Assignment 2 - Wine Quality Prediction

1. Data Exploration

1.1 Loading Data

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

wine = pd.read_csv("winequality-white.csv", delimiter=';')
```

1.2 Exploratory Data Analysis (EDA)

In [2]:
```
wine.head()
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45	8.8
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49	9.5
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44	10.1
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9

This dataset contains 11 features and 1 target:

- Features: fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, alcohol
- Target: quality

In [3]:
```
wine.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4898 entries, 0 to 4897
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   fixed acidity         4898 non-null   float64
 1   volatile acidity      4898 non-null   float64
 2   citric acid           4898 non-null   float64
 3   residual sugar        4898 non-null   float64
 4   chlorides             4898 non-null   float64
 5   free sulfur dioxide   4898 non-null   float64
 6   total sulfur dioxide  4898 non-null   float64
 7   density               4898 non-null   float64
 8   pH                    4898 non-null   float64
 9   sulphates             4898 non-null   float64
 10  alcohol               4898 non-null   float64
 11  quality               4898 non-null   int64
dtypes: float64(11), int64(1)
memory usage: 459.3 KB
```

There are 4898 entries and all are numerical (long float and long integer). Plus there is no null value in all of the columns.

In [4]:
```
wine.describe()
```

Out[4]:

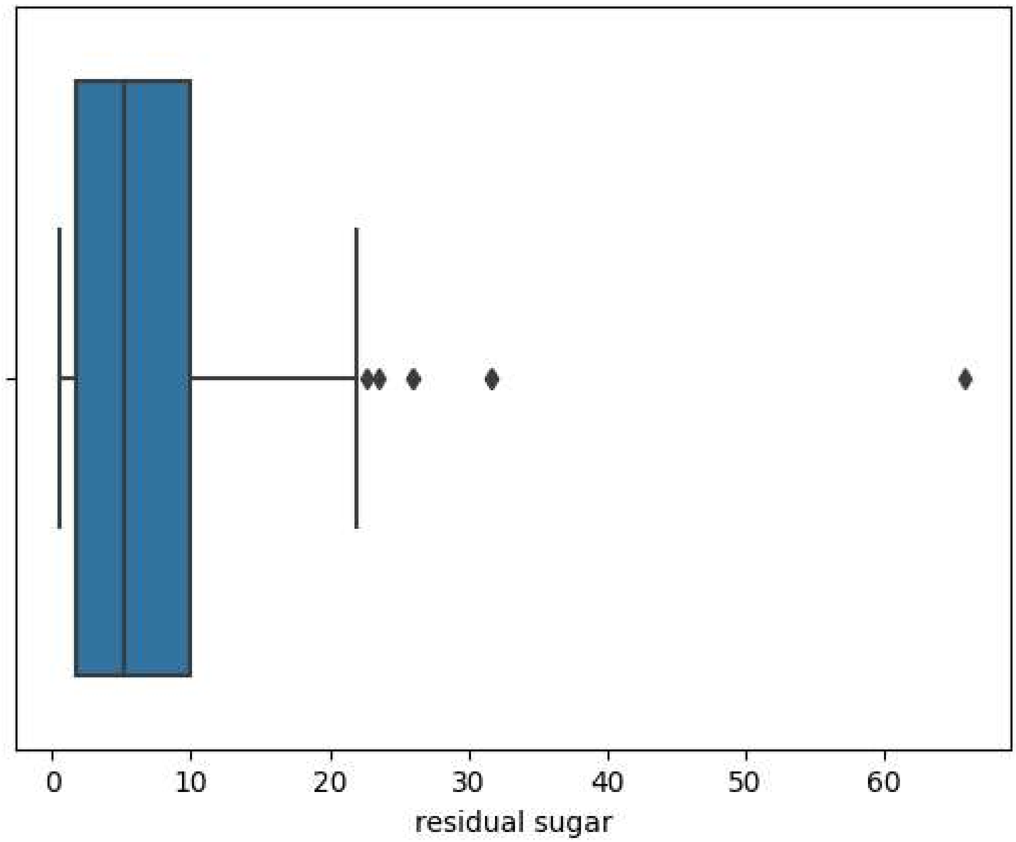
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfu dioxid
count	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.00000
mean	6.854788	0.278241	0.334192	6.391415	0.045772	35.308085	138.36065
std	0.843868	0.100795	0.121020	5.072058	0.021848	17.007137	42.49806
min	3.800000	0.080000	0.000000	0.600000	0.009000	2.000000	9.00000
25%	6.300000	0.210000	0.270000	1.700000	0.036000	23.000000	108.00000
50%	6.800000	0.260000	0.320000	5.200000	0.043000	34.000000	134.00000
75%	7.300000	0.320000	0.390000	9.900000	0.050000	46.000000	167.00000
max	14.200000	1.100000	1.660000	65.800000	0.346000	289.000000	440.00000

It seems like there are outliers in the residual sugar feature. We can see that 25% of the values are under 1.70 and 75% of them are under 9.90. Taking into account the mean at 6.39, the minimum value of 0.60 and maximum value of 65.80 seems like an outlier.

Using boxplot to visualize the outlier in residual sugar.

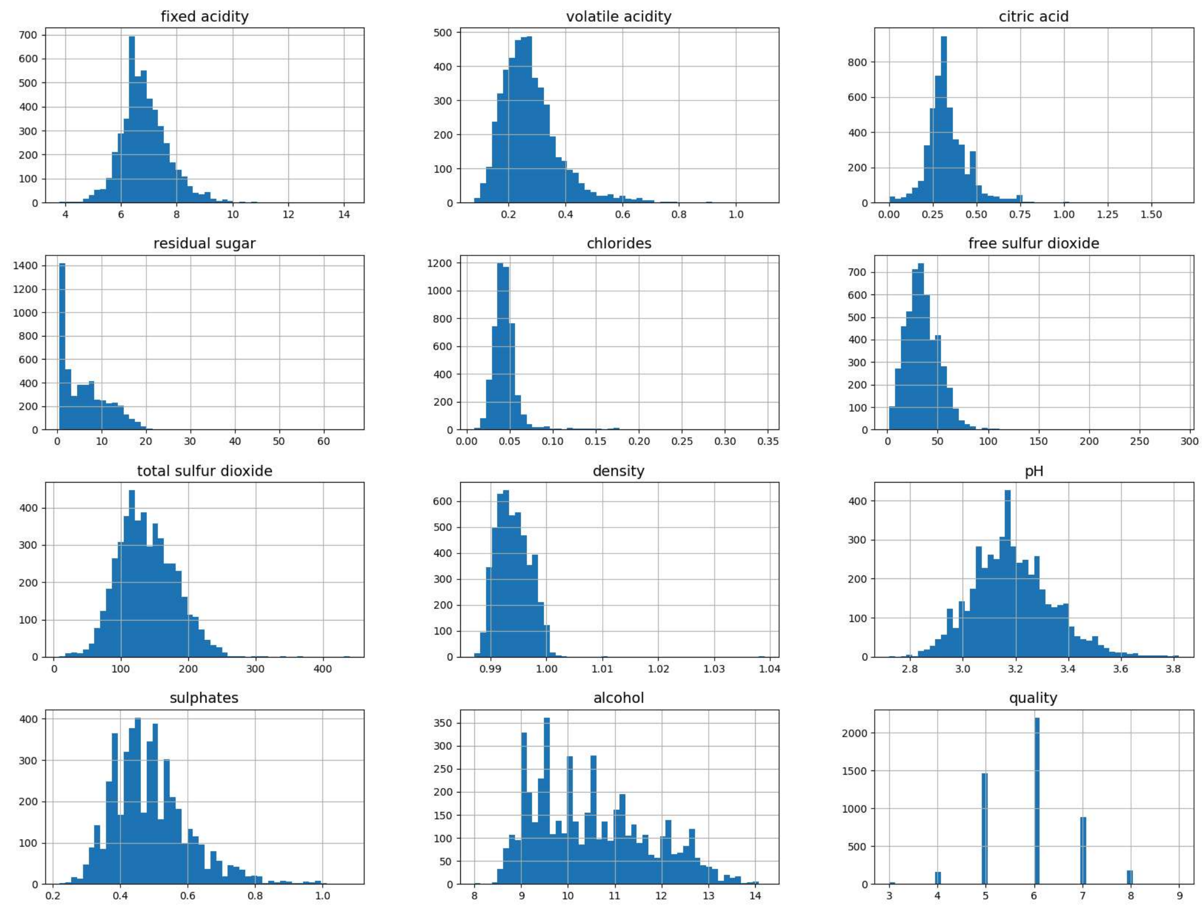
In [5]:
```
sns.boxplot(x=wine['residual sugar'])
```

Out[5]: <AxesSubplot: xlabel='residual sugar'>



It seems like residual sugar > 20 is considered outlier.

In [6]:
```
plt.rc('font', size=14)
plt.rc('axes', labelsize=14, titlesize=14)
plt.rc('legend', fontsize=14)
plt.rc('xtick', labelsize=10)
plt.rc('ytick', labelsize=10)
wine.hist(bins=50, figsize=(20,15))
plt.show()
```



Observations:

- most features are normally distributed except for residual sugar and alcohol
- a lot of features are skewed to the right (fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density)
- from quality, we can see that we have data imbalance problem where we might not have enough samples of high quality wine.

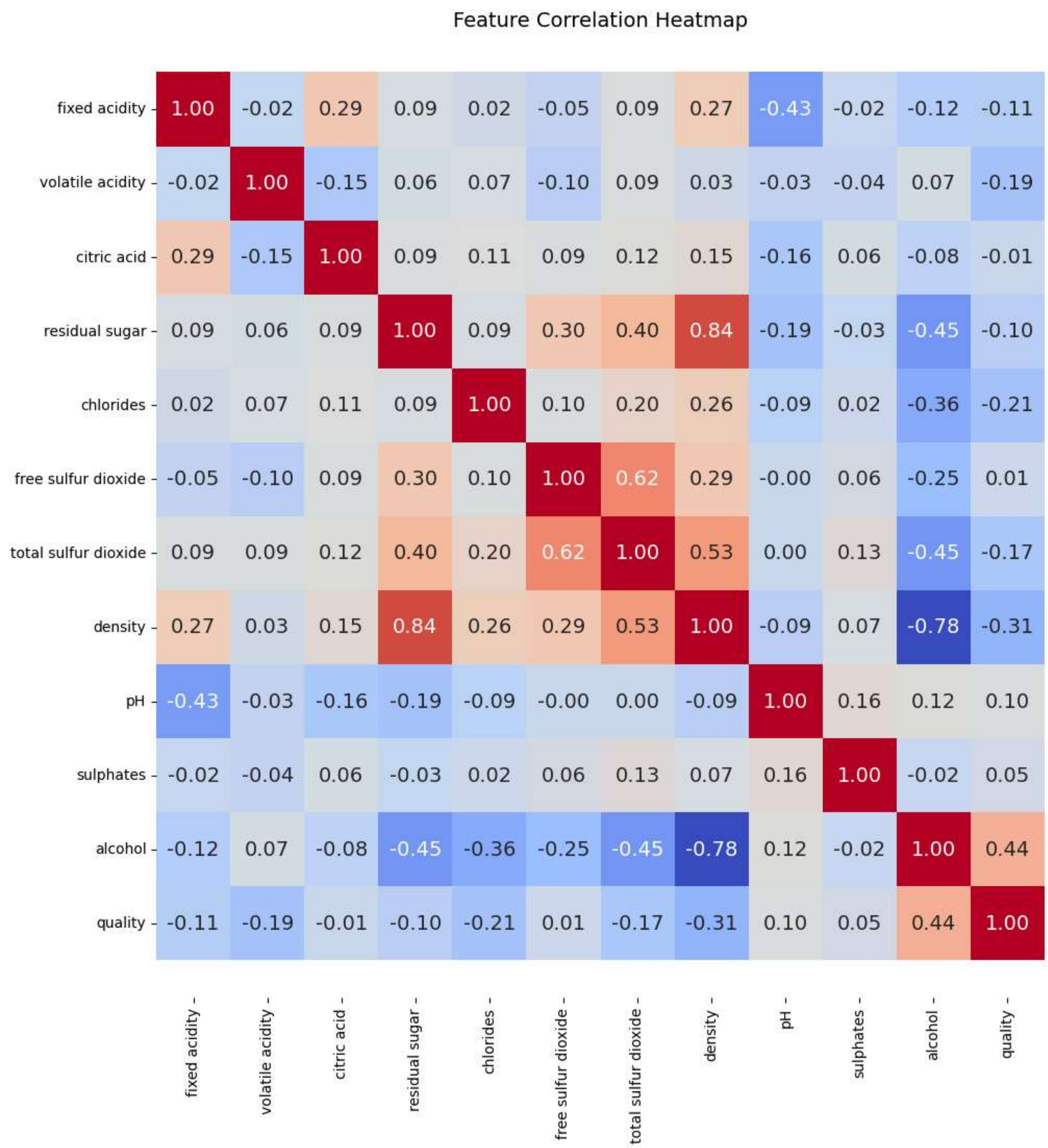
Checking class imbalance.

In [7]:
```
wine['quality'].value_counts()
```

Out[7]:
```
quality
6    2198
5    1457
7     880
8     175
4     163
3      20
9       5
Name: count, dtype: int64
```

1.3 Visualize Correlation between Features and Target

In [8]:
```
corr = wine.corr()

plt.figure(figsize=(12, 12))
sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm', square=True, cbar=Fa
lse)
b, t = plt.ylim()
plt.ylim(b+0.5, t-0.5)
plt.title("Feature Correlation Heatmap")
plt.show()
```



We can see that alcohol has the highest correlation with the wine quality followed by density, chlorides, and volatile acidity.

2. Data Preprocessing

2.1 Handling Outliers

Using z-score to find and remove outliers with threshold set to 3.

In [9]:
```
z = np.abs(stats.zscore(wine))
wine = wine[(z < 3).all(axis=1)]
print(wine.shape)

wine['quality'].value_counts()
```

```
(4487, 12)
```

Out[9]:
```
quality
6    2038
5    1309
7     855
8     161
4     124
Name: count, dtype: int64
```

After removing outliers, there are 4487 entries left. This means there are about 411 outliers (about 8.4%).

2.2 Split Features and Target

In [10]:
```
X = wine.drop('quality', axis=1)
print(X.shape)

y = wine['quality']
print(y.shape)
```

```
(4487, 11)
(4487,)
```

2.3 Perform Feature Scaling

In [11]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X = scaler.fit_transform(X)
```

2.4 Split Training and Test Data

In [12]:
```
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, rando
m_state=42, stratify=y)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(3589, 11)
(898, 11)
(3589,)
(898,)
```

3. Binary Classification

3.1 Categorizing Wine Quality

For binary classification task:

- high quality >= 7 quality rating
- low quality < 7 quality rating

In [13]:
```
y_train_hq = (y_train >= 7)
y_test_hq = (y_test >= 7)
```

3.2 Model Training

3.2.1 Logistic Regression

In [14]:
```
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression()
logreg.fit(X_train, y_train_hq)
```

Out[14]:
```
▾ LogisticRegression
LogisticRegression()
```

3.2.2 Support Vector Machine (SVM)

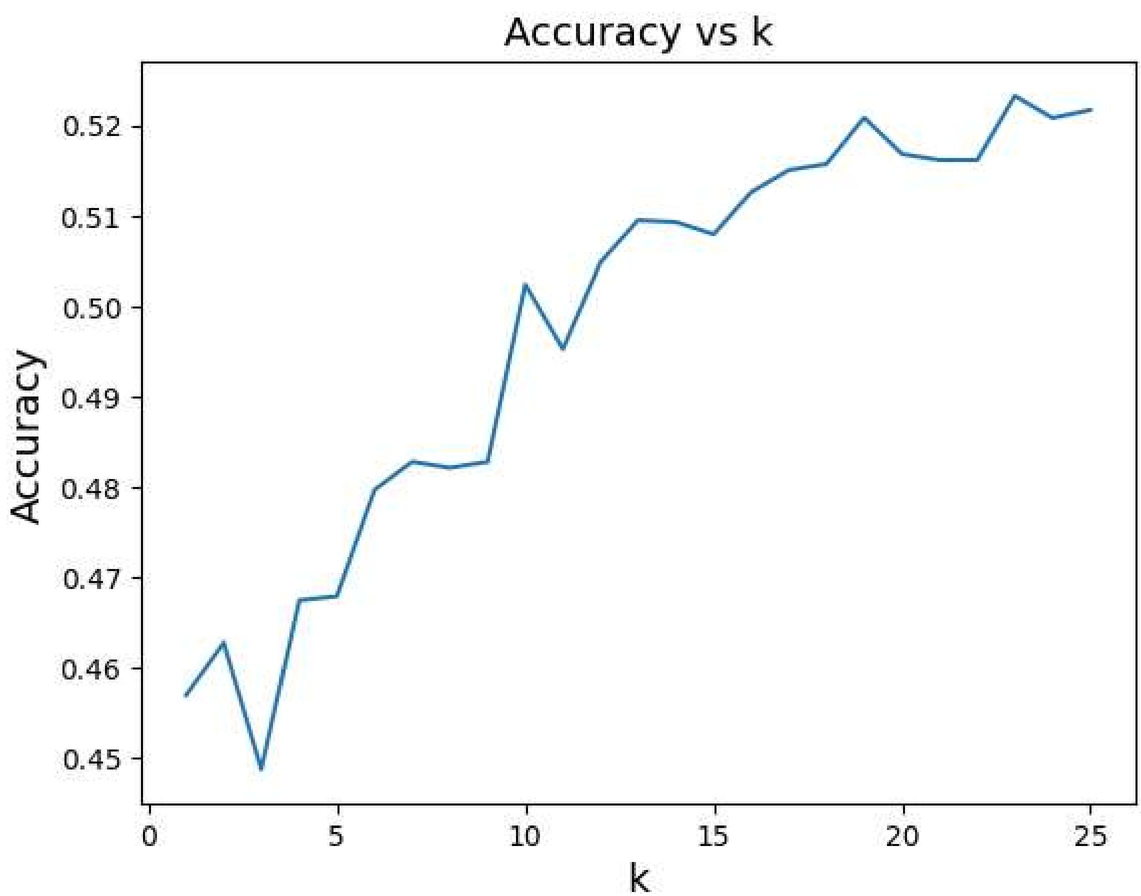
In [15]:
```
from sklearn.svm import SVC

svm = SVC(random_state=42)
svm.fit(X_train, y_train_hq)
```

Out[15]:
```
▾ SVC
SVC(random_state=42)
```

3.2.3 K-Nearest Neighbors (KNN)

Before training, lets see how the accuracy changed with number of K.

In [16]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score

# Range of k from 1 to 26
k_range = range(1, 26)

# List of cv scores
cv_scores = []

# Perform 10-fold cross validation
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
    cv_scores.append(scores.mean())

# Plot accuracy vs k
plt.plot(k_range, cv_scores)
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.title('Accuracy vs k')
plt.show()
```



We can see that highest accuracy is achieved when k equals to 19 or 23. Train the model with k = 23.

In [17]:
```
knn = KNeighborsClassifier(n_neighbors=23)
knn.fit(X_train, y_train_hq)
```

Out[17]:
```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=23)
```

3.2.4 Decision Tree

In [18]:
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train_hq)
```

Out[18]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

3.2.5 Random Forest

In [19]:
```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train_hq)
```

Out[19]:
```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

3.3 Model Evaluation

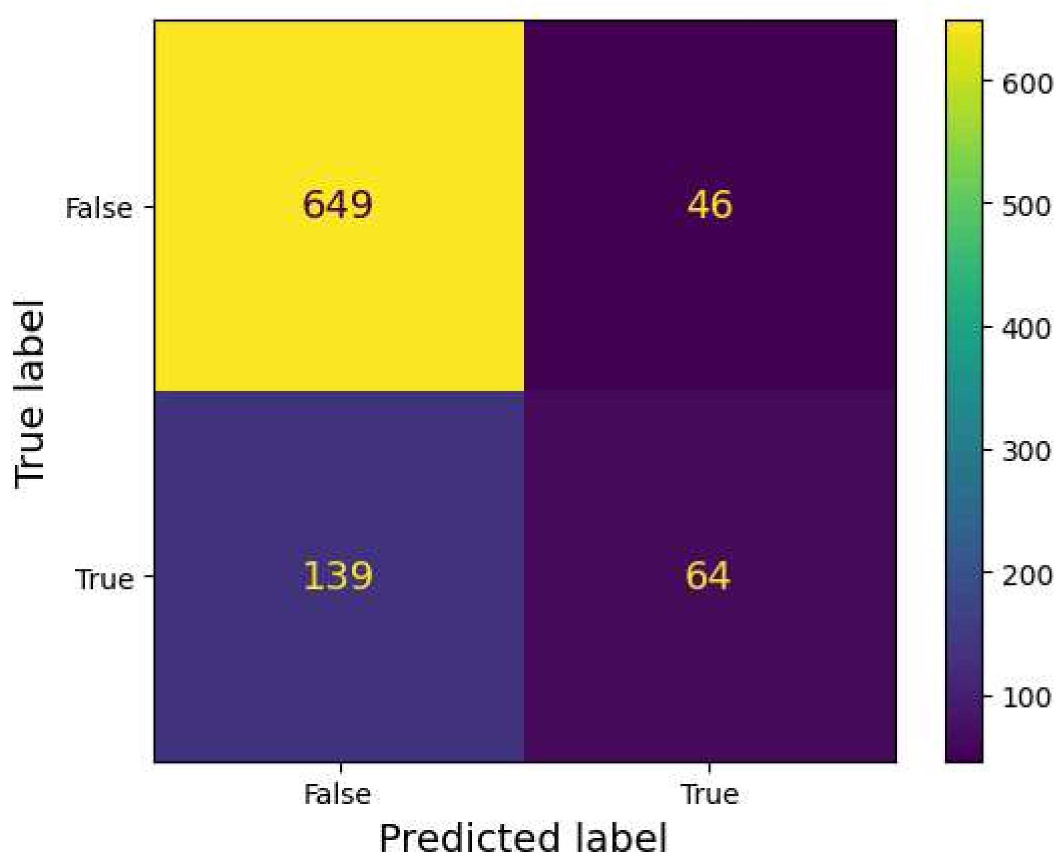
In model evaluation, the trained model will be cross-validated using 10-fold and tested using the test set.

In [20]:
```
# Cross-validation using 10-fold with accuracy scoring
y_cv_logreg = cross_val_score(logreg, X_train, y_train_hq, cv=10, scoring='acc
uracy')
y_cv_svm = cross_val_score(svm, X_train, y_train_hq, cv=10, scoring='accurac
y')
y_cv_knn = cross_val_score(knn, X_train, y_train_hq, cv=10, scoring='accurac
y')
y_cv_dt = cross_val_score(dt, X_train, y_train_hq, cv=10, scoring='accuracy')
y_cv_rf = cross_val_score(rf, X_train, y_train_hq, cv=10, scoring='accuracy')

# Predict using the test set
y_pred_logreg = logreg.predict(X_test)
y_pred_svm = svm.predict(X_test)
y_pred_knn = knn.predict(X_test)
y_pred_dt = dt.predict(X_test)
y_pred_rf = rf.predict(X_test)
```

3.3.1 Evaluation of Logistic Regression

In [21]:
```
from sklearn.metrics import classification_report, ConfusionMatrixDisplay

print(classification_report(y_test_hq, y_pred_logreg, digits=3, zero_division=
1))
print('Cross-validation accuracy score:', y_cv_logreg.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test_hq, y_pred_logreg)
plt.show()
```

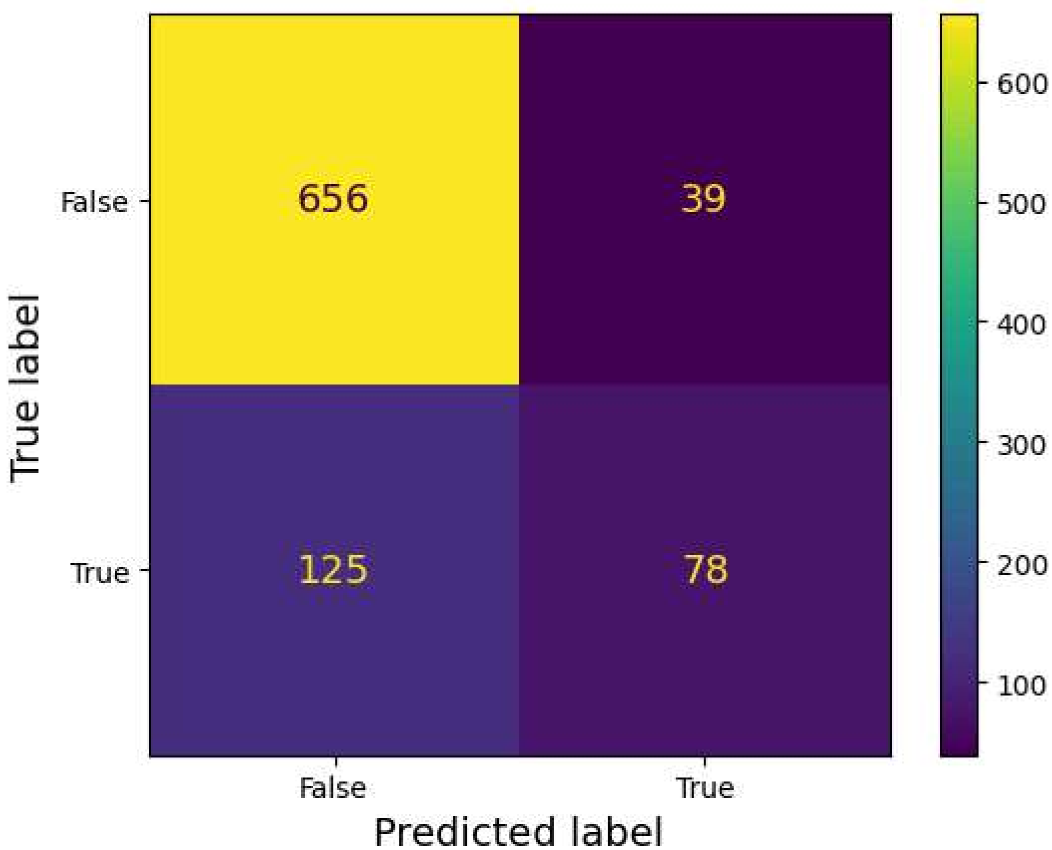
```
              precision    recall  f1-score   support

       False      0.824     0.934     0.875       695
        True      0.582     0.315     0.409       203

    accuracy                          0.794       898
   macro avg      0.703     0.625     0.642       898
weighted avg      0.769     0.794     0.770       898

Cross-validation accuracy score: 0.8013312895846626
```



3.3.2 Evaluation of SVM

In [22]:
```
print(classification_report(y_test_hq, y_pred_svm, digits=3, zero_division=1))
print('Cross-validation accuracy score:', y_cv_svm.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test_hq, y_pred_svm)
plt.show()
```

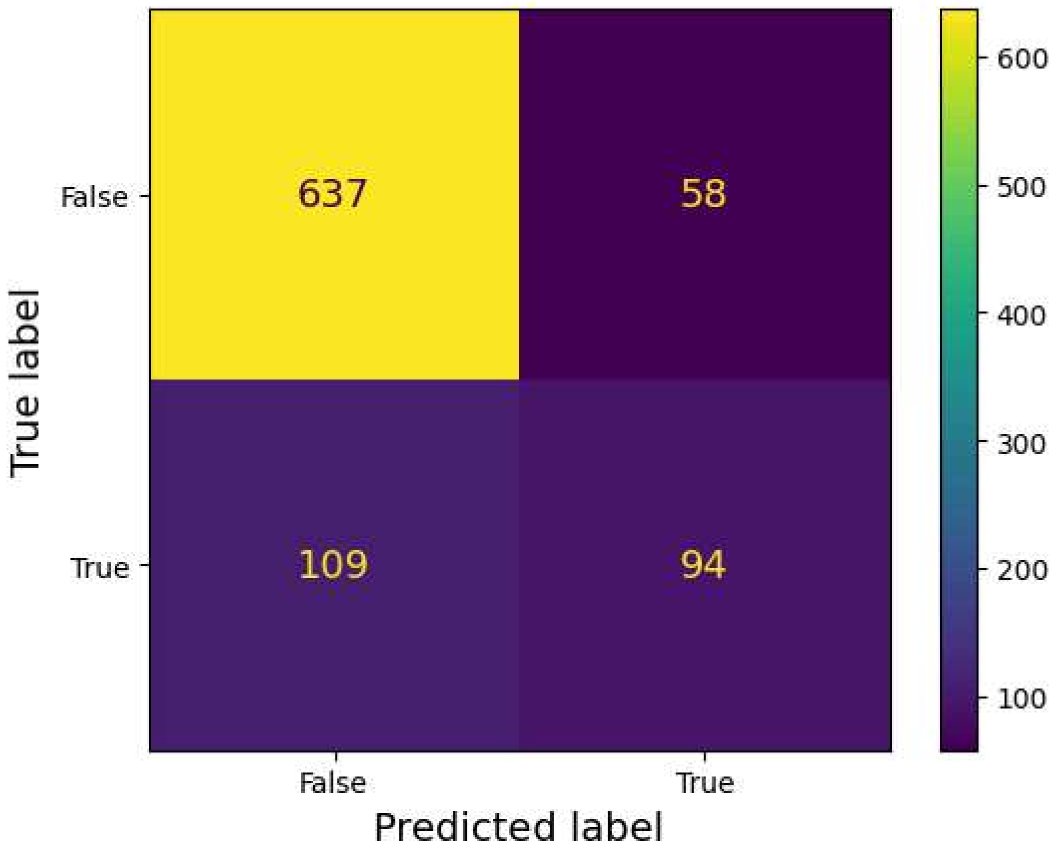
```
              precision    recall  f1-score   support

       False      0.840     0.944     0.889       695
        True      0.667     0.384     0.487       203

    accuracy                          0.817       898
   macro avg      0.753     0.664     0.688       898
weighted avg      0.801     0.817     0.798       898

Cross-validation accuracy score: 0.8183338261153732
```



3.3.3 Evaluation of KNN

```
In [23]: print(classification_report(y_test_hq, y_pred_knn, digits=3, zero_division=1))
         print('Cross-validation accuracy score:', y_cv_knn.mean())

         plt.rc('font', size=14)
         ConfusionMatrixDisplay.from_predictions(y_test_hq, y_pred_knn)
         plt.show()
```

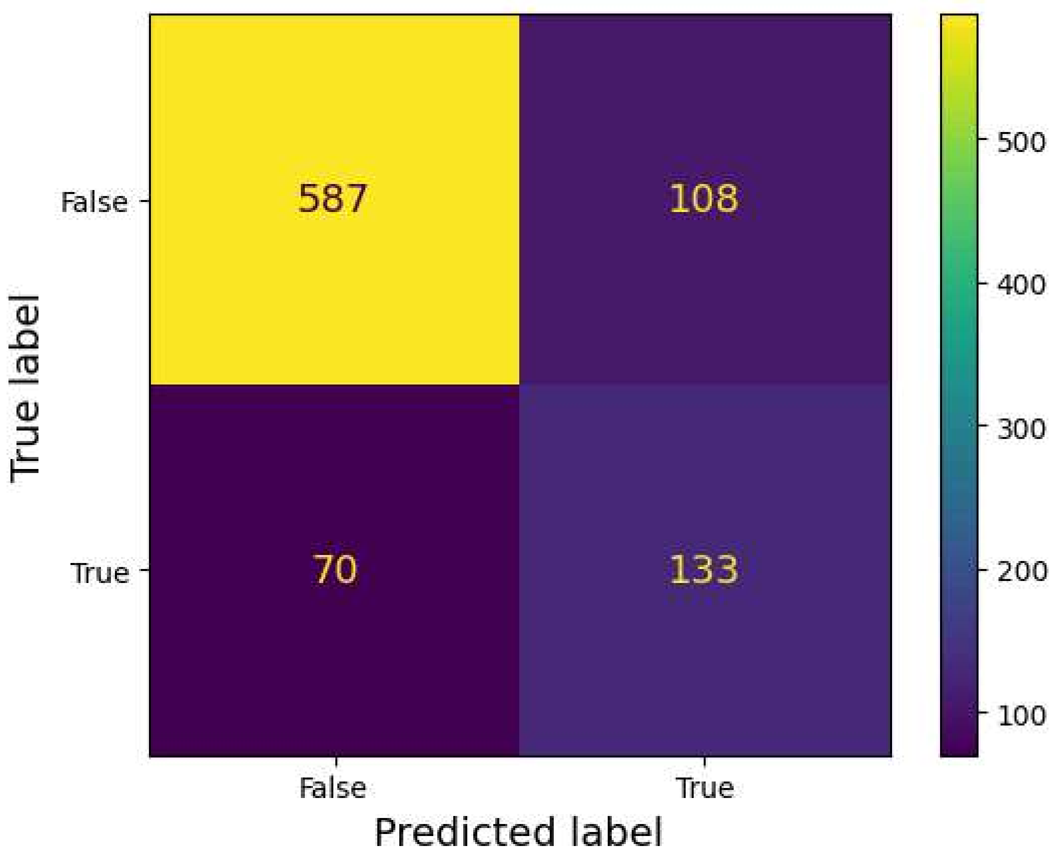
```
              precision    recall  f1-score   support

       False      0.854     0.917     0.884       695
        True      0.618     0.463     0.530       203

    accuracy                          0.814       898
   macro avg      0.736     0.690     0.707       898
weighted avg      0.801     0.814     0.804       898

Cross-validation accuracy score: 0.8144317704361898
```



3.3.4 Evaluation of Decision Tree

```
In [24]: print(classification_report(y_test_hq, y_pred_dt, digits=3, zero_division=1))
print('Cross-validation accuracy score:', y_cv_dt.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test_hq, y_pred_dt)
plt.show()
```

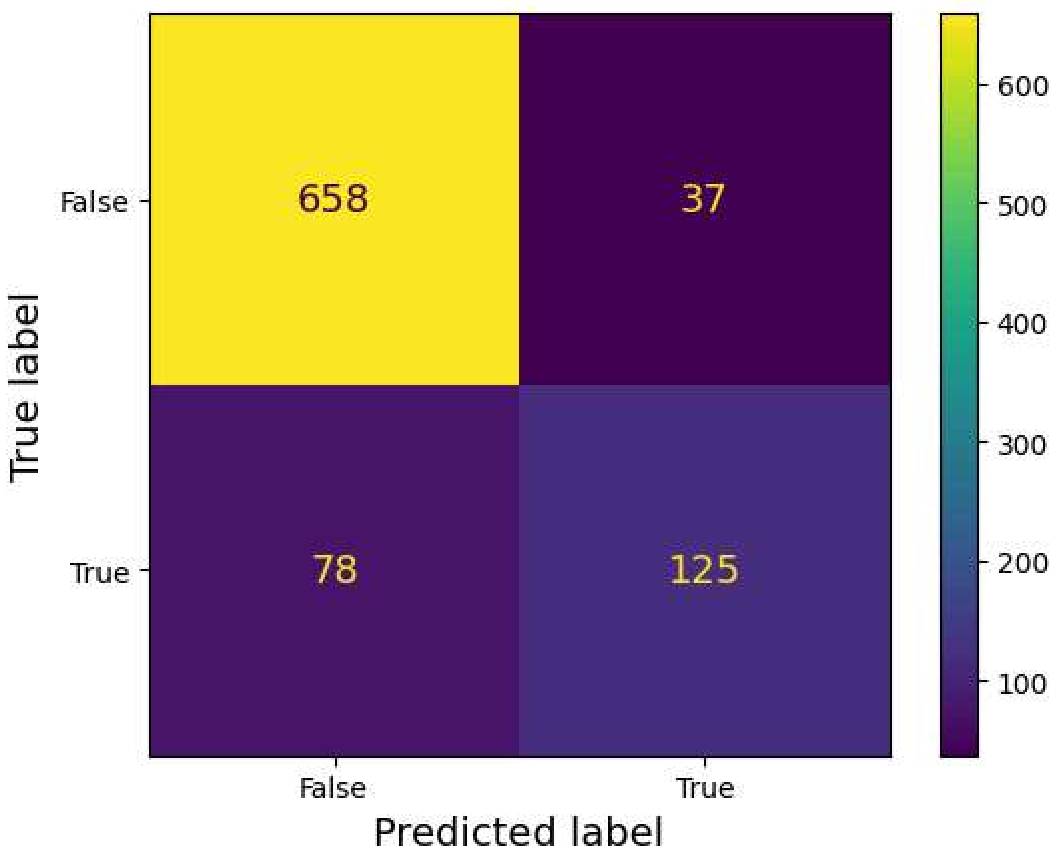
```
              precision    recall  f1-score   support

       False      0.893     0.845     0.868       695
        True      0.552     0.655     0.599       203

    accuracy                          0.802       898
   macro avg      0.723     0.750     0.734       898
weighted avg      0.816     0.802     0.807       898

Cross-validation accuracy score: 0.8339342680630553
```



3.3.5 Evaluation of Random Forest

In [25]:
```python
print(classification_report(y_test_hq, y_pred_rf, digits=3, zero_division=1))
print('Cross-validation accuracy score:', y_cv_rf.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test_hq, y_pred_rf)
plt.show()
```

```
              precision    recall  f1-score   support

       False      0.894     0.947     0.920       695
        True      0.772     0.616     0.685       203

    accuracy                          0.872       898
   macro avg      0.833     0.781     0.802       898
weighted avg      0.866     0.872     0.867       898

Cross-validation accuracy score: 0.873226373694776
```



Ranking:

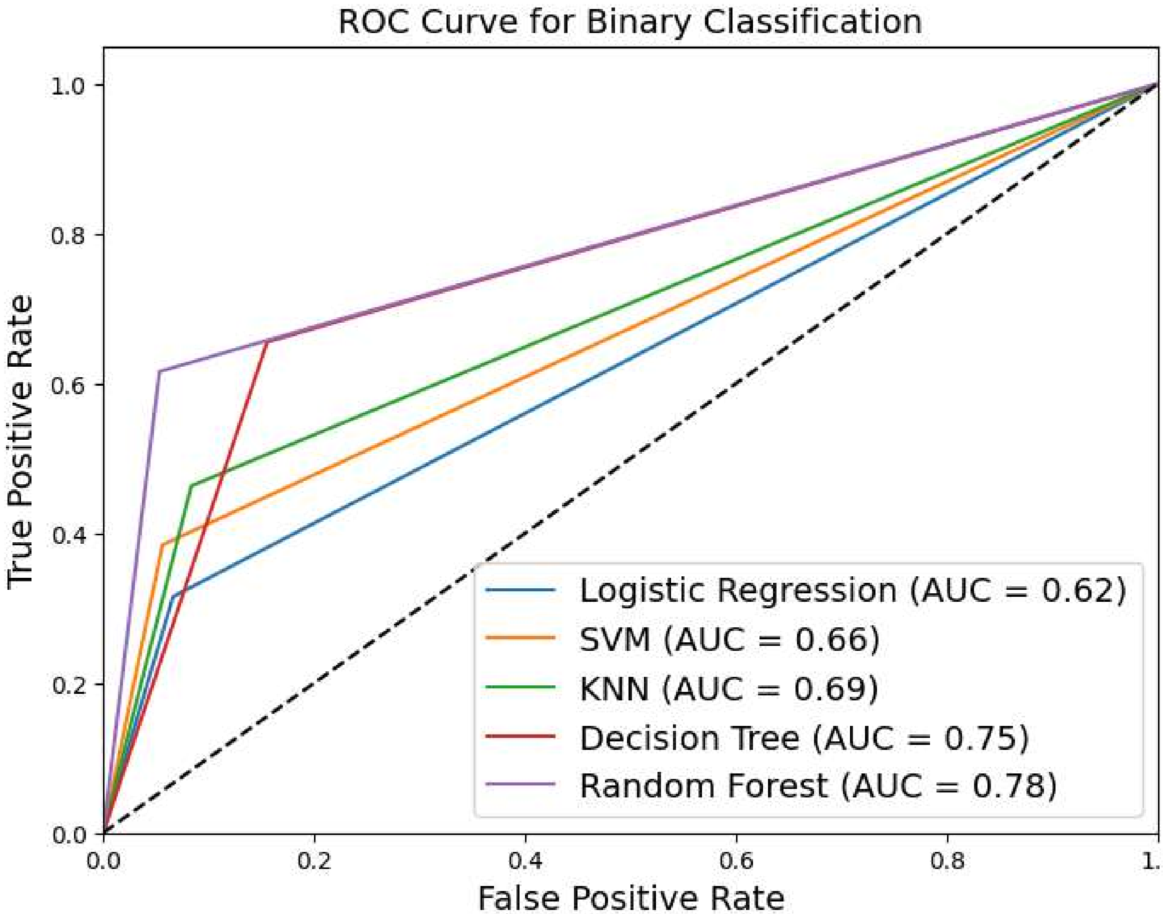
- CV Accuracy : RF, DT, SVM, KNN, LOGREG
- Precision : RF, DT, KNN, SVM, LOGREG
- Recall : RF, KNN, DT, SVM, LOGREG
- F1-Score : RF, DT, KNN, SVM, LOGREG

Observations:

- Random Forest is the best at binary classification for this white wine quality prediction.
- However, Decision Tree is better at recall high quality wine.

3.4 ROC Curve Analysis

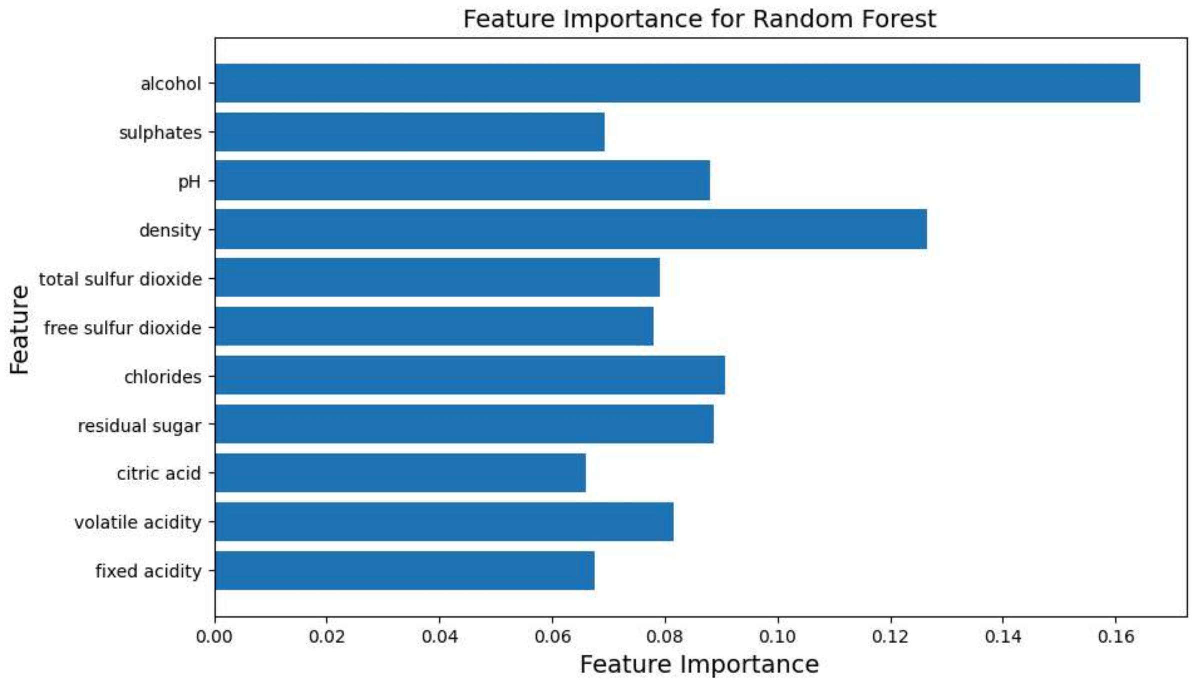
In [26]:
```
from sklearn.metrics import roc_curve, auc

models = [logreg, svm, knn, dt, rf]
model_names = ['Logistic Regression', 'SVM', 'KNN', 'Decision Tree', 'Random F
orest']

plt.figure(figsize=(8, 6))

# Plot ROC curve for each model
for model, name in zip(models, model_names):
    y_pred = model.predict(X_test)
    fpr, tpr, thresholds = roc_curve(y_test_hq, y_pred)
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label='%s (AUC = %0.2f)' % (name, roc_auc))

# Plot the random guess line
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('ROC Curve for Binary Classification')
plt.legend(loc="lower right")
plt.show()
```



From the ROC curve, we can observe that Random Forest have the highest ROC AUC which is 0.78. Although this value is quite low (ROC AUC = 1 being the perfect), it is the best we can achieved among the 5 chosen algorithms with imbalanced dataset.

3.5 Feature Importance for Binary Classification

In [27]:
```
feature_importances = rf.feature_importances_

# Plot the feature importance for Random Forest
plt.figure(figsize=(10, 6))
plt.barh(wine.columns[:-1], feature_importances)
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.title('Feature Importance for Random Forest')
plt.show()
```



For binary classification, alcohol and density are the most important features to distinguish low quality wine and high quality wine (binary). This might not be the case for multiclass classification.

4. Multiclass Classification

4.1 Model Training

Logistic Regression and Support Vector Machine, by default, is limited to binary classification problems. However, we can utilize extensions like One-vs-One (OvO) and One-vs-Rest (OvR) to be used for multiclass classification problems. Other algorithms such as K-Nearest Neighbors, Decision Tree, and Random Forest inherently support multiclass classification.

4.1.1 Logistic Regression

One-vs-One approach.

In [28]:
```
from sklearn.multiclass import OneVsOneClassifier

# One-vs-One
ovo_logreg = OneVsOneClassifier(LogisticRegression())
ovo_logreg.fit(X_train, y_train)
```

Out[28]:
```
▸ OneVsOneClassifier
▸ estimator: LogisticRegression
    ▸ LogisticRegression
```

One-vs-Rest approach.

In [29]:
```
from sklearn.multiclass import OneVsRestClassifier

# One-vs-Rest
ovr_logreg = OneVsRestClassifier(LogisticRegression())
ovr_logreg.fit(X_train, y_train)
```

Out[29]:
```
▸ OneVsRestClassifier
▸ estimator: LogisticRegression
    ▸ LogisticRegression
```

4.1.2 Support Vector Machines (SVM)

One-vs-One approach.

In [30]:
```
ovo_svm = OneVsOneClassifier(SVC(random_state=42))
ovo_svm.fit(X_train, y_train)
```

Out[30]:
```
▸ OneVsOneClassifier
  ▸ estimator: SVC
      ▸ SVC
```

One-vs-Rest approach.

In [31]:
```
ovr_svm = OneVsRestClassifier(SVC(random_state=42))
ovr_svm.fit(X_train, y_train)
```

Out[31]:
```
OneVsRestClassifier
  estimator: SVC
    SVC
```

4.1.3 K-Nearest Neighbors (KNN)

In [32]:
```
knn = KNeighborsClassifier(n_neighbors=23)
knn.fit(X_train, y_train)
```

Out[32]:
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=23)
```

4.1.4 Decision Tree

In [33]:
```
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
```

Out[33]:
```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

4.1.5 Random Forest

In [34]:
```
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)
```

Out[34]:
```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

4.2 Model Evaluation

For multiclass classification, it is recommended to find AUC score using cross validation method by passing roc_auc_ovr parameter. Evaluating the model with this method is advantageous when there is a high class imbalance. Also it does not require to set a classification threshold.

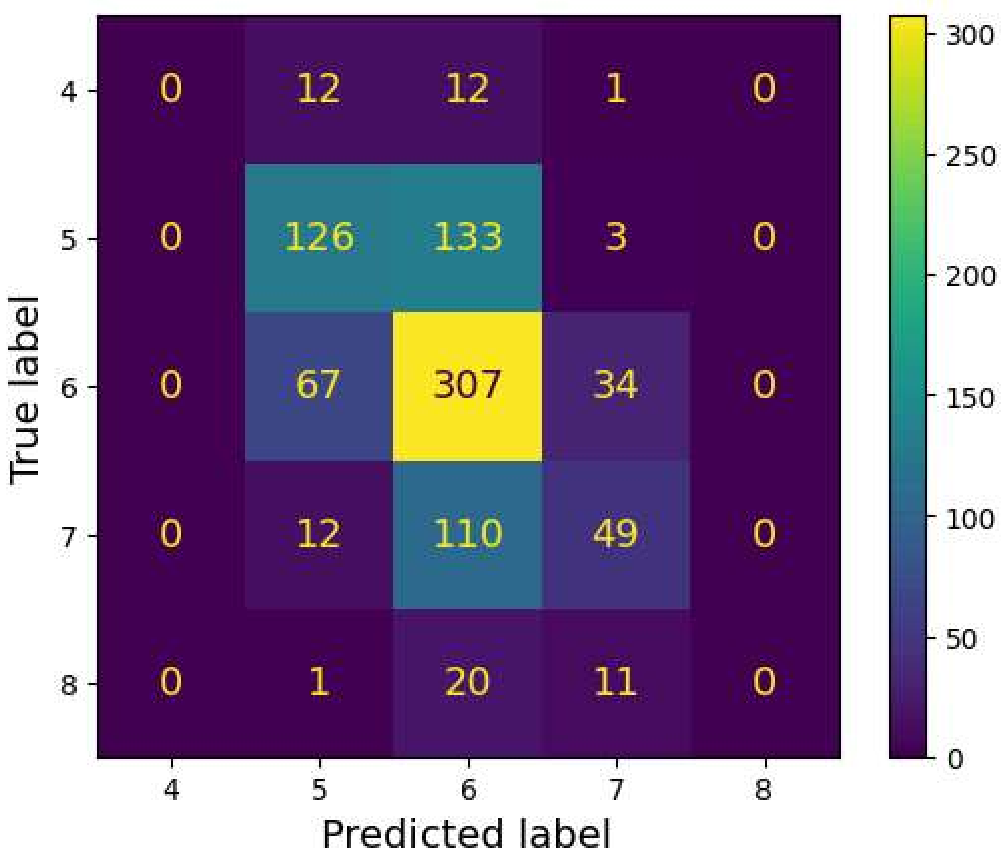
In [35]:
```
# Cross-validation using 10-fold with accuracy scoring
y_cv_ovo_logreg = cross_val_score(ovo_logreg, X_train, y_train, cv=10, scoring
='accuracy')
y_cv_ovr_logreg = cross_val_score(ovr_logreg, X_train, y_train, cv=10, scoring
='accuracy')
y_cv_ovo_svm = cross_val_score(ovo_svm, X_train, y_train, cv=10, scoring='accu
racy')
y_cv_ovr_svm = cross_val_score(ovr_svm, X_train, y_train, cv=10, scoring='accu
racy')
y_cv_knn = cross_val_score(knn, X_train, y_train, cv=10, scoring='accuracy')
y_cv_dt = cross_val_score(dt, X_train, y_train, cv=10, scoring='accuracy')
y_cv_rf = cross_val_score(rf, X_train, y_train, cv=10, scoring='accuracy')

# Predict using the test set
y_pred_ovo_logreg = ovo_logreg.predict(X_test)
y_pred_ovr_logreg = ovr_logreg.predict(X_test)
y_pred_ovo_svm = ovo_svm.predict(X_test)
y_pred_ovr_svm = ovr_svm.predict(X_test)
y_pred_knn = knn.predict(X_test)
y_pred_dt = dt.predict(X_test)
y_pred_rf = rf.predict(X_test)
```

4.2.1 Evaluation of Logistic Regression

One-vs-One.

In [36]:
```
print(classification_report(y_test, y_pred_ovo_logreg, digits=3, zero_division
=1))
print('Cross-validation accuracy score:', y_cv_ovo_logreg.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_ovo_logreg)
plt.show()
```

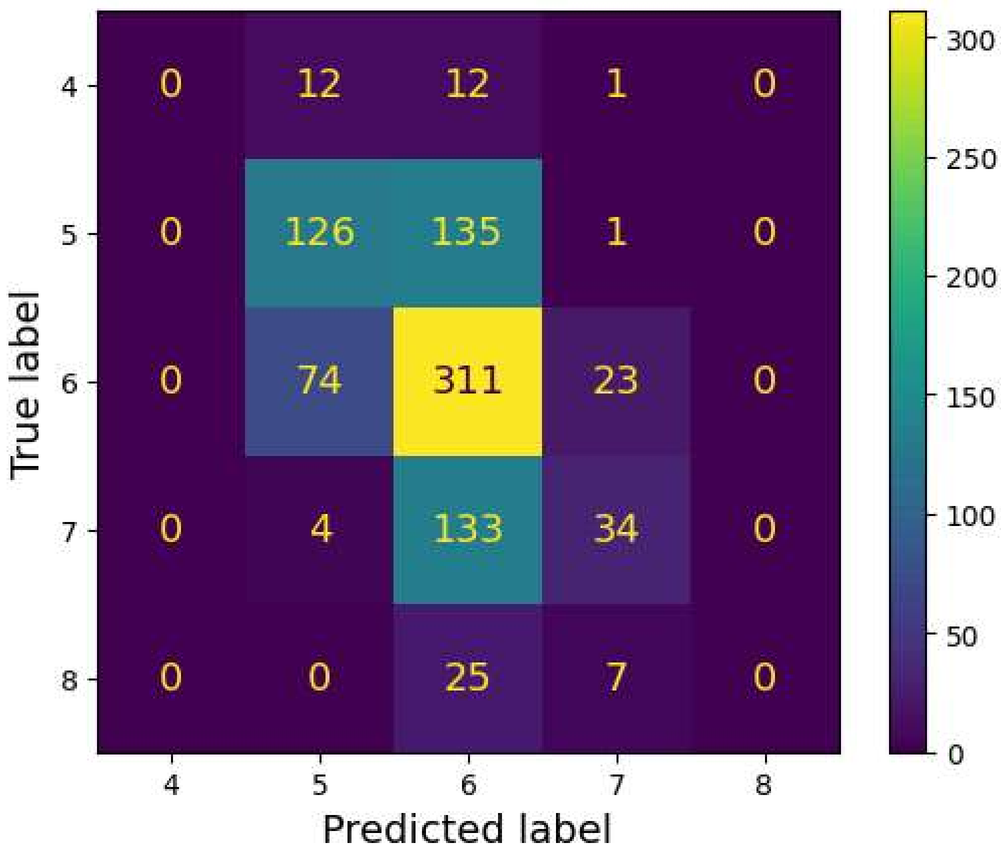
```
              precision    recall  f1-score   support

           4      1.000     0.000     0.000        25
           5      0.578     0.481     0.525       262
           6      0.527     0.752     0.620       408
           7      0.500     0.287     0.364       171
           8      1.000     0.000     0.000        32

    accuracy                          0.537       898
   macro avg      0.721     0.304     0.302       898
weighted avg      0.567     0.537     0.504       898

Cross-validation accuracy score: 0.5391473833273681
```



One-vs-Rest.

In [37]:
```
print(classification_report(y_test, y_pred_ovr_logreg, digits=3, zero_division
=1))
print('Cross-validation accuracy score:', y_cv_ovr_logreg.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_ovr_logreg)
plt.show()
```

```
              precision    recall  f1-score   support

           4      1.000     0.000     0.000        25
           5      0.583     0.481     0.527       262
           6      0.505     0.762     0.607       408
           7      0.515     0.199     0.287       171
           8      1.000     0.000     0.000        32

    accuracy                          0.524       898
   macro avg      0.721     0.288     0.284       898
weighted avg      0.561     0.524     0.484       898

Cross-validation accuracy score: 0.5469476043012091
```



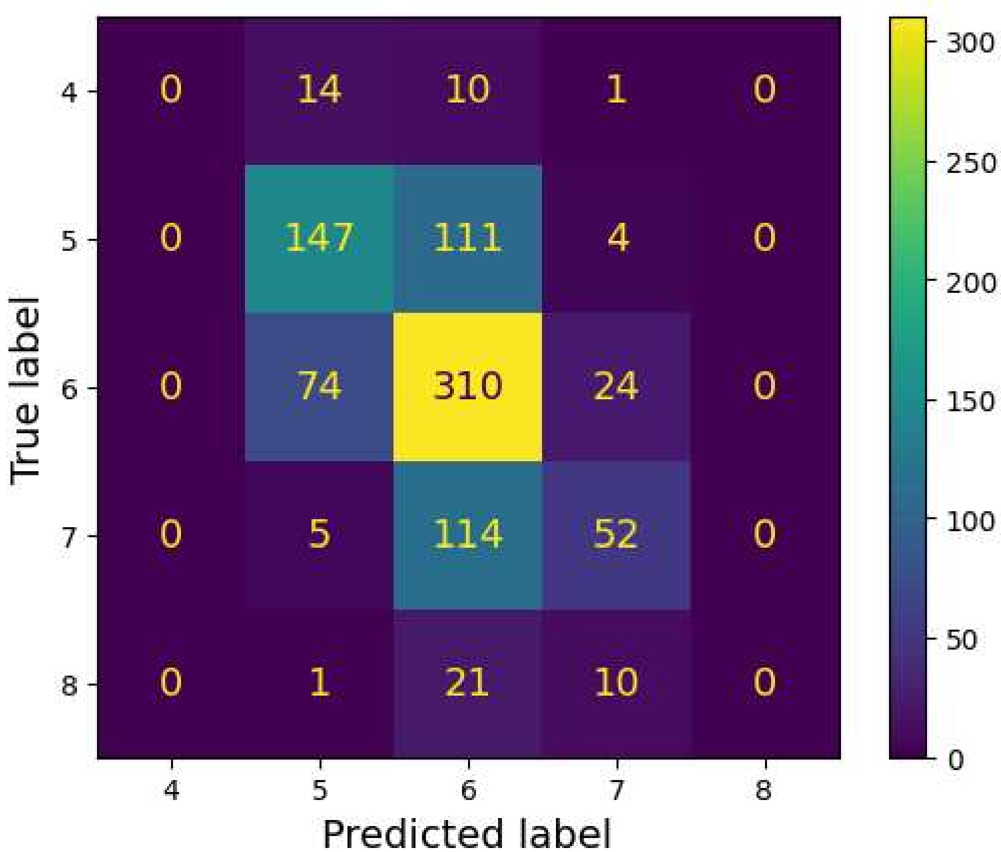
Although the OvR method achieved higher cross-validation accuracy, the OvO achieved better performance in all aspects (accuracy, precision, recall, f1-score) during testing.

4.2.2 Evaluation of SVM

One-vs-One.

In [38]:
```
print(classification_report(y_test, y_pred_ovo_svm, digits=3, zero_division=
1))
print('Cross-validation accuracy score:', y_cv_ovo_svm.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_ovo_svm)
plt.show()
```

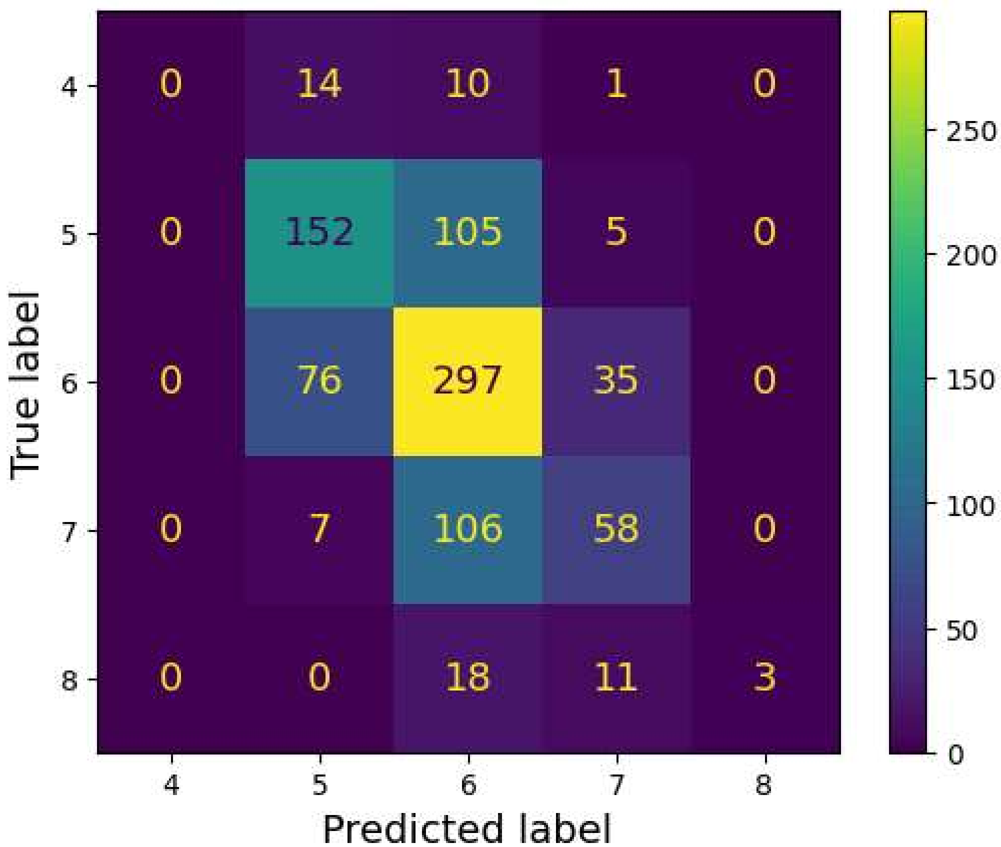
```
              precision    recall  f1-score   support

           4      1.000     0.000     0.000        25
           5      0.610     0.561     0.584       262
           6      0.548     0.760     0.637       408
           7      0.571     0.304     0.397       171
           8      1.000     0.000     0.000        32

    accuracy                          0.567       898
   macro avg      0.746     0.325     0.324       898
weighted avg      0.599     0.567     0.535       898

Cross-validation accuracy score: 0.579545136241266
```



One-vs-Rest.

In [39]:
```
print(classification_report(y_test, y_pred_ovr_svm, digits=3, zero_division=
1))
print('Cross-validation accuracy score:', y_cv_ovr_svm.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_ovr_svm)
plt.show()
```

```
              precision    recall  f1-score   support

           4      1.000     0.000     0.000        25
           5      0.610     0.580     0.595       262
           6      0.554     0.728     0.629       408
           7      0.527     0.339     0.413       171
           8      1.000     0.094     0.171        32

    accuracy                          0.568       898
   macro avg      0.738     0.348     0.362       898
weighted avg      0.594     0.568     0.544       898

Cross-validation accuracy score: 0.5739756617544078
```

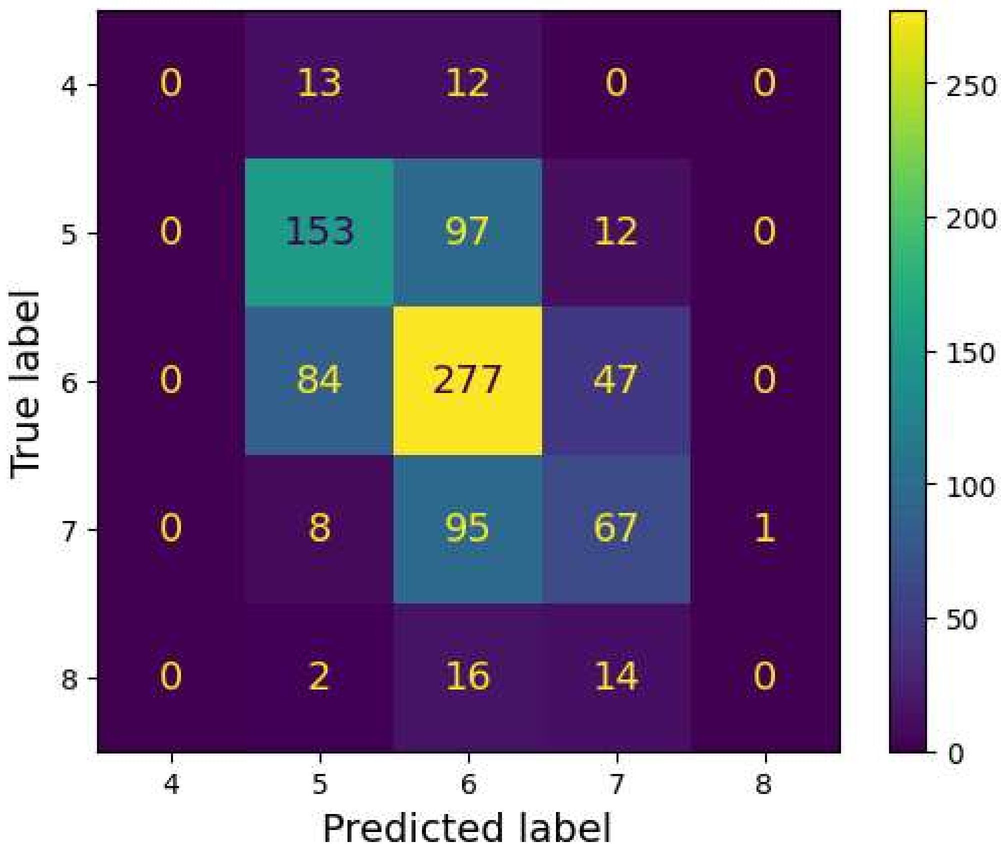


SVM however achieved better performance using the OvR method. Plus, it is the first time a model is able to predict samples with quality class 8.

4.2.3 Evaluation of KNN

```
In [40]: print(classification_report(y_test, y_pred_knn, digits=3, zero_division=1))
print('Cross-validation accuracy score:', y_cv_knn.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_knn)
plt.show()
```

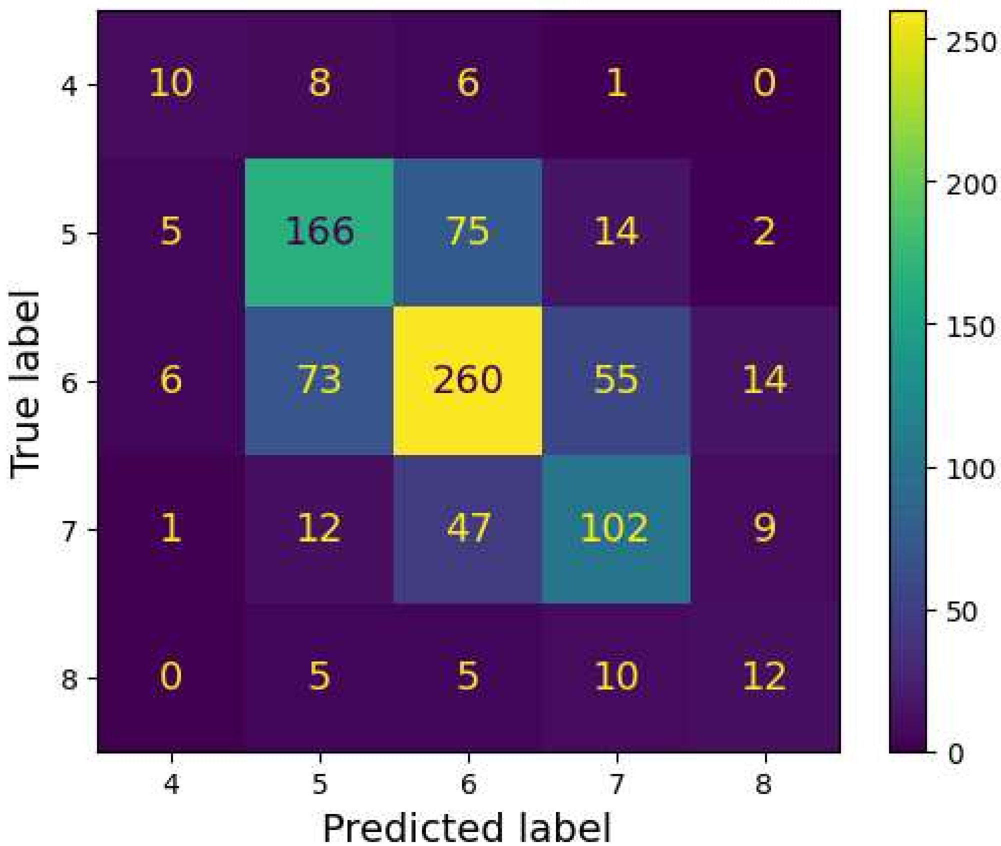
```
              precision    recall  f1-score   support

           4      1.000     0.000     0.000        25
           5      0.588     0.584     0.586       262
           6      0.557     0.679     0.612       408
           7      0.479     0.392     0.431       171
           8      0.000     0.000     0.000        32

    accuracy                          0.553       898
   macro avg      0.525     0.331     0.326       898
weighted avg      0.544     0.553     0.531       898

Cross-validation accuracy score: 0.5550240425763682
```



4.2.4 Evaluation of Decision Tree

In [41]:
```
print(classification_report(y_test, y_pred_dt, digits=3, zero_division=1))
print('Cross-validation accuracy score:', y_cv_dt.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_dt)
plt.show()
```

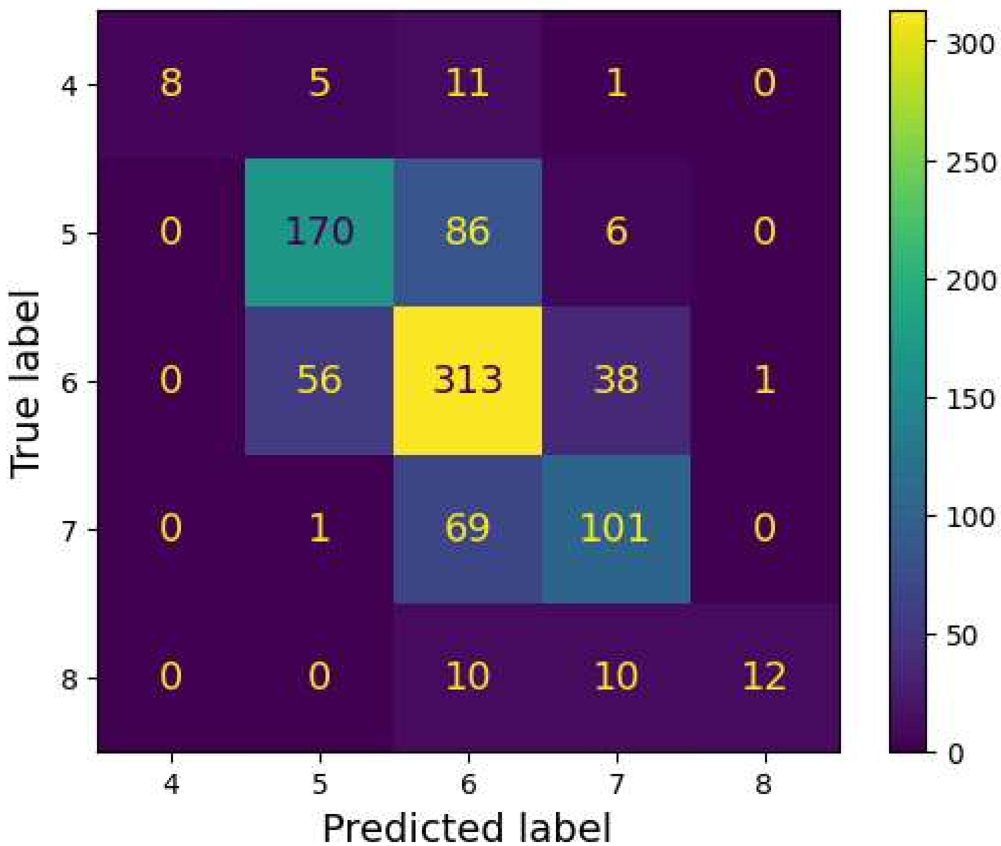
```
              precision    recall  f1-score   support

           4      0.455     0.400     0.426        25
           5      0.629     0.634     0.631       262
           6      0.662     0.637     0.649       408
           7      0.560     0.596     0.578       171
           8      0.324     0.375     0.348        32

    accuracy                          0.612       898
   macro avg      0.526     0.528     0.526       898
weighted avg      0.615     0.612     0.613       898

Cross-validation accuracy score: 0.6154946234885856
```



4.2.5 Evaluation of Random Forest

In [42]:
```
print(classification_report(y_test, y_pred_rf, digits=3, zero_division=1))
print('Cross-validation accuracy score:', y_cv_rf.mean())

plt.rc('font', size=14)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_rf)
plt.show()
```

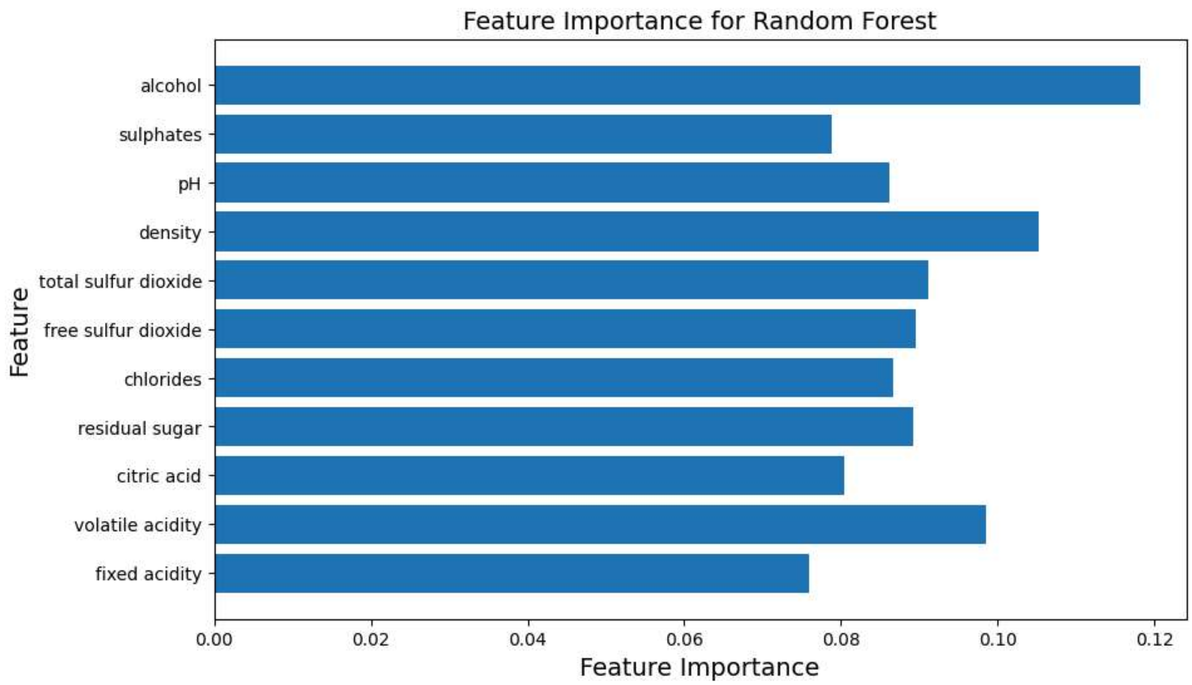
```
              precision    recall  f1-score   support

           4      1.000     0.320     0.485        25
           5      0.733     0.649     0.688       262
           6      0.640     0.767     0.698       408
           7      0.647     0.591     0.618       171
           8      0.923     0.375     0.533        32

    accuracy                          0.673       898
   macro avg      0.789     0.540     0.604       898
weighted avg      0.689     0.673     0.668       898

Cross-validation accuracy score: 0.6904452156051104
```



Random forest is the best algorithm for the multiclass classification of wine quality. It achieved the highest cross-validation accuracy, testing accuracy, precision, recall, and f1-score. However, decision tree is better at recall for minority classes. This is the exact case as in binary classification.

4.3 Feature Importance for Multiclass Classification

In [43]:
```
feature_importances = rf.feature_importances_

# Plot the feature importance for Random Forest
plt.figure(figsize=(10, 6))
plt.barh(wine.columns[:-1], feature_importances)
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.title('Feature Importance for Random Forest')
plt.show()
```



For multiclass classification, alcohol and density are still the most important features as in binary classification. However, we can also see that volatile acidity has high importance during training.