MEX #3 - Geyzson Kristoffer

SN:2023-21036

https://uvle.upd.edu.ph/mod/assign/view.php?id=538688

In [ ]:

```
import matplotlib.pyplot as plt
from icecream import ic
import pandas as pd
import seaborn as sns
from sklearn.metrics import (accuracy_score, classification_report,
                             confusion_matrix, ConfusionMatrixDisplay, f1_score,
                             precision_score, recall_score)
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.model_selection import RandomizedSearchCV, train_test_split
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC, SVR
from time import time
```

In [ ]:

```
df = pd.read_csv('winequality-red.csv', delimiter=';')
df
```

Out[ ]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8	5
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8	5
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8	6
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	6
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6

1599 rows × 12 columns

In [ ]:

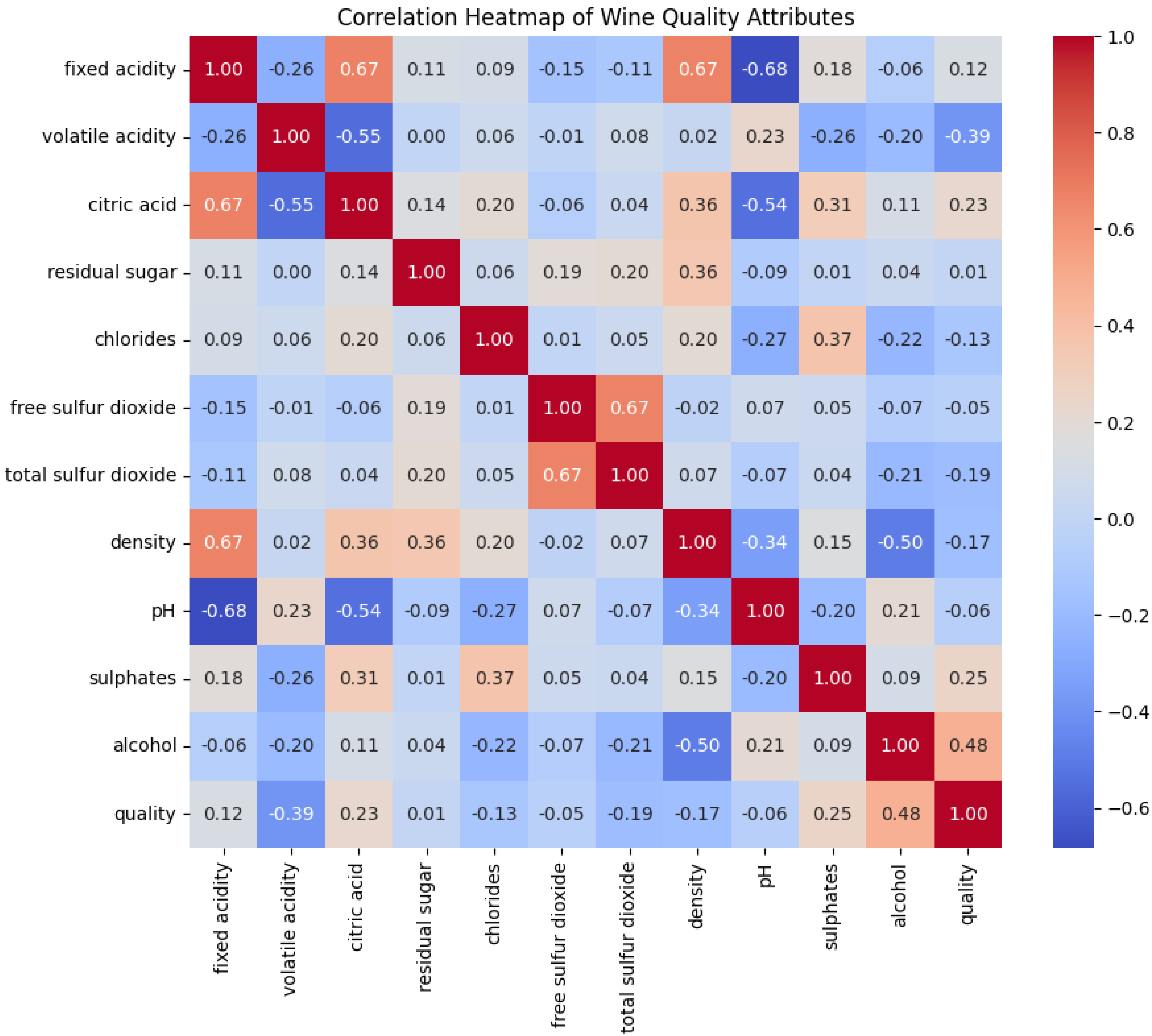
```
ic(df.dtypes, df.isna().sum(), df.isnull().sum())
```

```
ic| df.dtypes: fixed acidity           float64
               volatile acidity        float64
               citric acid             float64
               residual sugar          float64
               chlorides               float64
               free sulfur dioxide     float64
               total sulfur dioxide    float64
               density                 float64
               pH                      float64
               sulphates               float64
               alcohol                 float64
               quality                   int64
               dtype: object
    df.isna().sum(): fixed acidity           0
                     volatile acidity        0
                     citric acid             0
                     residual sugar          0
                     chlorides               0
                     free sulfur dioxide     0
                     total sulfur dioxide    0
                     density                 0
                     pH                      0
                     sulphates               0
                     alcohol                 0
                     quality                 0
                     dtype: int64
    df.isnull().sum(): fixed acidity           0
                       volatile acidity        0
                       citric acid             0
                       residual sugar          0
                       chlorides               0
                       free sulfur dioxide     0
                       total sulfur dioxide    0
                       density                 0
                       pH                      0
                       sulphates               0
                       alcohol                 0
                       quality                 0
                       dtype: int64
```

Out[ ]:
```
(fixed acidity           float64
 volatile acidity        float64
 citric acid             float64
 residual sugar          float64
 chlorides               float64
 free sulfur dioxide     float64
 total sulfur dioxide    float64
 density                 float64
 pH                      float64
 sulphates               float64
 alcohol                 float64
 quality                   int64
 dtype: object,
 fixed acidity           0
 volatile acidity        0
 citric acid             0
 residual sugar          0
 chlorides               0
 free sulfur dioxide     0
 total sulfur dioxide    0
 density                 0
 pH                      0
 sulphates               0
 alcohol                 0
 quality                 0
 dtype: int64,
 fixed acidity           0
 volatile acidity        0
 citric acid             0
 residual sugar          0
 chlorides               0
 free sulfur dioxide     0
 total sulfur dioxide    0
 density                 0
 pH                      0
 sulphates               0
 alcohol                 0
 quality                 0
 dtype: int64)
```

In [ ]:
```
corr = df.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm', square=True)
plt.title('Correlation Heatmap of Wine Quality Attributes')
plt.show()
```


Correlation Heatmap of Wine Quality Attributes
fixed acidity
volatile acidity
citric acid
residual sugar
chlorides
free sulfur dioxide
total sulfur dioxide
density
pH
sulphates
alcohol
quality
1.00 -0.26 0.67 0.11 0.09 -0.15 -0.11 0.67 -0.68 0.18 -0.06 0.12
-0.26 1.00 -0.55 0.00 0.06 -0.01 0.08 0.02 0.23 -0.26 -0.20 -0.39
0.67 -0.55 1.00 0.14 0.20 -0.06 0.04 0.36 -0.54 0.31 0.11 0.23
0.11 0.00 0.14 1.00 0.06 0.19 0.20 0.36 -0.09 0.01 0.04 0.01
0.09 0.06 0.20 0.06 1.00 0.01 0.05 0.20 -0.27 0.37 -0.22 -0.13
-0.15 -0.01 -0.06 0.19 0.01 1.00 0.67 -0.02 0.07 0.05 -0.07 -0.05
-0.11 0.08 0.04 0.20 0.05 0.67 1.00 0.07 -0.07 0.04 -0.21 -0.19
0.67 0.02 0.36 0.36 0.20 -0.02 0.07 1.00 -0.34 0.15 -0.50 -0.17
-0.68 0.23 -0.54 -0.09 -0.27 0.07 -0.07 -0.34 1.00 -0.20 0.21 -0.06
0.18 -0.26 0.31 0.01 0.37 0.05 0.04 0.15 -0.20 1.00 0.09 0.25
-0.06 -0.20 0.11 0.04 -0.22 -0.07 -0.21 -0.50 0.21 0.09 1.00 0.48
0.12 -0.39 0.23 0.01 -0.13 -0.05 -0.19 -0.17 -0.06 0.25 0.48 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

In [ ]:

```
# i tried to improve the accuracy by removing these columns, but the accuracy is still low
# X = df.iloc[:, :11].drop(columns=['fixed acidity', 'free sulfur dioxide'])

X = df.iloc[:, :11]
y = df['quality']
X
```

Out[ ]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4
...	...	...	...	...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0

1599 rows × 11 columns

In [ ]:

```
param_grid = {'svc__C': [0.1, 1, 10, 100, 1000],
              'svc__gamma': [1, 0.1, 0.01, 0.001, 0.0001],
              'svc__kernel': ['rbf','linear','poly','sigmoid'],
              'svc__class_weight': ['balanced']}

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, stratify=y)

model = make_pipeline(StandardScaler(), SVC()).fit(X_train, y_train)
random_search = RandomizedSearchCV(model, param_grid, n_iter=10, cv=5, scoring='accuracy', n_jobs=-1, verbose=2, refit=True)

start = time()
random_search.fit(X_train, y_train)
print("RandomSearchCV took %.2f seconds for %d candidate parameter settings."
      % (time() - start, len(random_search.cv_results_["params"])))
```

```
print(random_search.best_params_)
print(random_search.best_estimator_)

predictions = random_search.best_estimator_.predict(X_test)
print(classification_report(y_test, predictions))
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
RandomSearchCV took 188.48 seconds for 10 candidate parameter settings.
{'svc__kernel': 'poly', 'svc__gamma': 1, 'svc__class_weight': 'balanced', 'svc__C': 10}
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('svc',
                 SVC(C=10, class_weight='balanced', gamma=1, kernel='poly'))])
              precision    recall  f1-score   support

           3       0.00      0.00      0.00         3
           4       0.11      0.19      0.14        16
           5       0.67      0.64      0.65       204
           6       0.60      0.55      0.58       192
           7       0.41      0.47      0.44        60
           8       0.10      0.20      0.13         5

    accuracy                           0.56       480
   macro avg       0.32      0.34      0.32       480
weighted avg       0.58      0.56      0.57       480
```

In [ ]:

```
best_model = random_search.best_estimator_
best_model.score(X_train, y_train), model.score(X_test, y_test)
```

Out[ ]:

```
(0.9338695263628239, 0.6229166666666667)
```

Problem a

In [ ]:

```
y_pred_test = best_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_test)
precision = precision_score(y_test, y_pred_test, average='weighted')
recall = recall_score(y_test, y_pred_test, average='weighted')
f1 = f1_score(y_test, y_pred_test, average='weighted')
cfm = pd.DataFrame(
    confusion_matrix(y_test, y_pred_test, labels=range(11)),
    index=range(11),
    columns=range(11)
)
```

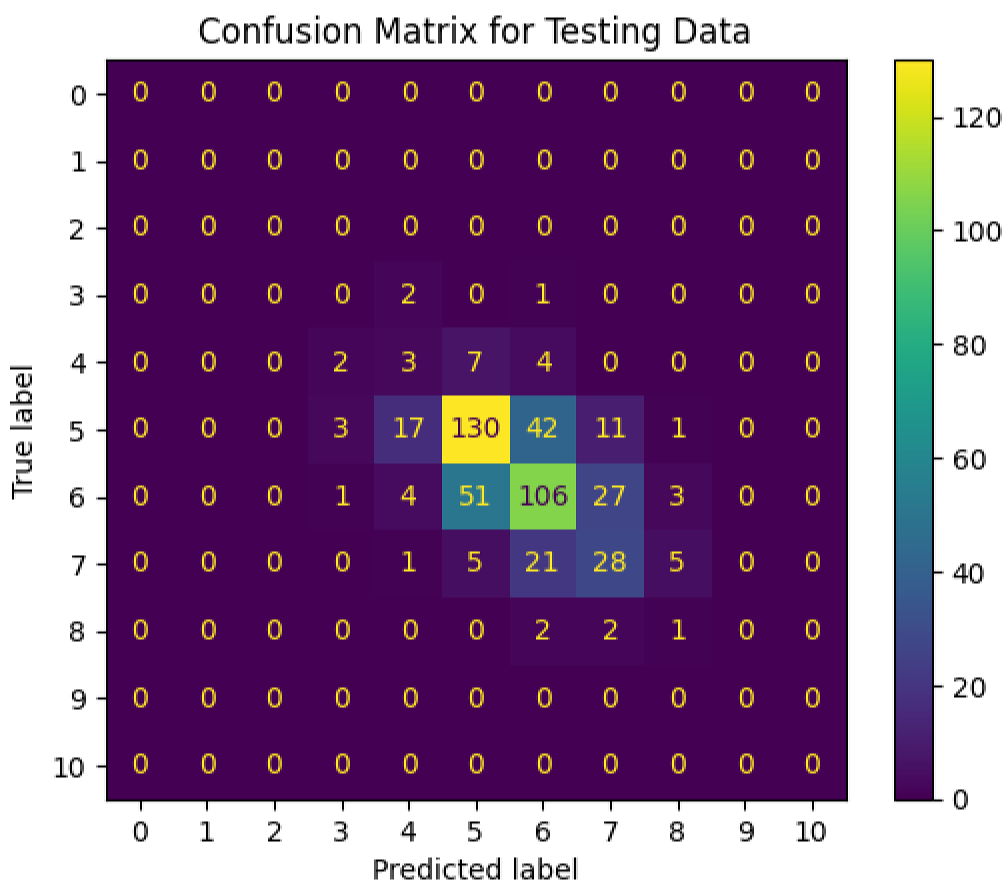
```python
print(f'Accuracy: {accuracy:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')
```

```
Accuracy: 0.5583
Precision: 0.5834
Recall: 0.5583
F1 Score: 0.5695
```

In [ ]:

```python
cm_display = ConfusionMatrixDisplay(confusion_matrix=cfm.values, display_labels=range(11))

cm_display.plot()
plt.title('Confusion Matrix for Testing Data')
plt.show()
```



Problem b

In [ ]:
```
param_grid = {
    'svr__C': [0.1, 1, 10],
    'svr__epsilon': [0.1, 0.2],
    'svr__kernel': ['linear', 'rbf'],
}

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, stratify=y)

model = make_pipeline(StandardScaler(), SVR()).fit(X_train, y_train)
random_search = RandomizedSearchCV(model, param_grid, n_iter=5, cv=5, scoring='neg_mean_squared_error', n_jobs=-1, verbose=2, refi

start = time()
random_search.fit(X_train, y_train)
print("RandomizedSearchCV took %.2f seconds for %d candidate parameter settings."
      % (time() - start, len(random_search.cv_results_["params"])))

print(random_search.best_params_)
print(random_search.best_estimator_)

predictions = random_search.best_estimator_.predict(X_test)


mse = mean_squared_error(y_test, predictions)
r2 = r2_score(y_test, predictions)
mad = mean_absolute_error(y_test, predictions)

print(f'Mean Squared Error (MSE): {mse:.4f}')
print(f'R-squared (R2): {r2:.4f}')
print(f'Mean Absolute Deviation (MAD): {mad:.4f}')
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
RandomizedSearchCV took 0.37 seconds for 5 candidate parameter settings.
{'svr__kernel': 'rbf', 'svr__epsilon': 0.1, 'svr__C': 1}
Pipeline(steps=[('standardscaler', StandardScaler()), ('svr', SVR(C=1))])
Mean Squared Error (MSE): 0.3759
R-squared (R2): 0.4202
Mean Absolute Deviation (MAD): 0.4505
```

Problem b answer

When I reworked the problem using regression and trained an SVR model, my accuracy are only around 50-60% no matter how many times i've ran the randomsearch, which falls short of the paper's results.

This initial outcome suggests that with additional hyperparameter tuning and model refinement, there's potential to improve the model's performance.

Based on your results, discuss the difference of treating this problem as classification or regression. How will this decision impact the users of your model?

My hyperparameter tuning attempt at finding the best settings for both the SVC and SVR models didn't turn out great as the accuracy on the test data was lower compared to what is in the paper.

Treating the problem as a classification problem vs a regression provides their own pros and cons. In classification, it's how the wines can be put in their respective category when the users of the model want to put them on their respective shelves with the same quality.

Regression, on the other hand, gives us a smoother scale, which will be harder for model users who are not that into wines. But to those who are wine connoisseurs, they might be keen to use the regression model.

Whether going for classification or regression, one should depend on what the people using the model need.

If they need clear categories, go with classification. If they want to capture all the little details, regression might be better.