zad2

June 8, 2024

1 Jan Bronicki 249011

1.1 Zadanie 2

Korzystając ze zbioru danych z pliku „injection_molding_dataset”, przeanalizować dane i zbudować model regresji logistycznej. Trzeba przeanalizować zależność między parametrami, ich wzajemny wpływ oraz wpływ na jakość otrzymanych części. Parametrem zależnym (tym, który chcemy prognozować) w zbiorze danych jest jakość produkowanych części. Należy spróbować zbudować model regresji logistycznej o dokładności powyżej 90%. Wyniki należy zaprezentować w formie raportu w formacie PDF.

[93]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (
    accuracy_score,
    classification_report,
    confusion_matrix,
    roc_auc_score,
    roc_curve,
)
import matplotlib.pyplot as plt
import seaborn as sns
```

[11]:

```
file_path = "injection_molding_dataset.csv"
df: pd.DataFrame = pd.read_csv(file_path, delimiter=";")
df
```

[11]:

```
      Melt temperature  Mold temperature  time_to_fill  \
0           106.476184            80.617         7.124
1           105.505000            81.362         6.968
2           105.505000            80.411         6.864
3           106.474827            81.162         6.864
4           106.466140            81.471         6.864
…                …                …            …
1446        106.072000            81.493         6.188
1447        106.026000            81.456         6.084
```

```
1448        106.064000            81.420         6.188
1449        106.131000            81.401         6.188
1450        106.100000            81.427         6.136

      ZDx - Plasticizing time  ZUx - Cycle time  SKx - Closing force  \
0                        3.16             74.83           886.900000
1                        3.16             74.81           919.409791
2                        4.08             74.81           908.600000
3                        3.16             74.82           879.410871
4                        3.22             74.83           885.644260
…                       …               …                  …
1446                     2.87             75.65           905.500000
1447                     2.87             75.63           906.800000
1448                     2.84             75.66           905.900000
1449                     2.89             75.67           907.200000
1450                     2.86             75.65           906.400000

      SKs - Clamping force peak value  Ms - Torque peak value current cycle  \
0                          904.000000                                 116.9
1                          935.900000                                 113.9
2                          902.344823                                 120.5
3                          902.033653                                 127.3
4                          902.821269                                 120.5
…                               …                                   …
1446                       920.800000                                 114.5
1447                       922.500000                                 122.3
1448                       922.100000                                 125.2
1449                       921.500000                                 120.8
1450                       920.300000                                 124.9

      Mm - Torque mean value current cycle  \
0                               104.300000
1                               104.900000
2                               106.503496
3                               104.900000
4                               106.700000
…                                    …
1446                            107.500000
1447                            106.600000
1448                            110.700000
1449                            106.900000
1450                            108.900000

      APSs - Specific back pressure peak value  \
0                                        145.6
1                                        145.6
2                                        147.0
```

```
3                                        145.6
4                                        145.6
…                                        …
1446                                     145.5
1447                                     144.9
1448                                     147.5
1449                                     145.4
1450                                     147.3

      APVs - Specific injection pressure peak value  \
0                                             922.3
1                                             930.5
2                                             933.1
3                                             922.3
4                                             917.5
…                                             …
1446                                          907.3
1447                                          905.6
1448                                          921.6
1449                                          895.5
1450                                          908.2

      CPn - Screw position at the end of hold pressure  SVo - Shot volume  \
0                                                 8.82              18.73
1                                                 8.59              18.73
2                                                 8.80              18.98
3                                                 8.85              18.73
4                                                 8.80              18.75
…                                                …                …
1446                                              8.96              18.61
1447                                              8.92              18.65
1448                                              8.97              18.60
1449                                              8.93              18.63
1450                                              9.01              18.56

      quality
0         1.0
1         1.0
2         1.0
3         1.0
4         1.0
…       …
1446      4.0
1447      4.0
1448      4.0
1449      4.0
1450      4.0
```

```
[1451 rows x 14 columns]
```

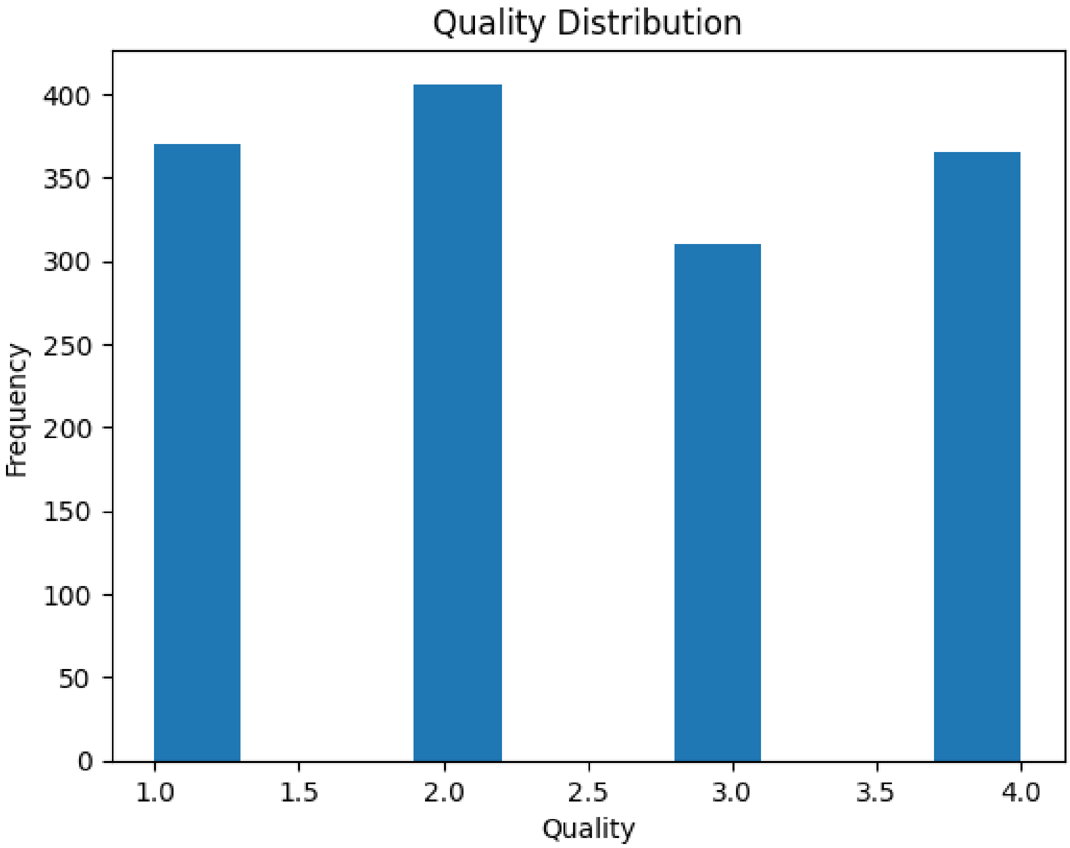
[14]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1451 entries, 0 to 1450
Data columns (total 14 columns):
 #   Column                                       Non-Null Count  Dtype  
---  ------                                       --------------  -----  
 0   Melt temperature                             1451 non-null   float64
 1   Mold temperature                             1451 non-null   float64
 2   time_to_fill                                 1451 non-null   float64
 3   ZDx - Plasticizing time                      1451 non-null   float64
 4   ZUx - Cycle time                             1451 non-null   float64
 5   SKx - Closing force                          1451 non-null   float64
 6   SKs - Clamping force peak value              1451 non-null   float64
 7   Ms - Torque peak value current cycle         1451 non-null   float64
 8   Mm - Torque mean value current cycle         1451 non-null   float64
 9   APSs - Specific back pressure peak value     1451 non-null   float64
 10  APVs - Specific injection pressure peak value  1451 non-null   float64
 11  CPn - Screw position at the end of hold pressure  1451 non-null   float64
 12  SVo - Shot volume                            1451 non-null   float64
 13  quality                                      1451 non-null   float64
dtypes: float64(14)
memory usage: 158.8 KB
```

[127]:

```
plt.hist(df["quality"])
plt.title("Quality Distribution")
plt.xlabel("Quality")
plt.ylabel("Frequency")
plt.show()
```



[18]:
```
# Split the dataset into features and target
x = df.drop("quality", axis=1)
y = df["quality"]
```

[132]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    x, y, test_size=0.25, random_state=123
)


# Initialize the scaler
scaler = StandardScaler()

# Fit and transform the training data, transform the test data
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize the model
logisticRegr = LogisticRegression(max_iter=1000)
```

```
# Train the model
logisticRegr.fit(X_train_scaled, y_train)

# Predict on the test set
y_pred = logisticRegr.predict(X_test_scaled)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
accuracy
```

[132]:

```
0.8705234159779615
```

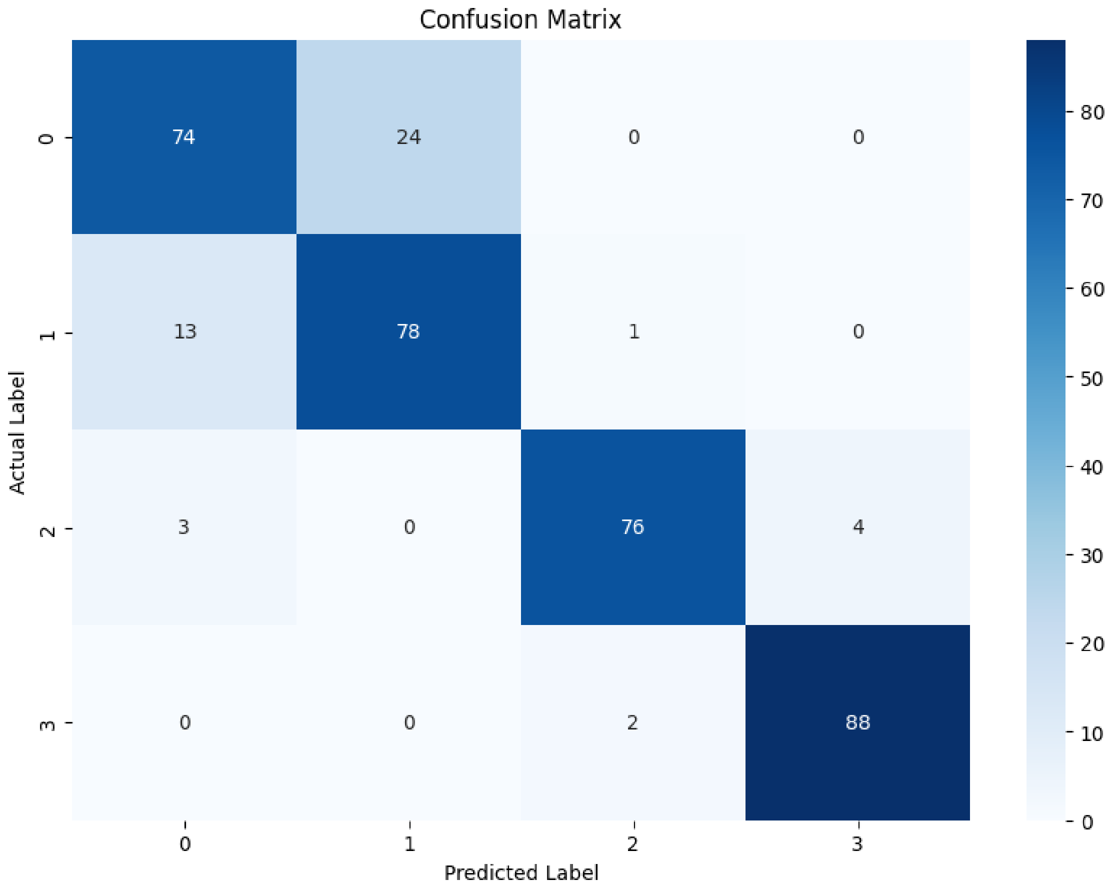
[133]:

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

```
              precision    recall  f1-score   support

         1.0       0.82      0.76      0.79        98
         2.0       0.76      0.85      0.80        92
         3.0       0.96      0.92      0.94        83
         4.0       0.96      0.98      0.97        90

    accuracy                           0.87       363
   macro avg       0.88      0.87      0.87       363
weighted avg       0.87      0.87      0.87       363
```

[134]:

```
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix")
plt.ylabel("Actual Label")
plt.xlabel("Predicted Label")
plt.show()
```



[135]:
```
roc_auc = roc_auc_score(
    y_test, logisticRegr.predict_proba(X_test_scaled), multi_class="ovr"
)
print(f"ROC AUC: {roc_auc}")
```

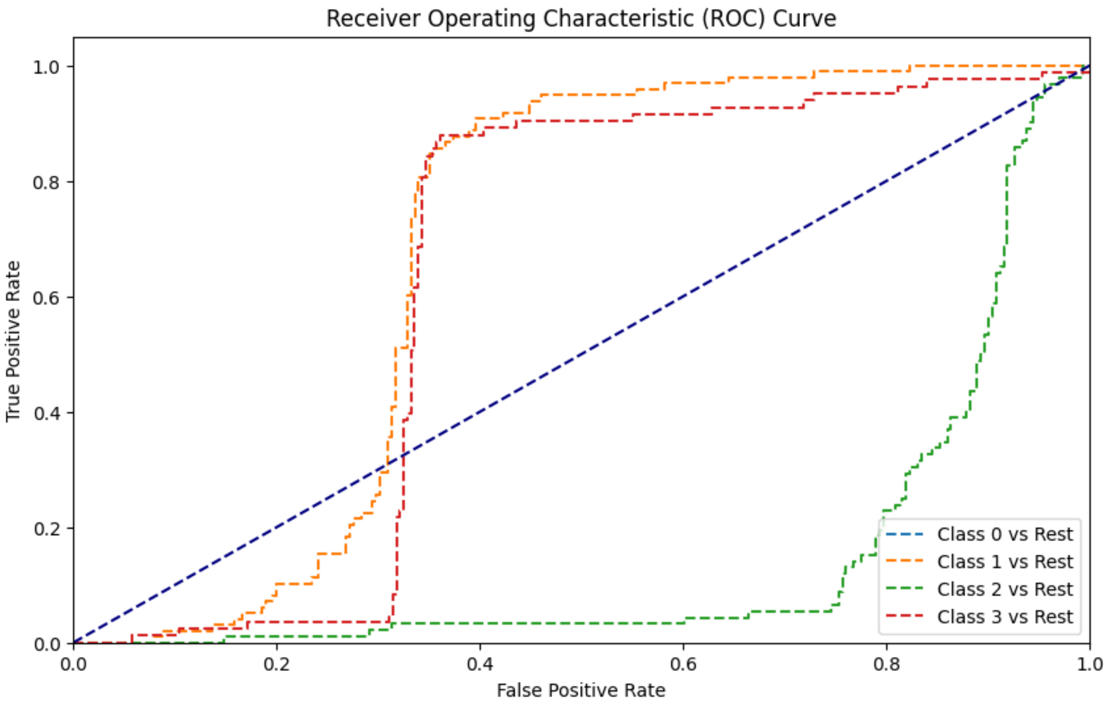
```
ROC AUC: 0.966415035305559
```

[136]:
```
fpr = {}
tpr = {}
thresh = {}

n_class = len(logisticRegr.classes_)
n_class
```

[136]:
```
4
```

[137]:
```
for i in range(n_class):
    fpr[i], tpr[i], thresh[i] = roc_curve(
        y_test, logisticRegr.predict_proba(X_test_scaled)[:, i], pos_label=i
    )

plt.figure(figsize=(10, 6))
for i in range(n_class):
    plt.plot(fpr[i], tpr[i], linestyle="--", label=f"Class {i} vs Rest")
plt.plot([0, 1], [0, 1], color="navy", linestyle="--")
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) Curve")
plt.legend(loc="lower right")
plt.show()
```

```
/Users/john/Documents/University/ZIP/metody-inteligentne-w-org-
prod/venv/lib/python3.11/site-packages/sklearn/metrics/_ranking.py:1183:
UndefinedMetricWarning: No positive samples in y_true, true positive value
should be meaningless
  warnings.warn(
```


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
Class 0 vs Rest
Class 1 vs Rest
Class 2 vs Rest
Class 3 vs Rest