In [55]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import warnings
warnings.filterwarnings('ignore')
```

In [56]:
```python
dataframe = pd.read_csv("winequality.csv")
dataframe.head()
```

Out[56]:

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

In [57]:
```python
dataframe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6497 entries, 0 to 6496
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   type                  6497 non-null   object 
 1   fixed acidity         6487 non-null   float64
 2   volatile acidity      6489 non-null   float64
 3   citric acid           6494 non-null   float64
 4   residual sugar        6495 non-null   float64
 5   chlorides             6495 non-null   float64
 6   free sulfur dioxide   6497 non-null   float64
 7   total sulfur dioxide  6497 non-null   float64
 8   density               6497 non-null   float64
 9   pH                    6488 non-null   float64
 10  sulphates             6493 non-null   float64
 11  alcohol               6497 non-null   float64
 12  quality               6497 non-null   int64  
dtypes: float64(11), int64(1), object(1)
memory usage: 660.0+ KB
```

In [58]:
```python
dataframe.describe().T
```

Out[58]:

	count	mean	std	min	25%	50%	75%	max
fixed acidity	6487.0	7.216579	1.296750	3.80000	6.40000	7.00000	7.70000	15.90000
volatile acidity	6489.0	0.339691	0.164649	0.08000	0.23000	0.29000	0.40000	1.58000
citric acid	6494.0	0.318722	0.145265	0.00000	0.25000	0.31000	0.39000	1.66000
residual sugar	6495.0	5.444326	4.758125	0.60000	1.80000	3.00000	8.10000	65.80000

chlorides	6495.0	0.056042	0.035036	0.00900	0.03800	0.04700	0.06500	0.61100
free sulfur dioxide	6497.0	30.525319	17.749400	1.00000	17.00000	29.00000	41.00000	289.00000
total sulfur dioxide	6497.0	115.744574	56.521855	6.00000	77.00000	118.00000	156.00000	440.00000
density	6497.0	0.994697	0.002999	0.98711	0.99234	0.99489	0.99699	1.03898
pH	6488.0	3.218395	0.160748	2.72000	3.11000	3.21000	3.32000	4.01000
sulphates	6493.0	0.531215	0.148814	0.22000	0.43000	0.51000	0.60000	2.00000
alcohol	6497.0	10.491801	1.192712	8.00000	9.50000	10.30000	11.30000	14.90000
quality	6497.0	5.818378	0.873255	3.00000	5.00000	6.00000	6.00000	9.00000

In [59]:

```
dataframe.isnull().sum()
```

Out[59]:

```
type                     0
fixed acidity           10
volatile acidity         8
citric acid              3
residual sugar           2
chlorides                2
free sulfur dioxide      0
total sulfur dioxide     0
density                  0
pH                       9
sulphates                4
alcohol                  0
quality                  0
dtype: int64
```

In [60]:

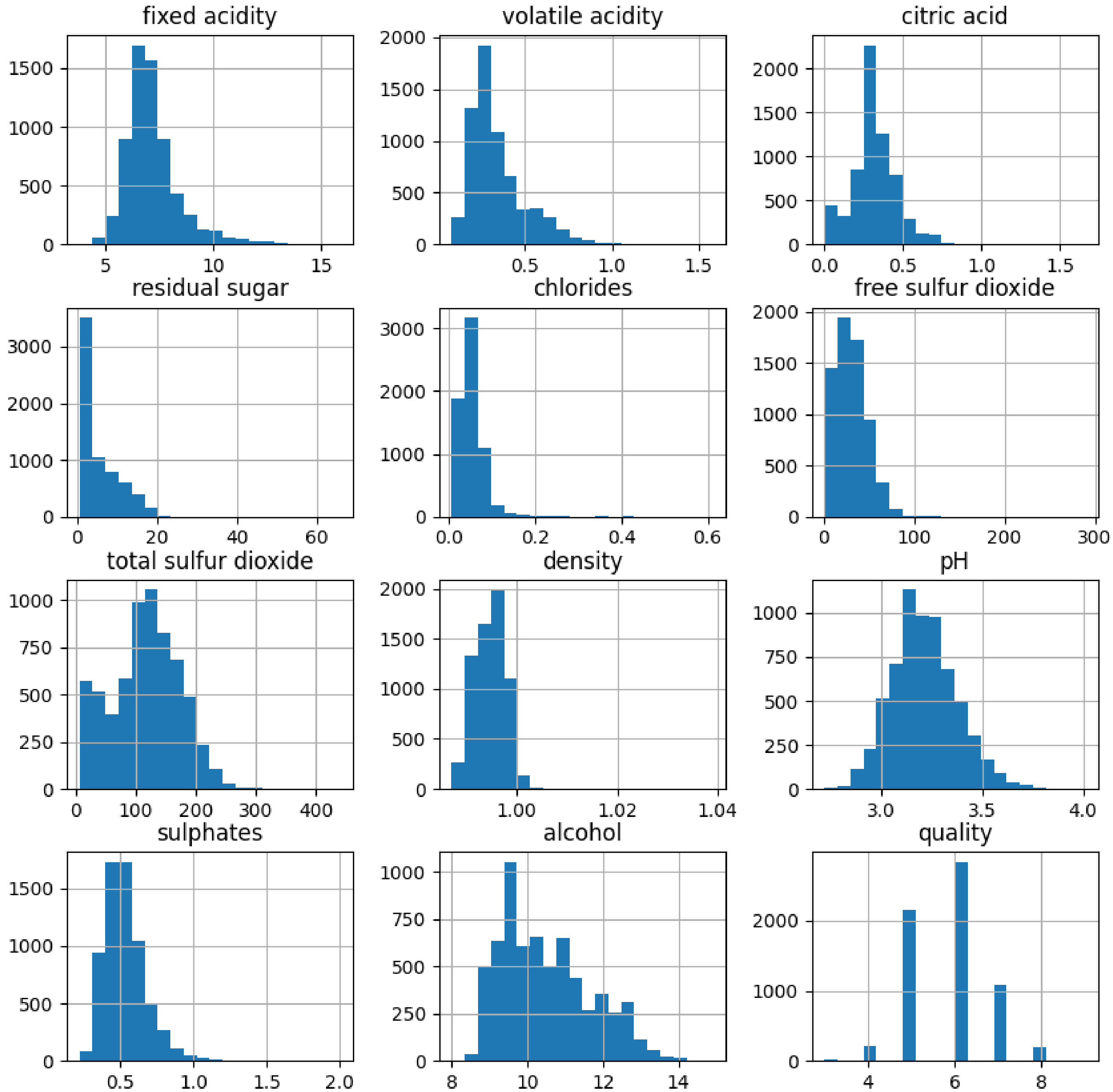
```
for col in dataframe.columns:
    if dataframe[col].isnull().sum() > 0:
        dataframe[col] = dataframe[col].fillna(dataframe[col].mean())

dataframe.isnull().sum().sum()
```

Out[60]:

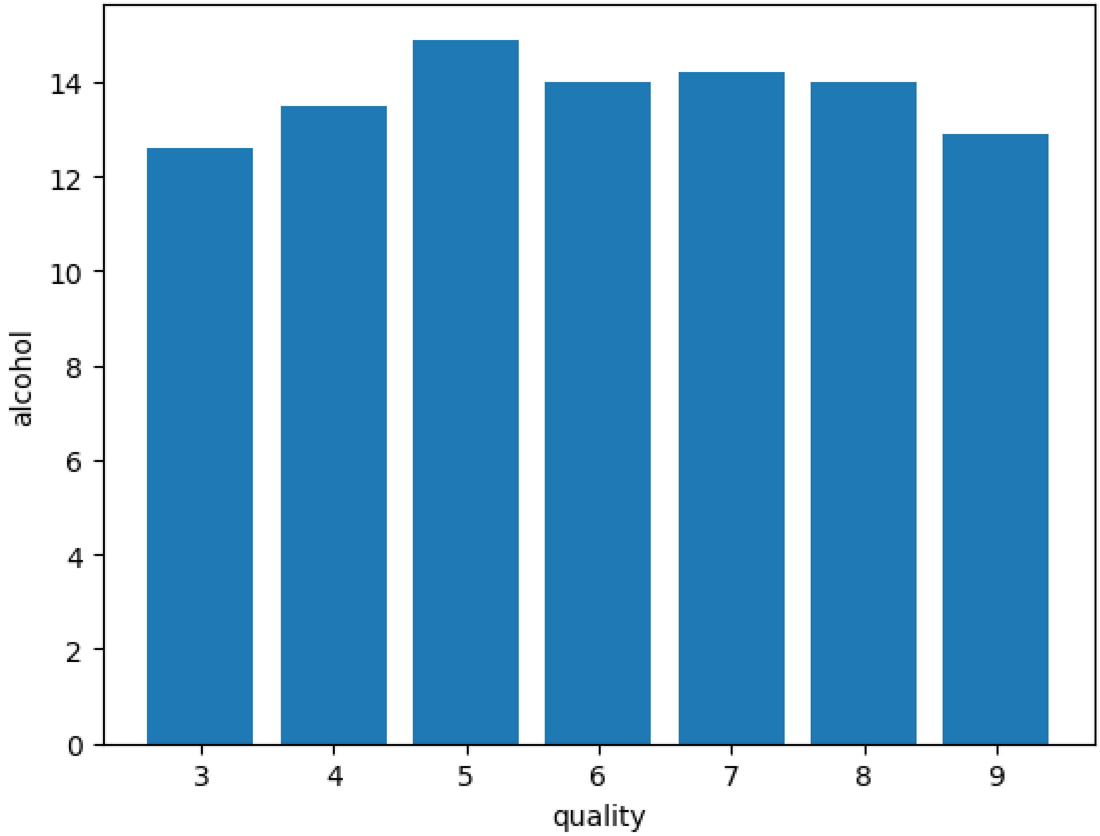
```
0
```

In [61]:

```
dataframe.hist(bins = 20, figsize = (10, 10))
plt.show()
```

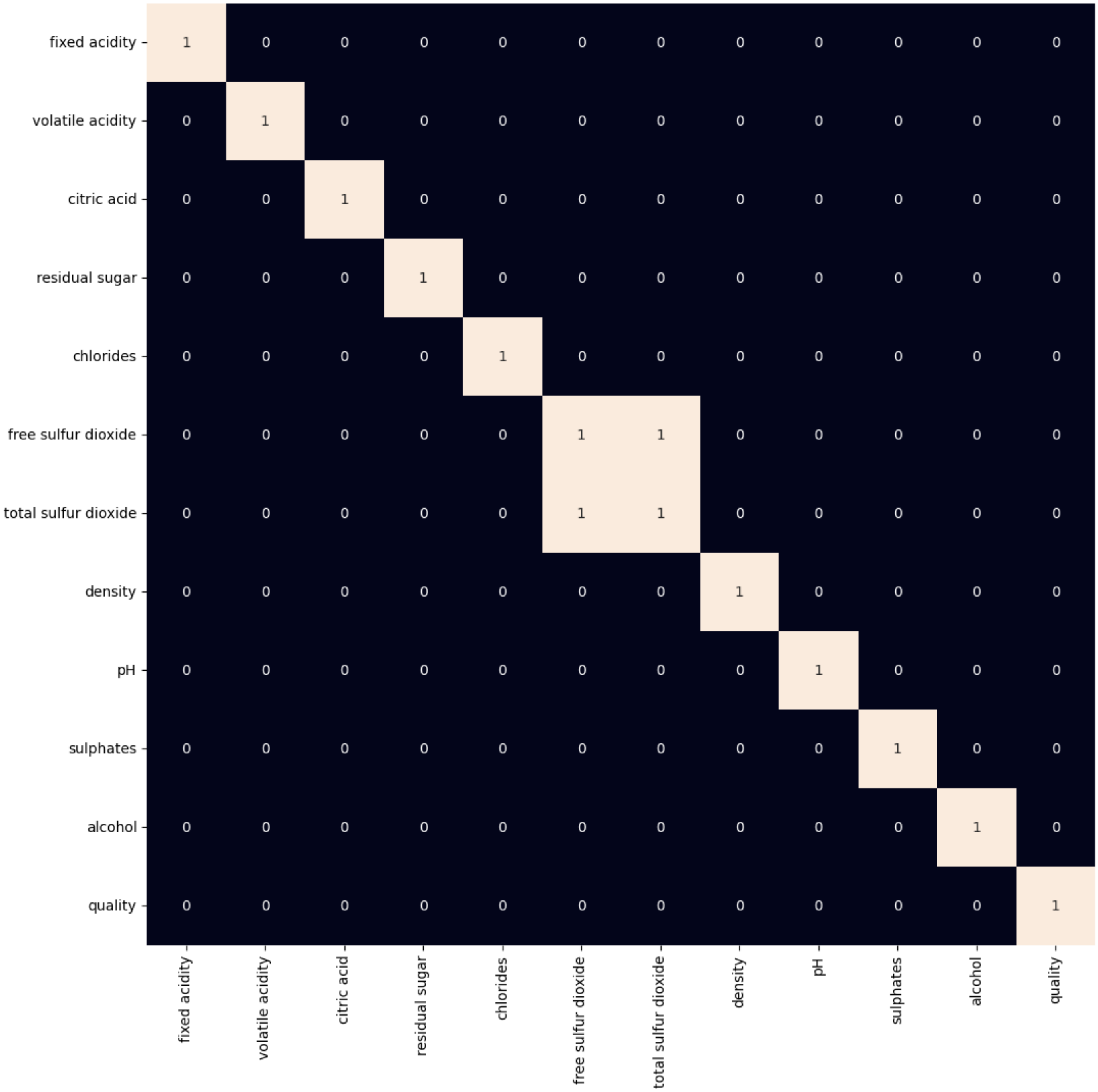


In [62]:
```
plt.bar(dataframe['quality'], dataframe['alcohol'])
plt.xlabel('quality')
plt.ylabel('alcohol')
plt.show()
```



In [63]:

```
plt.figure(figsize = (12, 12))
range_except_date = dataframe.loc[:, dataframe.columns != 'type']
sb.heatmap(range_except_date.corr() > 0.7, annot = True, cbar = False)
plt.show()
```



In [64]:
```
dataframe = dataframe.drop('total sulfur dioxide', axis = 1)
```

In [65]:
```
dataframe = dataframe.drop('free sulfur dioxide', axis = 1)
```

In [66]:
```
dataframe.head()
```

Out[66]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	density	pH	sulphates	alcohol	quality
0	white	7.0	0.27	0.36	20.7	0.045	1.0010	3.00	0.45	8.8	6
1	white	6.3	0.30	0.34	1.6	0.049	0.9940	3.30	0.49	9.5	6
2	white	8.1	0.28	0.40	6.9	0.050	0.9951	3.26	0.44	10.1	6
3	white	7.2	0.23	0.32	8.5	0.058	0.9956	3.19	0.40	9.9	6
4	white	7.2	0.23	0.32	8.5	0.058	0.9956	3.19	0.40	9.9	6

In [67]:
```
dataframe['best quality'] = [1 if x > 5 else 0 for x in dataframe.quality]
```

In [68]:
```
dataframe.head()
```

Out[68]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	density	pH	sulphates	alcohol	quality	best quality
0	white	7.0	0.27	0.36	20.7	0.045	1.0010	3.00	0.45	8.8	6	1
1	white	6.3	0.30	0.34	1.6	0.049	0.9940	3.30	0.49	9.5	6	1
2	white	8.1	0.28	0.40	6.9	0.050	0.9951	3.26	0.44	10.1	6	1
3	white	7.2	0.23	0.32	8.5	0.058	0.9956	3.19	0.40	9.9	6	1
4	white	7.2	0.23	0.32	8.5	0.058	0.9956	3.19	0.40	9.9	6	1

In [69]:
```
dataframe.replace({'white': 1, 'red': 0}, inplace = True)
```

In [70]:
```
dataframe.head()
```

Out[70]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	density	pH	sulphates	alcohol	quality	best quality
0	1	7.0	0.27	0.36	20.7	0.045	1.0010	3.00	0.45	8.8	6	1
1	1	6.3	0.30	0.34	1.6	0.049	0.9940	3.30	0.49	9.5	6	1
2	1	8.1	0.28	0.40	6.9	0.050	0.9951	3.26	0.44	10.1	6	1
3	1	7.2	0.23	0.32	8.5	0.058	0.9956	3.19	0.40	9.9	6	1
4	1	7.2	0.23	0.32	8.5	0.058	0.9956	3.19	0.40	9.9	6	1

In [71]:
```
features = dataframe.drop(['quality', 'best quality'], axis = 1)
target = dataframe['best quality']

xtrain, xtest, ytrain, ytest = train_test_split(features, target, test_size = 0.2, rando

xtrain.shape, xtest.shape
```

Out[71]:
```
((5197, 10), (1300, 10))
```

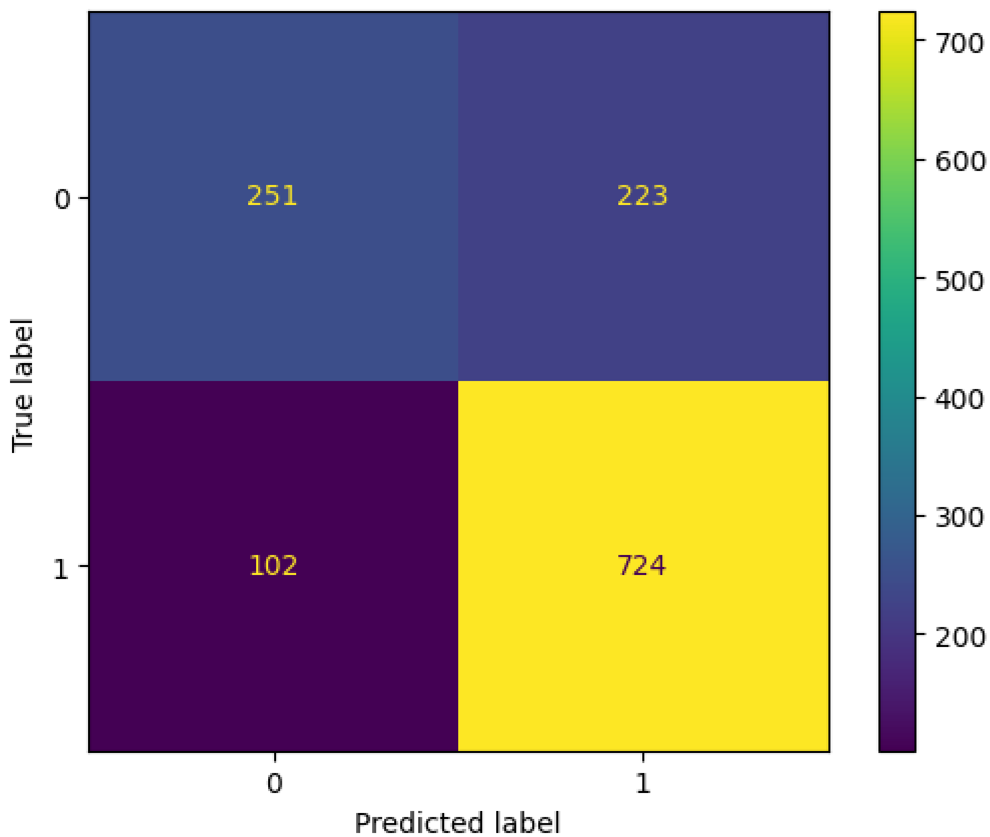
In [72]:
```
norm = MinMaxScaler()
xtrain = norm.fit_transform(xtrain)
xtest = norm.transform(xtest)
```

In [73]:
```
models = [LogisticRegression(), XGBClassifier(), SVC(kernel = 'rbf')]
for i in range(3):
    models[i].fit(xtrain, ytrain)
    print(f'{models[i]} : ')
    print('Training Accuracy : ', metrics.roc_auc_score(ytrain, models[i].predict(xtrain
    print('Validation Accuracy : ', metrics.roc_auc_score(ytest, models[i].predict(xtest
    print()
```

```
LogisticRegression() :
Training Accuracy :  0.7019886368161423
Validation Accuracy :  0.7019518599115251

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
```

```
                    multi_strategy=None, n_estimators=None, n_jobs=None,
                    num_parallel_tree=None, random_state=None, ...) :
Training Accuracy :  0.969661860064318
Validation Accuracy :  0.788761353071587

SVC() :
Training Accuracy :  0.706251343942582
Validation Accuracy :  0.7030245910850932
```

In [74]:
```
clf = SVC(random_state = 0)
clf.fit(xtrain, ytrain)
predictions = clf.predict(xtest)
cm = confusion_matrix(ytest, predictions, labels = clf.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix = cm, display_labels = clf.classes_)
disp.plot()
plt.show()
```



In [75]:
```
print(metrics.classification_report(ytest, models[1].predict(xtest)))
```

```
              precision    recall  f1-score   support

           0       0.76      0.70      0.73       474
           1       0.84      0.87      0.85       826

    accuracy                           0.81      1300
   macro avg       0.80      0.79      0.79      1300
weighted avg       0.81      0.81      0.81      1300
```