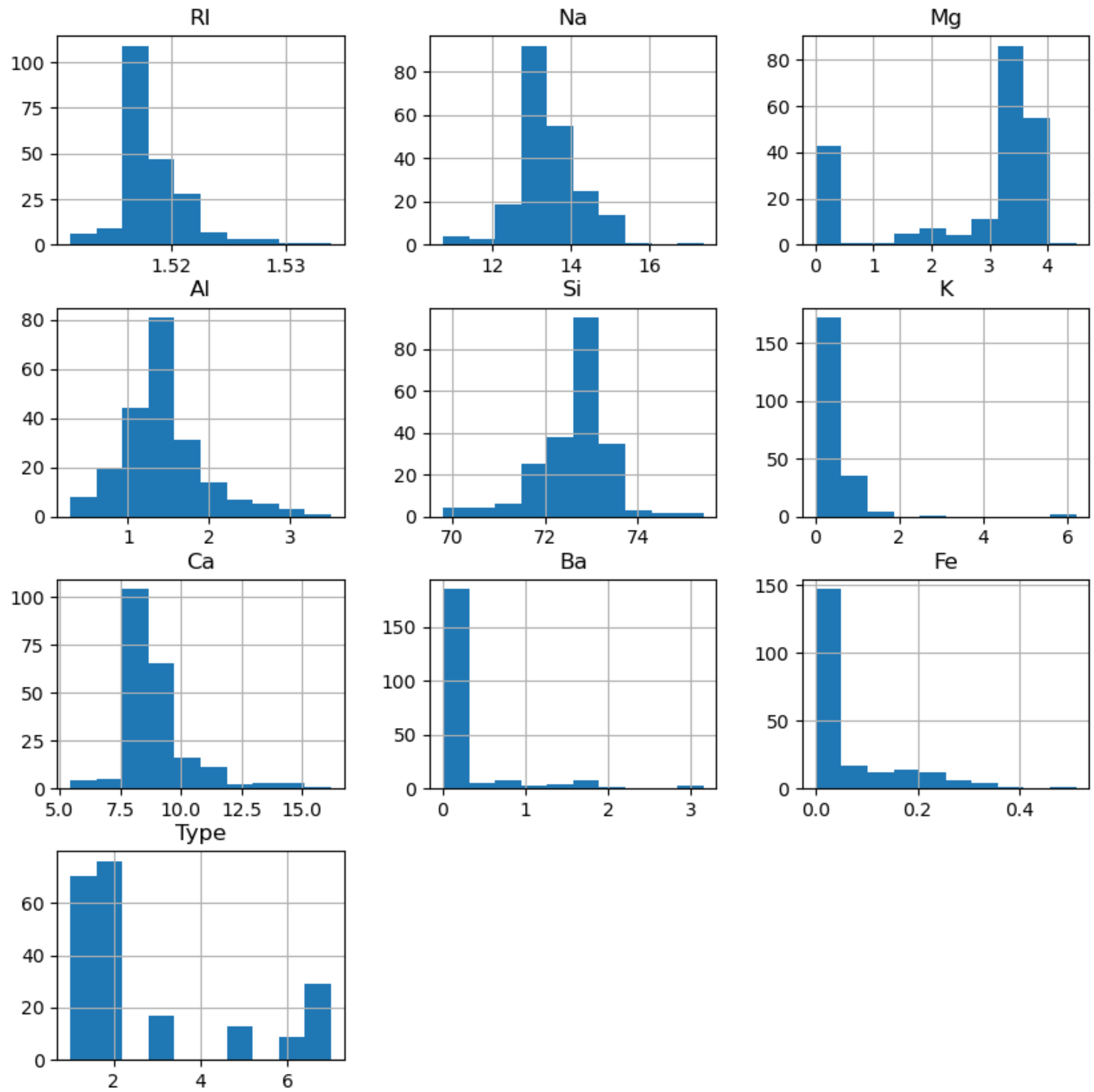
[109]:

```
#getting information about the data
df.info()
```

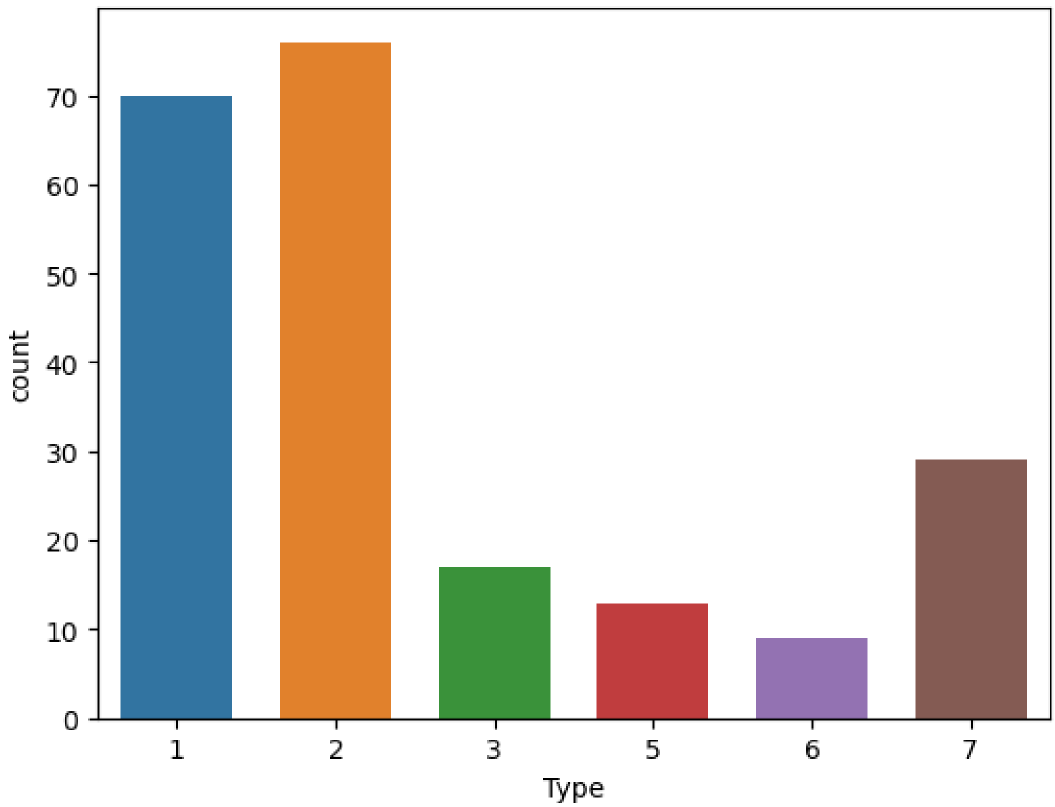
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 214 entries, 0 to 213
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   RI      214 non-null    float64
 1   Na      214 non-null    float64
 2   Mg      214 non-null    float64
 3   Al      214 non-null    float64
 4   Si      214 non-null    float64
 5   K       214 non-null    float64
 6   Ca      214 non-null    float64
 7   Ba      214 non-null    float64
 8   Fe      214 non-null    float64
 9   Type    214 non-null    int64
dtypes: float64(9), int64(1)
memory usage: 16.8 KB
```

[110]:

```
# understanding the correlation between the data
df.hist(figsize=(10,10));
```



[111]:
```python
# analyzing the number and types of outputs
sns.countplot(x=df["Type"], width=0.7);
```



[112]:
```
# finding the total number of possible outcomes
df.Type.unique(), len(df.Type.unique())
```

[112]: (array([1, 2, 3, 5, 6, 7]), 6)

Inference

As the data outcomes are discrete, we would use a multiclass classification algorithm such as non-binary multiclass classification.

For this data, I will use **Random Forest Classifier** Algorithm.

1.0.2 Model Creation and Training

[113]:
```
# splitting the data into labels and outcomes
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
X.shape , y.shape
```

[113]: ((214, 9), (214,))

[114]:
```
# splitting the data into train and test set with test size of 0.2 as the
 ↪availability of data is less
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)
```

[115]:
```
# importing necessary libraries for model creation
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
```

[116]:
```
# creating the pipeline for the model and getting the pipeline paramerters
pipe = Pipeline([
    ("scaler", StandardScaler()),
    ("randomForest", RandomForestClassifier())
])
pipe.get_params()
```

[116]:
```
{'memory': None,
 'steps': [('scaler', StandardScaler()),
  ('randomForest', RandomForestClassifier())],
 'verbose': False,
 'scaler': StandardScaler(),
 'randomForest': RandomForestClassifier(),
 'scaler__copy': True,
 'scaler__with_mean': True,
 'scaler__with_std': True,
 'randomForest__bootstrap': True,
 'randomForest__ccp_alpha': 0.0,
 'randomForest__class_weight': None,
 'randomForest__criterion': 'gini',
 'randomForest__max_depth': None,
 'randomForest__max_features': 'sqrt',
 'randomForest__max_leaf_nodes': None,
 'randomForest__max_samples': None,
 'randomForest__min_impurity_decrease': 0.0,
 'randomForest__min_samples_leaf': 1,
 'randomForest__min_samples_split': 2,
 'randomForest__min_weight_fraction_leaf': 0.0,
 'randomForest__n_estimators': 100,
 'randomForest__n_jobs': None,
 'randomForest__oob_score': False,
 'randomForest__random_state': None,
 'randomForest__verbose': 0,
 'randomForest__warm_start': False}
```

[117]:
```
# creating a cross validation estimator grid with estimators and maximum depth␣
↪as grid parameters

estimator = GridSearchCV(estimator=pipe, param_grid={
    'randomForest__n_estimators':[i for i in range(50,150,5)],
    'randomForest__max_depth':[i for i in range(1,11)]
}, scoring='accuracy', cv=3)
```

[118]:
```
# fitting the estimator
estimator.fit(X_train, y_train)
```

[118]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('randomForest',
                                        RandomForestClassifier())]),
             param_grid={'randomForest__max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9,
                                                     10],
                         'randomForest__n_estimators': [50, 55, 60, 65, 70, 75,
                                                        80, 85, 90, 95, 100,
                                                        105, 110, 115, 120, 125,
                                                        130, 135, 140, 145]},
             scoring='accuracy')
```

[119]:
```
# storing the results of the estimator in a dataframe
result_df = pd.DataFrame(estimator.cv_results_)
```

[120]:
```
# getting the parameters for the best optimum model
print(estimator.best_index_)
print(estimator.best_params_)
print(estimator.best_score_)
```

```
145
{'randomForest__max_depth': 8, 'randomForest__n_estimators': 75}
0.7543859649122807
```

[121]:
```
# getting the details about best optimum model from result database
result_df.iloc[150]
```

[121]:
```
mean_fit_time
0.135819
std_fit_time
0.00662
mean_score_time
0.009605
std_score_time
0.000944
param_randomForest__max_depth
```

```
8
param_randomForest__n_estimators
100
params                                  {'randomForest__max_depth': 8,
'randomForest__…
split0_test_score
0.561404
split1_test_score
0.824561
split2_test_score
0.719298
mean_test_score
0.701754
std_test_score
0.108148
rank_test_score
111
Name: 150, dtype: object
```

[122]:
```
# creating an improvised estimator with parameters close to best estimate of␣
↪previous estimator

estimator_improvised = GridSearchCV(estimator=pipe, param_grid={
    'randomForest__n_estimators':[i for i in range(50,61)],
    'randomForest__max_depth':[i for i in range(7,14)]
}, scoring='accuracy', cv=3)
```

[123]:
```
# fitting the improvised estimator
estimator_improvised.fit(X_train, y_train)
```

[123]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('randomForest',
                                        RandomForestClassifier())]),
             param_grid={'randomForest__max_depth': [7, 8, 9, 10, 11, 12, 13],
                         'randomForest__n_estimators': [50, 51, 52, 53, 54, 55,
                                                        56, 57, 58, 59, 60]},
             scoring='accuracy')
```

[124]:
```
# storing the results of improvised estimator in a dataframe
result2_df = pd.DataFrame(estimator.cv_results_)
```

[125]:
```
result2_df.to_csv("result2.csv")
```

[126]:
```
# getting the parameters for the best optimum model from the improvised␣
↪estimator
print(estimator_improvised.best_index_)
```

```
print(estimator_improvised.best_params_)
print(estimator_improvised.best_score_)
```

```
5
{'randomForest__max_depth': 7, 'randomForest__n_estimators': 55}
0.7719298245614036
```

[127]:
```
# getting the details about best optimum model from improvised result database
result2_df.iloc[181]
```

[127]:
```
mean_fit_time
0.078363
std_fit_time
0.000689
mean_score_time
0.006414
std_score_time
0.001151
param_randomForest__max_depth
10
param_randomForest__n_estimators
55
params                                    {'randomForest__max_depth': 10,
'randomForest_…
split0_test_score
0.596491
split1_test_score
0.842105
split2_test_score
0.77193
mean_test_score
0.736842
std_test_score
0.103295
rank_test_score
15
Name: 181, dtype: object
```

[128]:
```
# getting the top 2 estimators
model1 = estimator.best_estimator_
model2 = estimator_improvised.best_estimator_
```

1.0.3 Model Evaluation

[143]:
```
# comparing the top two models

from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
preds = model1.predict(X_test)
preds_train = model1.predict(X_train)
accuracy_test = accuracy_score(y_true=y_test, y_pred=preds)
accuracy_train = accuracy_score(y_true=y_train, y_pred=preds_train)
cmatrix = confusion_matrix(y_true=y_test, y_pred=preds)
print(f'Model 1 Metrics')
print(f'accuracy (test)       : {accuracy_test}\n\tin precentage :
 ↪\t{accuracy_test*100} %\n')
print(f'accuracy (train)      : {accuracy_train}\n\tin precentage :
 ↪\t{accuracy_train*100} %\n')
print(f'confusion matrix (for 6 outcomes):\n{cmatrix}')

preds = model2.predict(X_test)
preds_train = model2.predict(X_train)
accuracy_test = accuracy_score(y_true=y_test, y_pred=preds)
accuracy_train = accuracy_score(y_true=y_train, y_pred=preds_train)
cmatrix = confusion_matrix(y_true=y_test, y_pred=preds)
print(f'\nModel 2 Metrics')
print(f'accuracy (test)       : {accuracy_test}\n\tin precentage :
 ↪\t{accuracy_test*100} %\n')
print(f'accuracy (train)      : {accuracy_train}\n\tin precentage :
 ↪\t{accuracy_train*100} %\n')
print(f'confusion matrix (for 6 outcomes):\n{cmatrix}')
```

```
Model 1 Metrics
accuracy (test)       : 0.8837209302325582
        in precentage : 88.37209302325581 %

accuracy (train)      : 0.9883040935672515
        in precentage : 98.83040935672514 %

confusion matrix (for 6 outcomes):
[[11  0  0  0  0  0]
 [ 3 11  0  0  0  0]
 [ 1  0  2  0  0  0]
 [ 0  1  0  3  0  0]
 [ 0  0  0  0  3  0]
 [ 0  0  0  0  0  8]]

Model 2 Metrics
accuracy (test)       : 0.8604651162790697
        in precentage : 86.04651162790698 %
```

```
accuracy (train)       : 1.0
        in precentage : 100.0 %

confusion matrix (for 6 outcomes):
[[11  0  0  0  0  0]
 [ 1 11  1  0  0  1]
 [ 1  0  2  0  0  0]
 [ 0  2  0  2  0  0]
 [ 0  0  0  0  3  0]
 [ 0  0  0  0  0  8]]
```

We can see that *model2* perfoms better on train set than test set by a margin of **1.17%** and *model1* perfoms better on test set than train set by a margin of **2.325%**.

Hence, from this observation, we can say that model1 outperfoms model2.

Therefore model1 is the most optimum model.

1.0.4 Exporting the Model

[145]:
```python
# exporting the model in .joblib format
from joblib import dump
dump(model1, "glass_pred.joblib")
```

[145]: ['glass_pred.joblib']

[146]:
```python
# loading the model and finding its accuracy

from joblib import load
from sklearn.metrics import accuracy_score

load_model = load("./glass_pred.joblib")

pred_load = load_model.predict(X_test)
accuracy_load_model = accuracy_score(y_true=y_test,y_pred=pred_load)
print(f'Accuracy of the model loed : {accuracy_load_model*100} %')
```

```
Accuracy of the model loed : 88.37209302325581 %
```

1.0.5 Conclusion

Hence, a **Random Forest Classifier** algorithm is implemented on the given data and a Machine Learning model with 88% accuracy is obtained.