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Submit Date:05/04/2025

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1. Introduction

In the era of Industry 4.0, the convergence of Artificial Intelligence (AI), Internet of Things (IoT), and smart manufacturing technologies have fundamentally transformed traditional production systems. Among the most critical manufacturing processes, plastic injection moulding holds substantial industrial relevance due to its widespread use in producing complex, high-precision plastic components at scale. However, ensuring consistent quality in these components remains a major challenge due to the sensitivity of the process to various parameters such as mould temperature, injection pressure, and cooling time. Conventional quality control mechanisms, often based on post-production inspections, are not only time-intensive and costly but also prone to inefficiencies and human error.

To address these challenges, AI-powered solutions, particularly supervised machine learning (ML) models, offer the potential for real-time prediction of product quality. These systems can anticipate defects and inefficiencies during production, enabling proactive adjustments to process parameters. As a result, manufacturers can reduce material waste, optimize process efficiency, and ensure product standards are met consistently.

This coursework simulates a real-world industrial setting, where a dataset derived from plastic injection moulding processes is analysed to develop an intelligent classification system. Each row in the dataset represents a production cycle with features capturing critical process parameters. The target variable, "quality", is categorized into four distinct classes: Waste, Acceptable, Target, and Inefficient, each indicating the quality level of the final product.

My objective is to build and evaluate predictive models capable of classifying product quality using advanced ML algorithms. As part of this, I will explore and prepare the dataset, conduct statistical analysis including hypothesis testing and ANOVA, and apply classification models including, adhering to the predefined model constraints. Moreover, I will implement cross-validation techniques and hyperparameter tuning to optimize

performance and assess the effectiveness of each model using metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC.

To support real-world applicability, I will also develop an interactive dashboard using Streamlit to allow end-users to input parameters and receive real-time predictions. This tool will further visualise important metrics, including feature importances and confusion matrices, to provide transparency and actionable insights to the manufacturing team.

All findings, methodology, visual outputs, and interpretations will be presented in a professional technical report, demonstrating a complete end-to-end ML pipeline. This introduction sets the stage for a comprehensive AI-driven approach to enhancing product quality in industrial manufacturing environments.

2. Dataset

The first step in any machine learning pipeline is to clean and analyze the dataset. A model's performance and reliability are significantly influenced by the quality, consistency, and structure of the data used to train it. The goal of this coursework is to build a classification model that can predict the quality of plastic injection moulding products. Before developing a model, it is essential to thoroughly explore, understand, and preprocess the dataset. Data analysis and cleaning steps are outlined in this section.

2.1. Data Analysis

A number of Python libraries were used for exploratory data analysis (EDA), including pandas, NumPy, seaborn, and matplotlib. With these libraries, I could manipulate data, perform numerical operations, and create visual representations to better understand data trends, distributions, and relationships between features. The dataset was loaded and inspected with Pandas, statistical calculations were made

with NumPy, and plots, including histograms, box plots, and scatter plots, were generated with seaborn and matplotlib.

The dataset was loaded into the Googlecolab environment and the variable name data was assigned. To begin with, the dataset's dimensions were examined using .shape, revealing it consists of 1000 records (production cycles) and 13 variables, including the target variable quality. Features in the dataset represent parameters from the plastic injection moulding process, such as mould temperature, injection pressure, cycle time, and other critical control values. Four levels of product quality are represented by the target variable: *Waste, Acceptable, Target, and Inefficient*.

For determining the dataset's complexity and determining which columns might be redundant or less relevant for model training, it is vital to understand the number of features and instances. Data range, distribution, and potential anomalies were highlighted in early statistical summaries. To select features, detect outliers, and plan data cleaning steps like handling missing values, it is essential to have this understanding.

3. Import Necessary Libraries

```
[205] import pandas as pd
      import seaborn as sns
      import matplotlib.pyplot as plt
      import numpy as np
      import graphviz
      import matplotlib.pyplot as plt
      import math
      import warnings
      warnings.filterwarnings('ignore') # to make it easier to read
```

Figure 1: Import Libraries

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, classification_report
from sklearn.tree import plot_tree
from sklearn import tree
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.neighbors import LocalOutlierFactor
from scipy.stats import f_oneway
from statsmodels.stats.outliers_influence import variance_inflation_factor
import os #saving file /directory mangement
from sklearn.model_selection import train_test_split, cross_val_score, StratifiedKFold
from sklearn.pipeline import Pipeline
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.preprocessing import LabelEncoder
from scipy.stats import f_oneway
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
```

4. Import Dataset

```
# Import the dataset through Google Drive and read the dataset using the pandas library
df=pd.read_csv('/content/drive/MyDrive/Colab Notebooks/AI_Coursework/CW_Dataset_4127677.csv')

# Display the first few rows to confirm loading
print("Data File Preview:")
display(df.head())
```

```
# check shape,samples
print(f"Dataset size:{df.shape}")
print(f"Number of sample:{df.shape[0]}")
print(f"Number of variables:{df.shape[1]}")
```

As a first step, load all the data set into the Python environment using Panda Library. To verify the successful import, print few dataset rows into the Python environment.

5. Background of the dataset

This dataset contains information on the plastic injection moulding process, where each row represents a production cycle and includes process parameters such as:

- Mould temperature
- Injection pressure
- Cycle time
- Volume

5.1. Target Variable: *quality*

The target variable is a multiclass label categorizing product quality into four classes:

- Waste – Product fails basic standards and must be discarded.
- Acceptable – Meets minimum standards but is not ideal.
- Target – Meets desired quality specifications.
- Inefficient – Above acceptable but below target due to process inefficiencies.

The objective of this project is to classify the quality class of the products

6. Data Understanding

```
#To generate overview of the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column                                        Non-Null Count  Dtype
---  ------                                        --------------  -----
 0   Melt temperature                              1000 non-null   float64
 1   Mold temperature                              1000 non-null   float64
 2   time_to_fill                                  1000 non-null   float64
 3   ZDx - Plasticizing time                       1000 non-null   float64
 4   ZUx - Cycle time                              1000 non-null   float64
 5   SKx - Closing force                           1000 non-null   float64
 6   SKs - Clamping force peak value               1000 non-null   float64
 7   Ms - Torque peak value current cycle          1000 non-null   float64
 8   Mm - Torque mean value current cycle          1000 non-null   float64
 9   APSs - Specific back pressure peak value      1000 non-null   float64
 10  APVs - Specific injection pressure peak value 1000 non-null   float64
 11  CPn - Screw position at the end of hold pressure 1000 non-null float64
 12  SVo - Shot volume                             1000 non-null   float64
 13  quality                                       1000 non-null   float64
dtypes: float64(14)
memory usage: 109.5 KB
```

Figure 2: Features of the Dataset

Before training the model as a first step, it needs to be clear on the type of data present in the dataset and then transform it in such a way that training. And validation of the data can be carried out. Using df.info it will show that there are all the values are numerical float values. Before processing future analysis, it is important to explore the data future by checking for correlations, outliers, and patterns to ensure data quality and reliability.

If the dataset contains any categorical variables, they need to be converted into numerical values because most machine learning models work with numerical data instead of categorical values. This transformation is an essential part of data preprocessing to ensure the model can effectively interpret and process the information.

6.1. Checking Missing values, Duplicate Data

```python
# Count missing values
print(df.isnull().sum())

# Percentage of missing values
missing_percent = (df.isnull().sum() / len(df)) * 100
print(missing_percent)
```

```
Melt temperature                                  0
Mold temperature                                  0
time_to_fill                                      0
ZDx - Plasticizing time                           0
ZUx - Cycle time                                  0
SKx - Closing force                               0
SKs - Clamping force peak value                   0
Ms - Torque peak value current cycle              0
Mm - Torque mean value current cycle              0
APSs - Specific back pressure peak value          0
APVs - Specific injection pressure peak value     0
CPn - Screw position at the end of hold pressure  0
SVo - Shot volume                                 0
quality                                           0
dtype: int64
Melt temperature                                  0.0
Mold temperature                                  0.0
time_to_fill                                      0.0
ZDx - Plasticizing time                           0.0
ZUx - Cycle time                                  0.0
SKx - Closing force                               0.0
SKs - Clamping force peak value                   0.0
Ms - Torque peak value current cycle              0.0
Mm - Torque mean value current cycle              0.0
APSs - Specific back pressure peak value          0.0
APVs - Specific injection pressure peak value     0.0
CPn - Screw position at the end of hold pressure  0.0
SVo - Shot volume                                 0.0
quality                                           0.0
dtype: float64
```

Figure 3: Missing values of the Dataset

Using the df. isnull (). sum () command, we can confirm that the dataset does not contain any nulls for each feature. We also check duplicate data because, if duplicate data exists, the model may overlearn from those specific data points, resulting in the model becoming less generalizable to new and unknown data.

```
#Check for Duplicate
duplicates = df.duplicated()
print(f"Number of duplicate rows: {duplicates.sum()}")
```

```
Number of duplicate rows: 0
```

Figure 4: Check duplicates

Using the above output, we can say there is no any duplicate value. Having no duplicates reduces the risk of biased training and ensures that the machine learning model is learning from diverse examples instead of redundant ones. Additionally, it confirms that no repeated entries are present in the dataset, which would produce inaccurate statistics and inaccurate model results otherwise.

6.2. Checking for constant values

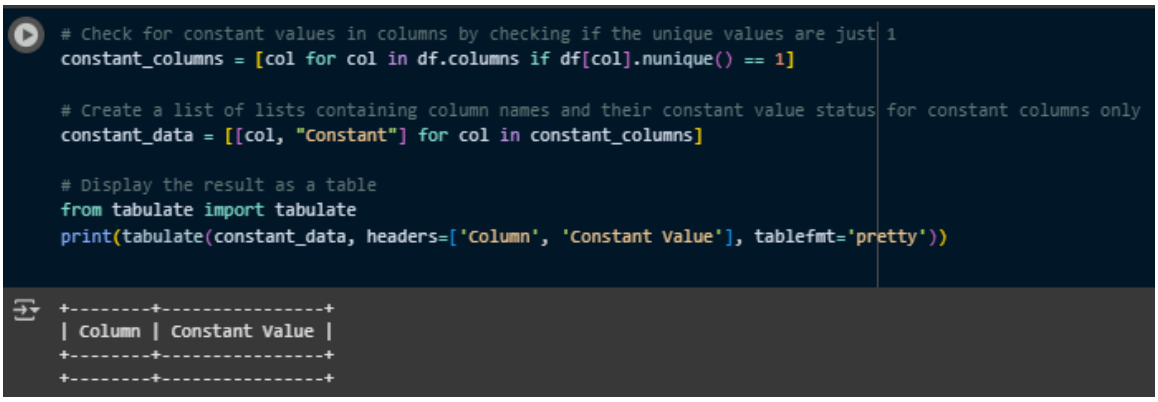


Figure 5:Check constant values

If there is no constant values in the dataset that means every process parameter changes across different product cycles. For machine learning, this is a good thing since it means every feature can be used to predict product quality. The model wouldn't work if a column had the same value across all rows.

7. Exploratory Data Analysis (EDA)

7.1. Check statistics for the dataset

	count	mean	std	min	25%	50%	75%	max
Melt temperature	1000.0	107.006080	6.072848	81.747	105.91700	106.088000	106.272468	154.925
Mold temperature	1000.0	81.335295	0.409202	78.409	81.12225	81.335000	81.445000	82.145
time_to_fill	1000.0	7.458776	1.688449	6.084	6.29200	6.968000	7.046000	11.232
ZDx - Plasticizing time	1000.0	3.230826	0.335893	2.780	3.00000	3.193213	3.290000	5.940
ZUx - Cycle time	1000.0	75.218310	0.432856	74.780	74.82000	74.830000	75.650000	75.790
SKx - Closing force	1000.0	901.738409	11.190968	878.000	893.30000	902.000000	909.050000	930.600
SKs - Clamping force peak value	1000.0	919.243196	10.899824	895.300	914.35000	918.600000	926.300000	946.500
Ms - Torque peak value current cycle	1000.0	116.731100	5.002890	94.200	114.20000	116.900000	119.900000	130.300
Mm - Torque mean value current cycle	1000.0	104.133574	4.814701	81.100	103.60000	105.100000	106.500000	114.900
APSs - Specific back pressure peak value	1000.0	146.242600	0.819339	144.800	145.70000	146.100000	146.700000	150.500
APVs - Specific injection pressure peak value	1000.0	900.698400	25.265908	780.500	886.40000	906.650000	918.050000	943.000
CPn - Screw position at the end of hold pressure	1000.0	8.809090	0.096791	8.330	8.77000	8.820000	8.860000	9.060
SVo - Shot volume	1000.0	18.756360	0.095390	18.510	18.71000	18.750000	18.790000	19.230
quality	1000.0	2.466000	1.122544	1.000	1.00000	2.000000	4.000000	4.000

Figure 6: Statistics of the dataset

As mentioned above, the dataset includes 1000 samples. According to the result, the melted temperature fluctuates moderately with a standard deviation of 6.07, while mould temperature remains relatively stable with a standard deviation of 0.41, suggesting consistent heating conditions. The cycle time and shot volume also exhibit minimal variation, indicating a well-controlled manufacturing process. However, quality has a mean of 2.47 and a standard deviation of 1.12, suggesting that the distribution of product quality classes may be unbalanced. To determine whether certain quality classes are underrepresented, as well as to assess the relationship between process parameters and product quality, further analysis is necessary.

7.2. Check Outliers Using Boxplot

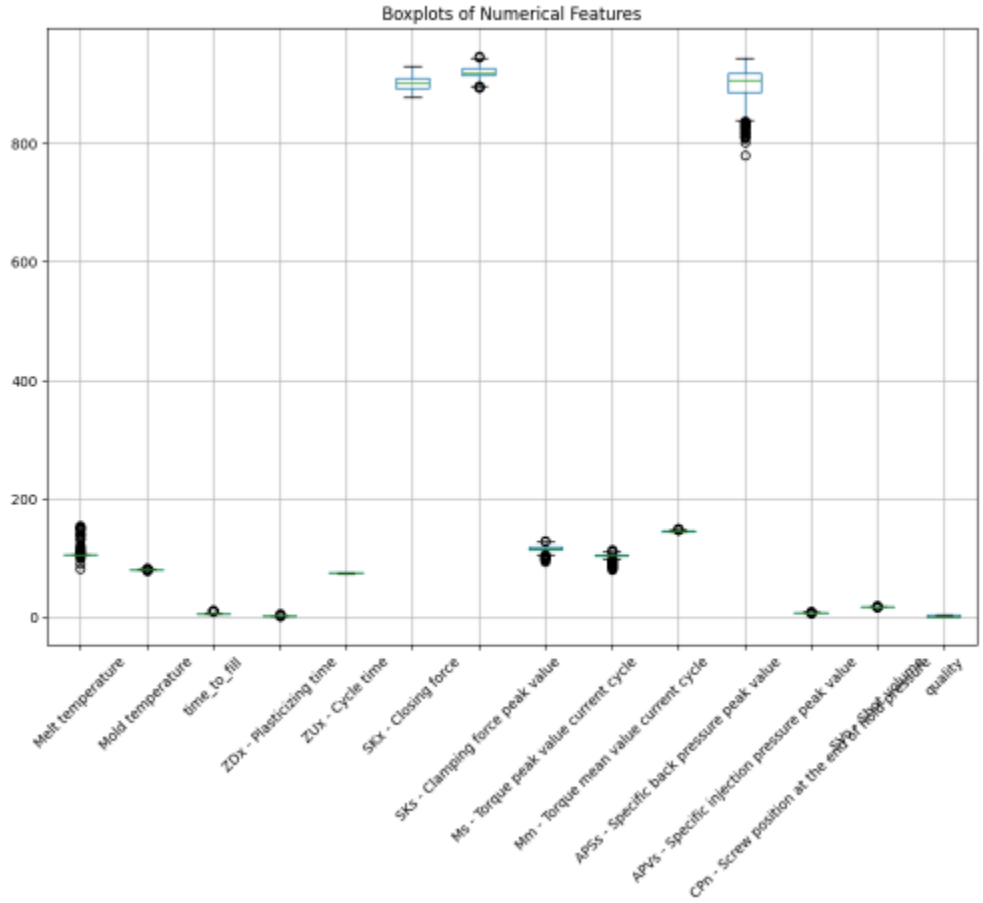


Figure 7: Visualise outliers using Boxplot

(Check the appendix 0.1 to check the code I have used for outlier detection and remove them.)

The boxplot shows that some features, like melt temperature, time to fill, plasticizing time, torque values, and specific injection pressure, have a lot of outliers. The reason may be unusual values, measurement errors, or just natural variations in the data. Also, some values like clamping force peak value and specific back pressure peak value, seem skewed, it is meaning their values not evenly spread. Some features also have a wider range, showing more variation in their values. To handle this, we might need to scale the data, remove extreme outliers, or transform the skewed features for better model performance. This part will cover the data preparation process.

7.3. Check Distribution of the Data Using Histogram

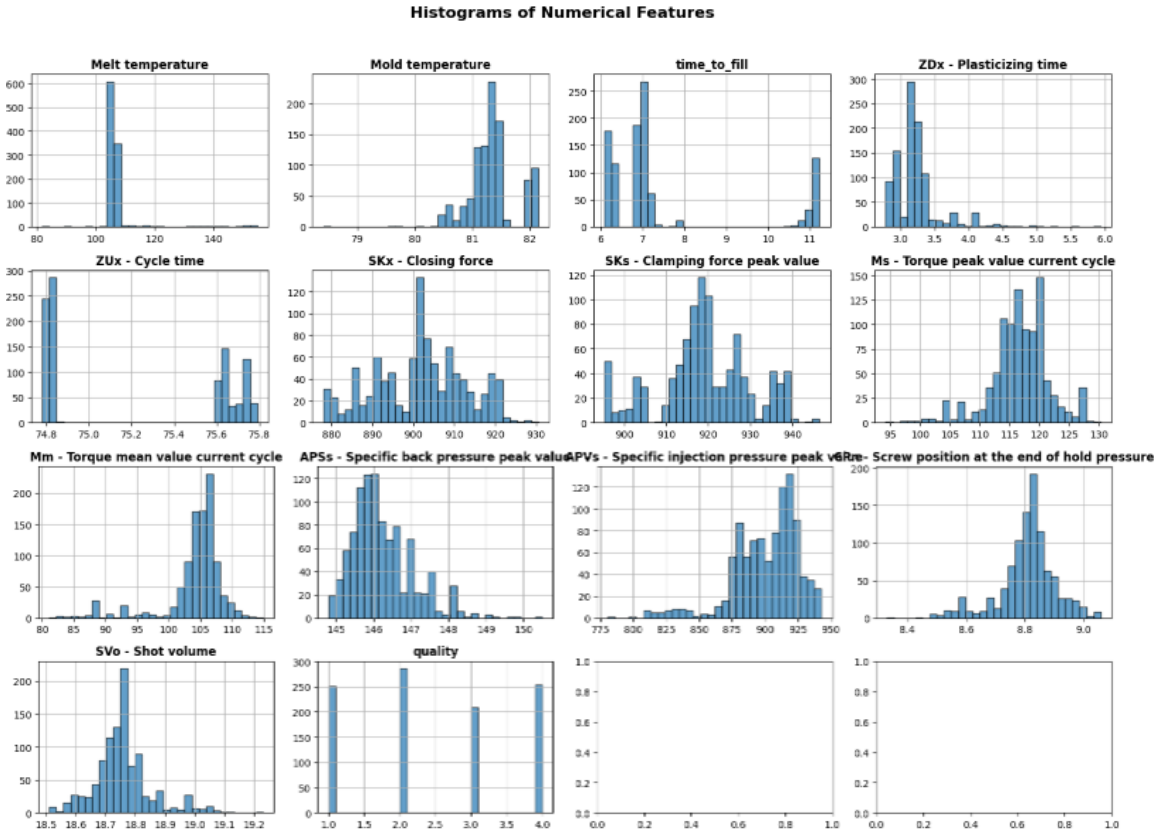
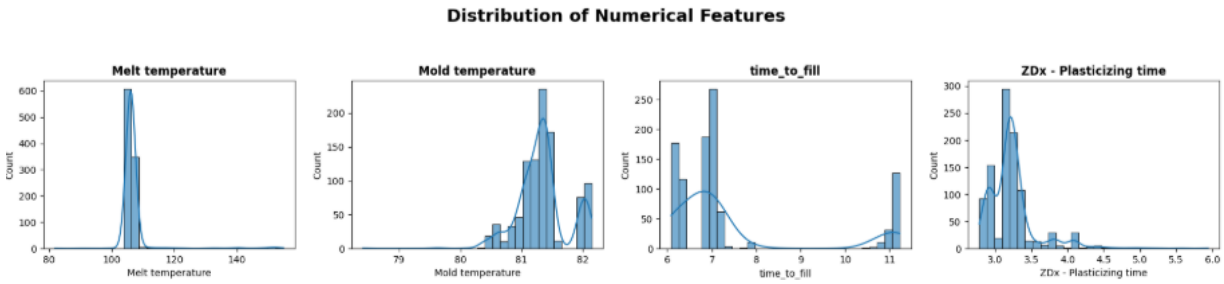


Figure 8: Visualize the distribution of the dataset using histograms

(Check the appendix 0.2 to check the code I have used for outlier detection and remove them.)



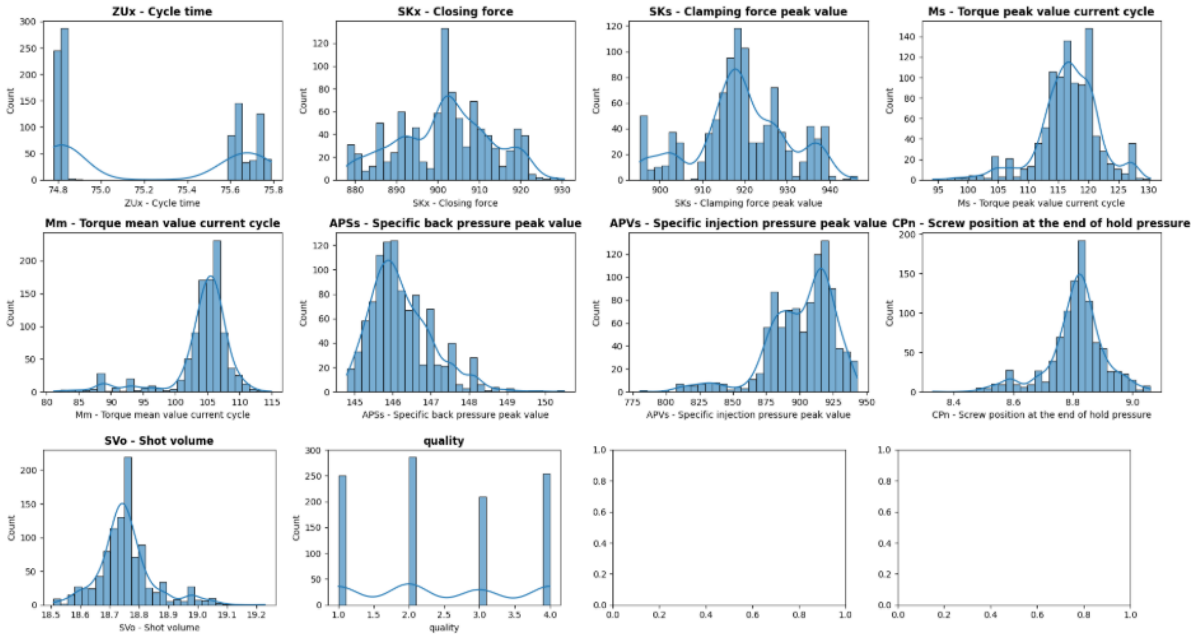


Figure 9: Balance of the dataset

(Check the appendix 0.3 to check the code I have used for outlier detection and remove them.)

Looking at the above histograms, we can see most of the data is not perfectly balanced, some data sets have positive skewness, and some datasets have negative skewness. For example, "melt temperature" and "plasticizing time" have most of their values on the lower side, but they stretch out towards higher values, indicating positive skewness.

Also, if we check properly, we can see some features like "specific back pressure" and "torque values" seem to have more values on the higher side, with a tail extending towards the lower end, it represents negative skewness, some features, like "shot volume represents fair balanced distribution.

Furthermore, the cycle time can be analysed further by examining the two peaks, which may indicate two different operating conditions. It is clear that the quality variable, which is the target for classification, can be divided into four categories, confirming the multiclass classification problem.

As a result of the above details, we can predict that the data is not evenly distributed across all features, which affects model performance directly. To handle this, we need to

do normalization to make it more suitable for machine learning models. Normalization will be covered in the data preprocessing section.

7.4. Check skewness, Kurtosis and Mode

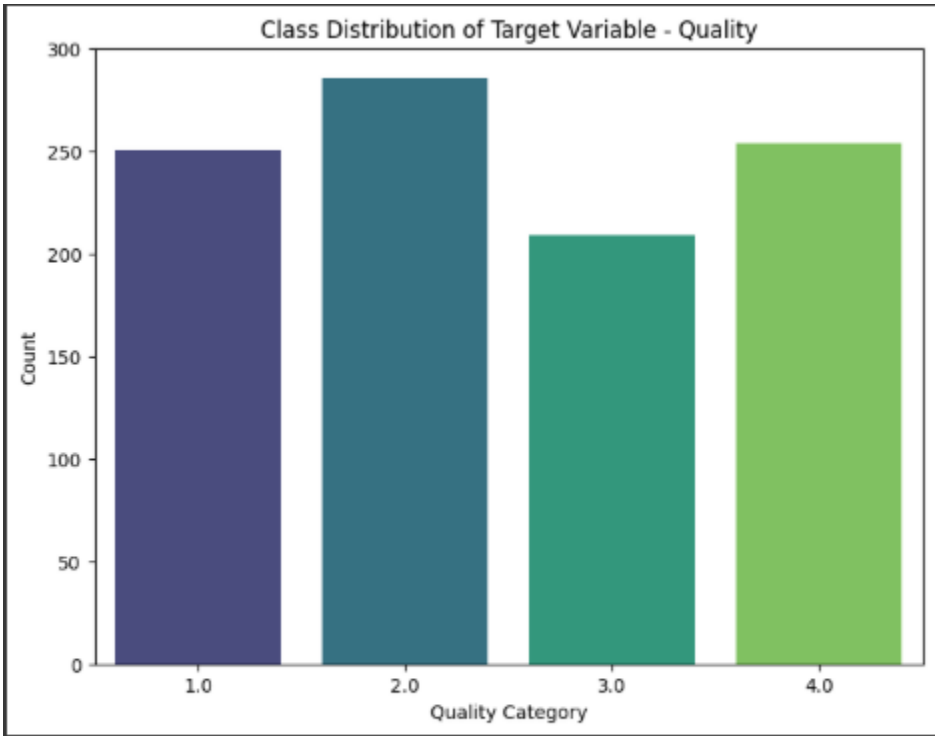
	Skewness	Kurtosis	Mode
Melt temperature	6.138765	40.274851	105.449
Mold temperature	-0.268426	2.836238	80.617
time_to_fill	1.565383	0.746203	6.968
ZDx - Plasticizing time	2.631126	11.470740	3.160
ZUx - Cycle time	0.161217	-1.943144	74.810
SKx - Closing force	-0.130958	-0.609911	908.600
SKs - Clamping force peak value	-0.184803	-0.196182	918.200
Ms - Torque peak value current cycle	-0.681057	1.791736	120.500
Mm - Torque mean value current cycle	-2.211573	5.380279	104.300
APSs - Specific back pressure peak value	0.980283	1.398767	146.100
APVs - Specific injection pressure peak value	-1.262104	2.179489	882.300
CPn - Screw position at the end of hold pressure	-0.838768	1.905408	8.850
SVo - Shot volume	0.884915	2.119567	18.730
quality	0.091292	-1.361631	2.000

Figure 10: check skewness, Kurtosis and Mode

(Check the appendix 0.4 to check the code I have used for outlier detection and remove them.)

The skewness and kurtosis have some high values, such as melting temperature and plasticizing time, indicate the presence of extreme values. Other features, such as cycling time and clamping force peak value, show more symmetrical and normal distribution example, the most common melt temperature is 105.45°C, and the most frequent shot volume is 18.73, indicating stable process conditions for these parameters. The mode for quality is 2, suggesting that the majority of products fall into the "Acceptable" quality category. With this information, we can identify potential outliers and assess whether data transformations are needed to improve model performance.

7.5. Class Distribution of Target Variable




```
quality
2.0    286
4.0    254
1.0    251
3.0    209
Name: count, dtype: int64
```

Figure 11:Distribution of Target Variable

(Check the appendix 0.5 to check the code I have used for outlier detection and remove them.)

According to the class distribution of the quality variable, the dataset is slightly imbalanced. For example, class 2(286 samples) is the most frequent, and class (209 samples) is the least. The important thing is that the imbalance is not extreme, because of that, standard machine-learning models should still perform reasonably well.

The model may predict the majority of classes more accurately while struggling with the minority classes. We should use balanced metrics like F1-score and ensure a stratified train-test split in order to address this issue.

7.6. Check the outliers in each variable

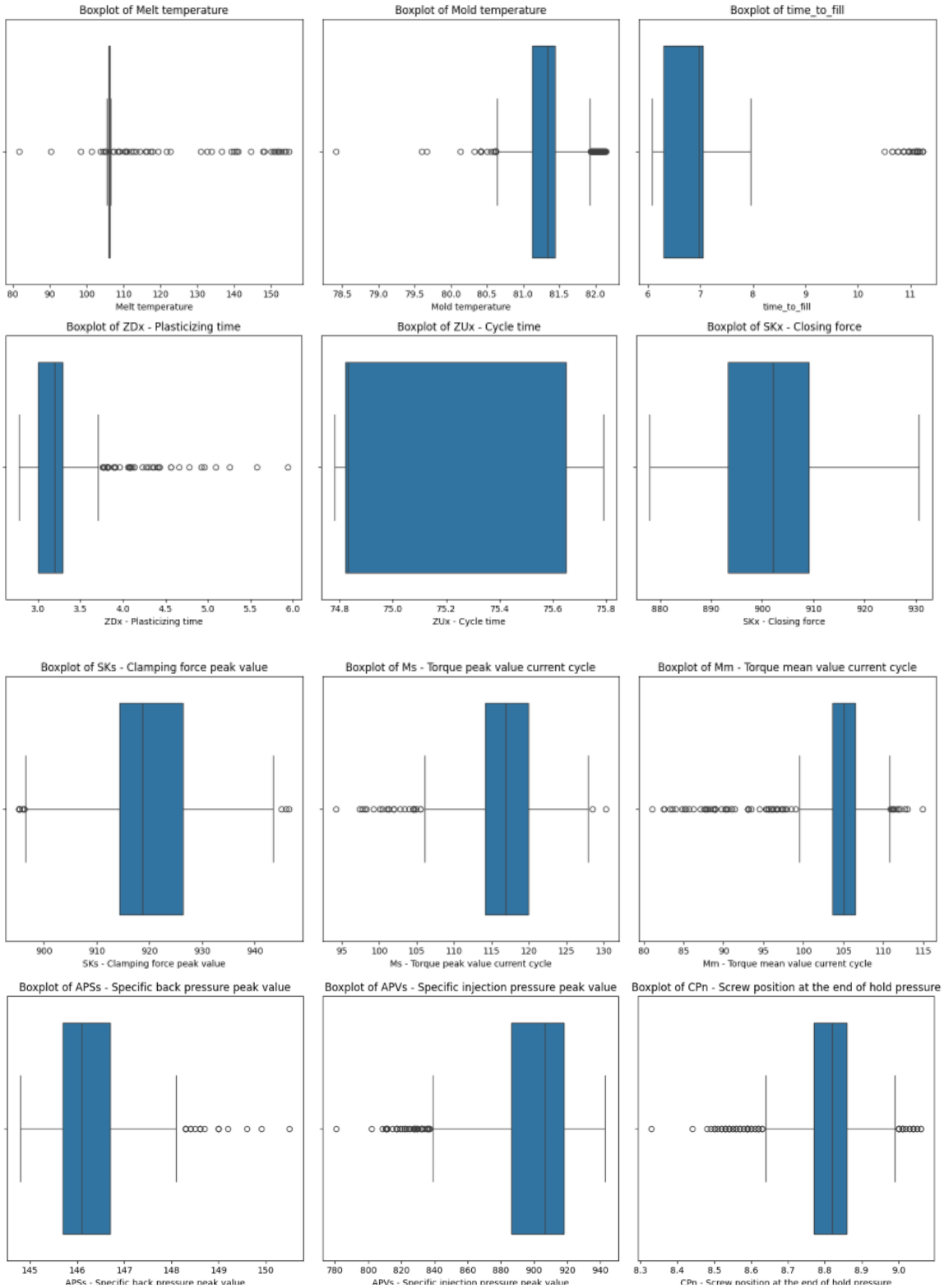
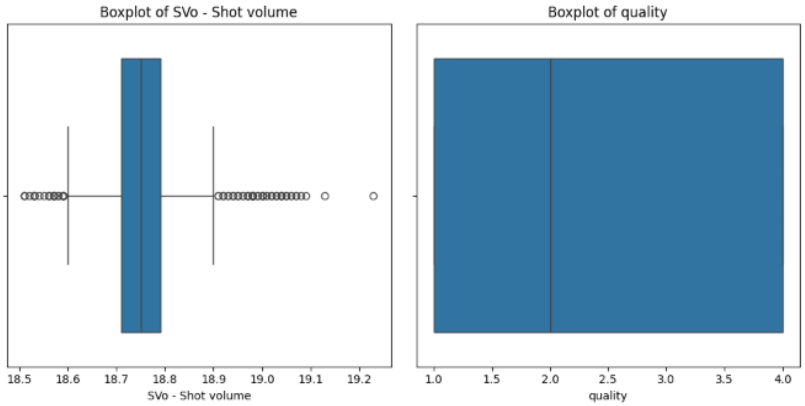


Figure 12:outliers in each variable



(Check the appendix 0.6 to check the code I have used for outlier detection and remove them.)

The above boxplot represents the outlier of each variable, and it visualizes very clearly. Most of the columns exhibit outliers and indicate anomalies or deviations from normal patterns.

The most significant outlier count is shown in "Mold temperature (229)","time_to_fill (172)","CPn - Screw position at the end of hold pressure (91)","SVo - Shot volume (106)".

Some columns have no outliers for example "ZUx - Cycle time", "SKx - Closing force" and "quality". That means those are relatively stable distributions.

We need to handle the outliers because models like regression and artificial neural networks (ANN) are sensitive to outliers, as they try to minimize error, which could cause extreme values. So, outliers handling part cover in the data preprocessing part using IQR method because IQR method because IQR method well work for skewed distribution.

7.7. Identify correlation Metrix

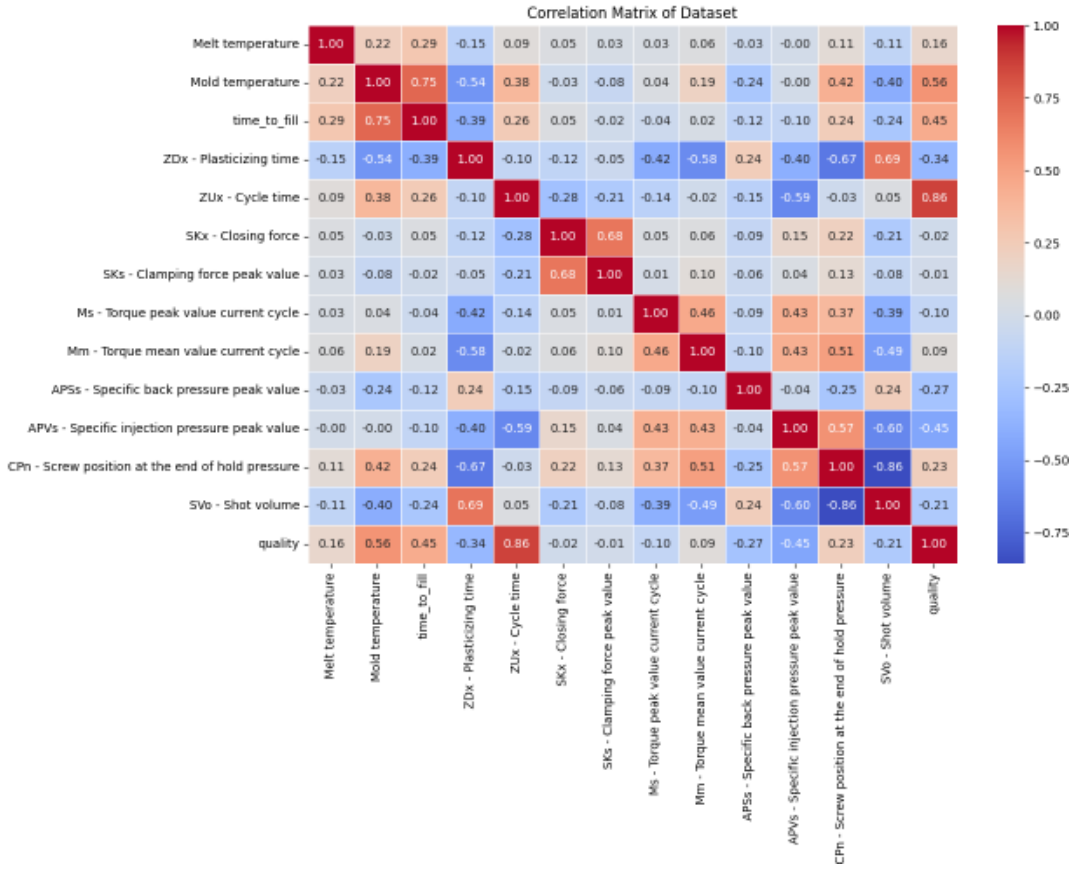


Figure 13:Correlation Metrix

(Check the appendix 0.7 to check the code I have used for outlier detection and remove them.)

Feature 1	Feature 2	Correlation Value	Description
time_to_fill	Mold temperature	0.745	As Mold temperature increases, time_to_fill also tends to increase.
SVo - Shot volume	CPn - Screw position at the end of hold pressure	-0.857	As Screw position increases, Shot volume tends to decrease significantly.
quality	ZUx - Cycle time	0.864	Higher cycle time is strongly associated with better quality classification.

There is a strong relationship between these values, which can cause problems for some machine learning algorithms. Overfitting may occur as a result of the algorithm not being able to determine which features are most important in predicting the target variable.

It is possible to address this problem by using Principal Component Analysis (PCA). Compared to linear models, tree-based models handle multicollinearity better, but may

still suffer from misleading feature importance scores. When data is handled properly, models are more interpretable, stable, and generalisable to new datasets.

8. Data Pre-processing

According to the process we need to handle the missing values and remove duplicate rows however based on EDA process I have identified there is no any outliers and duplicates in the dataset so based on that I do not need to work on the outliers and duplicates. That mean datasets are more consistent, reliable and easier to analyse.

8.1. Identify and Remove Inconsistencies

In the data preprocessing phase, identifying and removing inconsistencies is critical, especially for high-stakes applications like manufacturing quality prediction. Data inconsistencies-such as duplicates, contradictory values, or incorrect formats-can severely skew machine learning models' performance. As an example, if the same input features produce both "Waste" and "Target" quality labels in the same instance, the learning algorithm gets confused, and model accuracy is reduced. IoT-driven environments can be plagued by human errors in data entry, sensor malfunctions, and system noise. Especially when categorizing products into nuanced categories like “Acceptable” versus “Unacceptable,” cleaning such inconsistencies ensures data integrity, promotes better generalization in the model, and boosts prediction reliability. In engineering contexts where each parameter (e.g., injection pressure, mould temperature) has real-world implications, the data is aligned with domain knowledge, which is essential.

```
[86] # Check initial shape
     print("Original dataset shape:", df.shape)

     # Define columns with physical constraints
     invalid_cols = ['time_to_fill', 'ZDx - Plasticizing time', 'ZUx - Cycle time', 'Ms - Torque peak value current cycle']

     # Remove rows with zero or negative values
     for col in invalid_cols:
         df = df[df[col] > 0]

     # Check new shape
     print("Cleaned dataset shape:", df.shape)

Original dataset shape: (1000, 14)
Cleaned dataset shape: (1000, 14)
```

```
# Columns to validate
invalid_cols = ['time_to_fill', 'ZDx - Plasticizing time', 'ZUx - Cycle time', 'Ms - Torque peak value current cycle']

# Create a summary table
invalid_summary = pd.DataFrame({
    'Feature': invalid_cols,
    'Invalid_Count (≤ 0)': [ (df[col] <= 0).sum() for col in invalid_cols ],
    'Invalid_Percentage (%)': [ round((df[col] <= 0).mean() * 100, 2) for col in invalid_cols ]
})

display(invalid_summary)
```

	Feature	Invalid_Count (≤ 0)	Invalid_Percentage (%)
0	time_to_fill	0	0.0
1	ZDx - Plasticizing time	0	0.0
2	ZUx - Cycle time	0	0.0
3	Ms - Torque peak value current cycle	0	0.0

Manufacturing datasets, such as those used to predict product quality in plastic injection moulding, must adhere to real-world physical laws. Measurable physical quantities such as “time_to_fill”, plasticizing time, cycle time, and torque peak value current cycle are represented by variables like “time_to_fill”, ZDx, and ZUx. There can be no logical way for these values to be zero or negative under normal operating conditions. Having a cycle time of 0 seconds or a torque of 0 would indicate data recording error, sensor failure, or a data entry error.

To identify rows with zero or negative values which are physically implausible in the context of plastic injection moulding, a preliminary check was conducted on critical process features such as time_to_fill, ZDx - Plasticizing time, ZUx - Cycle time, and Ms - Torque peak value current cycle. However, we found no such inconsistencies, confirming that all data points were within acceptable operational ranges. At this stage, there is no need to conduct aggressive cleaning since the dataset is of high quality.

8.2. Outlier Detection Using KNN and LOF and remove them

A distance-based outlier detection technique such as K-Nearest Neighbors (KNN) or Local Outlier Factor (LOF) would be highly appropriate for this dataset to ensure data quality and improve model performance. A multiclass target variable representing product quality is included in this dataset, derived from plastic injection moulding processes. Continuous numerical features include injection pressure, cycle time, and temperature.

As a result of process irregularities, real-world industrial datasets like this often contain noise or anomalies.

This method identifies outliers by calculating the distance between each point and its k-nearest neighbors and flagging isolated instances that deviate from the general pattern. Particularly well-suited to continuous, low-dimensional data, it allows for the detection of abnormal process cycles that could lead to defects.

While LOF enhances this by comparing the local density of each point with that of its neighbors, which is ideal for scenarios where certain process settings are used more frequently, resulting in denser clusters. Because of this, LOF is particularly effective at identifying contextual outliers, such as high-quality products manufactured with atypical parameter combinations. By combining these methods, we are not only able to improve data quality but also create robust machine learning models.

Model	**Strengths**	**Suitability for Your Dataset**
ANN	Learns complex, non-linear relationships between process parameters and product quality.	Outlier removal via KNN/LOF helps avoid convergence issues and improves generalization.
Random Forest	Ensemble-based, handles noise well, offers feature importance insights.	Benefits from outlier removal to improve accuracy and interpretability.
AdaBoost	Boosting technique that's sensitive to data quality and noise.	Performs better when trained on clean, balanced data — outlier removal is crucial
Decision Tree	Easy to interpret, handles non-linear splits well.	Prone to overfitting on outliers; cleaning helps trees split meaningfully.

SVM	High-performance with well-separated classes but very sensitive to outliers.	Distance-based outlier removal (LOF/KNN) is critical to avoid distorted decision boundaries.

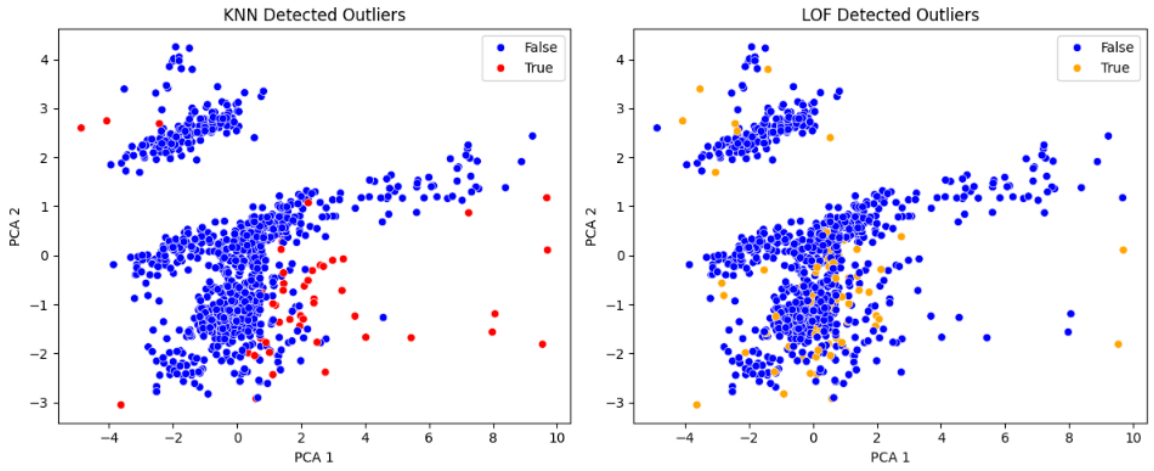
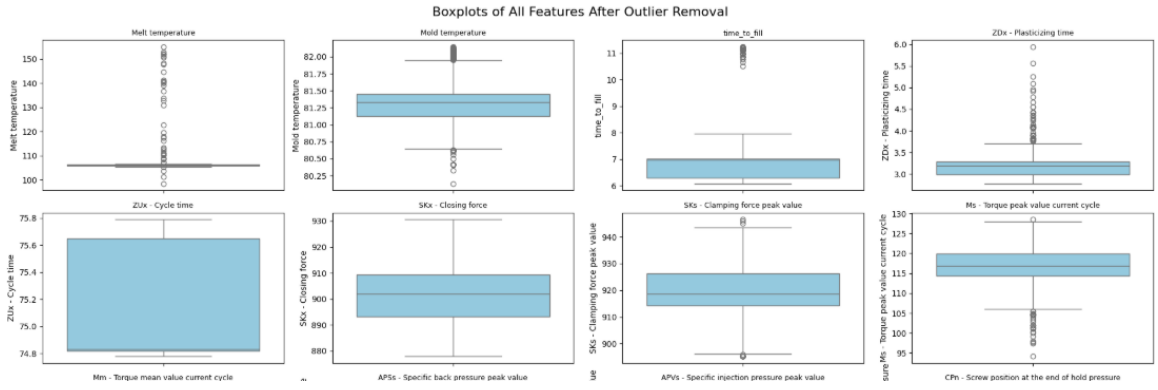
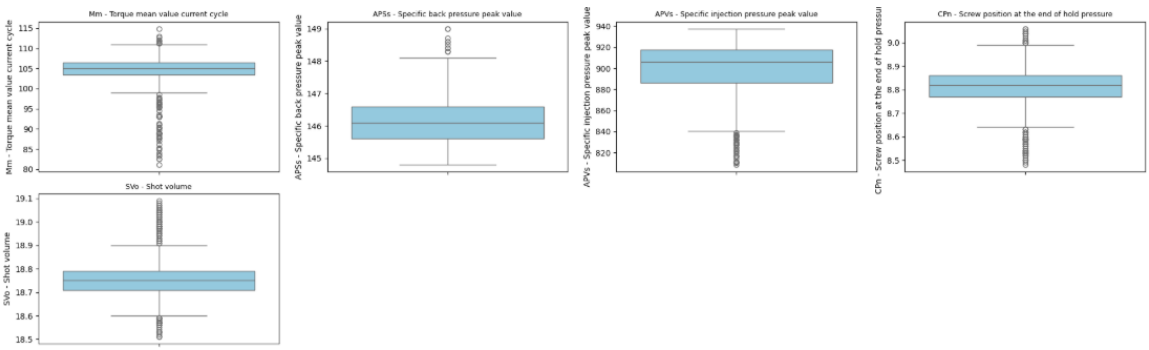


Figure 14:After outlier remove

```
Original shape: (1000, 14)
Cleaned shape: (919, 14)
```

(Check the appendix 0.8 to check the code I have used for outlier detection and remove them.)





(Check the appendix 0.9 to check the code I have used for outlier detection and remove them.)

Following the application of LOF-based cleaning, boxplots were generated for each numerical feature in order to visually confirm the effectiveness of the outlier detection process. Most anomalous data points have been successfully removed from the plots as they show tighter distributions with fewer extreme values. Additionally, this step identified possible skewness in some variables, which could guide future feature transformations or scaling decisions

The LOF was applied to remove density-based anomalies, but boxplot visualizations still show points outside the whiskers, which is expected since boxplots define outliers based on interquartile range (IQR), not density. In order to preserve natural variance, we retained the remaining points which represent statistically extreme values but may not be true anomalies.

8.3. Feature Scaling with StandardScaler

KNN and LOF are distance-based methods and rely on how far a point is from others. This was covered in process 6.2 (Outlier Detection Using KNN and LOF).

Without scaling, a large-scale feature (like injection pressure) could dominate the distance calculation, leading to biased detection. Therefore, process 6.2 covers feature scaling with standardScaler.

In order to ensure that the few features are visible before and after scaling.

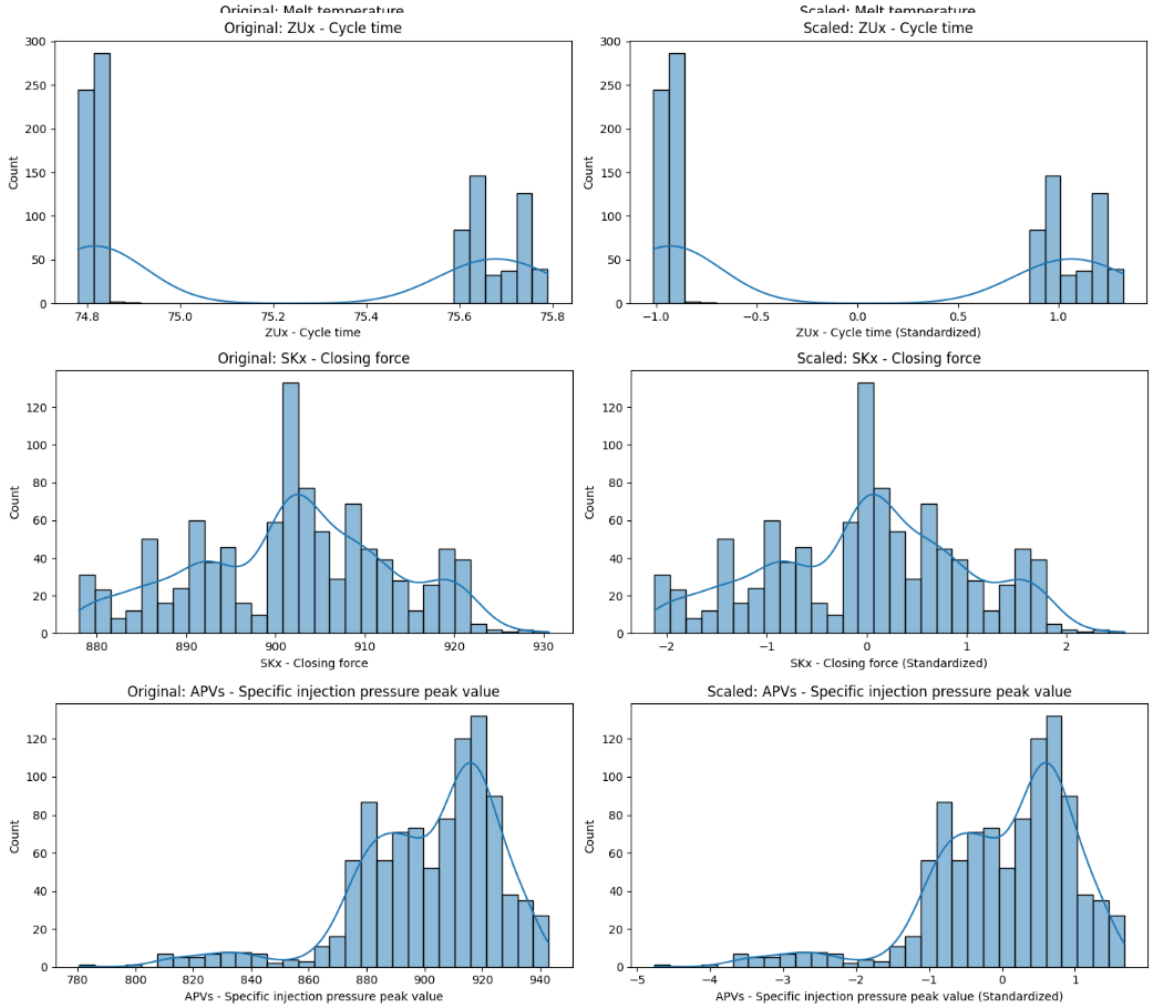


Figure 15:Feature Scaling with StandardScaler

(Check the appendix 0.10 to check the code I have used for outlier detection and remove them.)

As can be seen in the above visual comparison, the distribution of selected features is standardized as opposed to the original version which exhibited varying ranges and skewness. This helps improve the performance and convergence of the model.

8.4. check for Multicollinearity Using Correlation + VIF

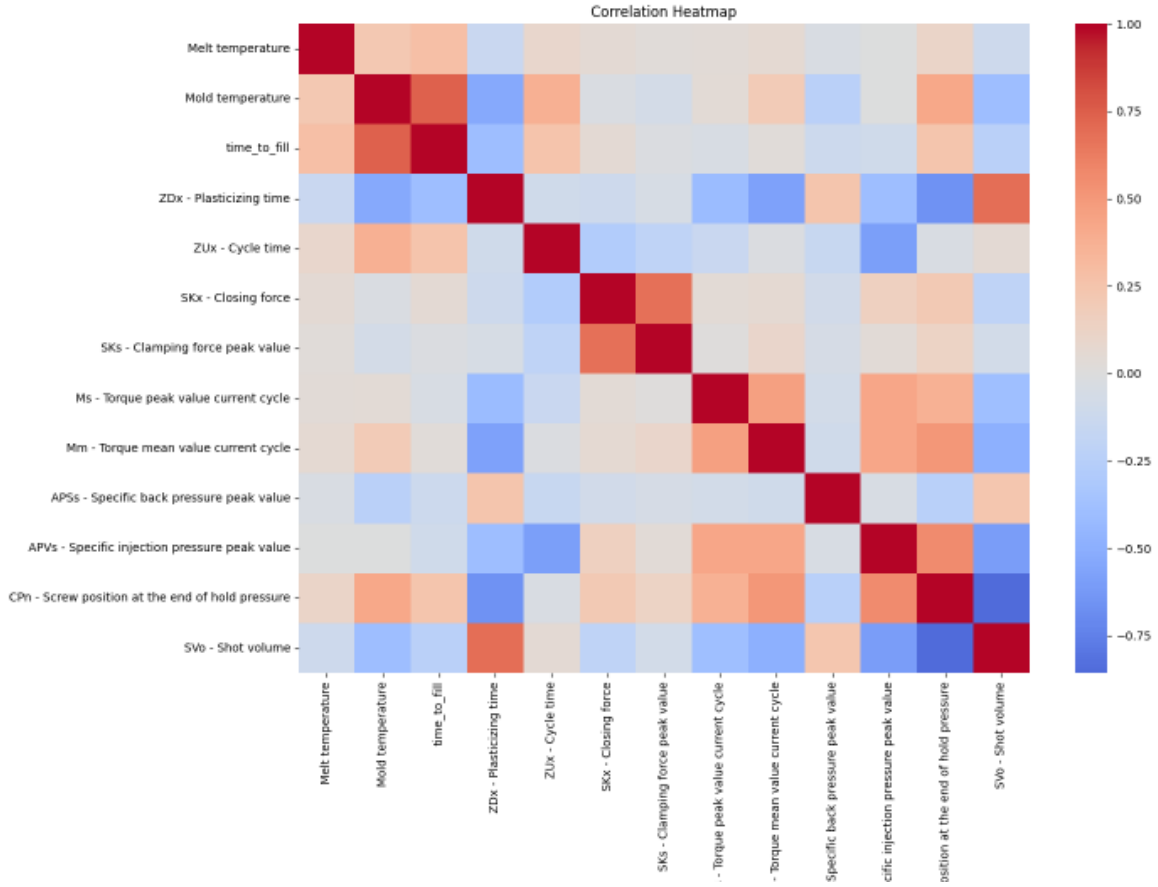


Figure 16:Multicollinearity Using Correlation + VIF

12	SVo - Shot volume	4.646876
11	CPn - Screw position at the end of hold pressure	4.372568
10	APVs - Specific injection pressure peak value	3.958442
1	Mold temperature	3.248230
3	ZDx - Plasticizing time	2.922457
4	ZUx - Cycle time	2.718630
2	time_to_fill	2.606343
5	SKx - Closing force	2.110260
6	SKs - Clamping force peak value	1.989647
8	Mm - Torque mean value current cycle	1.867780
7	Ms - Torque peak value current cycle	1.467016
9	APSs - Specific back pressure peak value	1.131163
0	Melt temperature	1.096229

(Check the appendix 0.11 to check the code I have used for outlier detection and remove them.)

We checked for multicollinearity among the input features using Variance Inflation Factor (VIF) analysis. All features had VIF values below 5, which means there aren't any strong

linear dependencies between them. The feature with the highest VIF was SVo – Shot volume (4.65), followed by CPn – Screw position at the end of hold pressure (4.37). Since none of the features exceeded the commonly accepted threshold of 10, we kept all features. This confirms that our current feature set is suitable for model development, especially for algorithms sensitive to multicollinearity, such as SVM and ANN.

8.5. Encode the Target Variable (Label Encoding / One-Hot)

A variable called "quality" is a multiclass categorical variable ("Waste","Target","Acceptable","Inefficient"), and it needs to be converted into a numerical variable.

```
[29] from sklearn.preprocessing import LabelEncoder

     label_encoder = LabelEncoder()
     y_encoded = label_encoder.fit_transform(df_cleaned["quality"])
```

```
[30] # Print label mappings
     for label, encoded in zip(label_encoder.classes_, range(len(label_encoder.classes_))):
         print(f"{label} → {encoded}")
```

```
     1.0 → 0
     2.0 → 1
     3.0 → 2
     4.0 → 3
```

```
[31] import pandas as pd

     # Wrap encoded y into a Series for visualization
     y_encoded_series = pd.Series(y_encoded, name="Encoded Quality")

     plt.figure(figsize=(8, 5))
     sns.countplot(x=y_encoded_series)
     plt.title("Class Distribution (Encoded Labels)")
     plt.xlabel("Encoded Label")
     plt.ylabel("Count")
     plt.show()
```

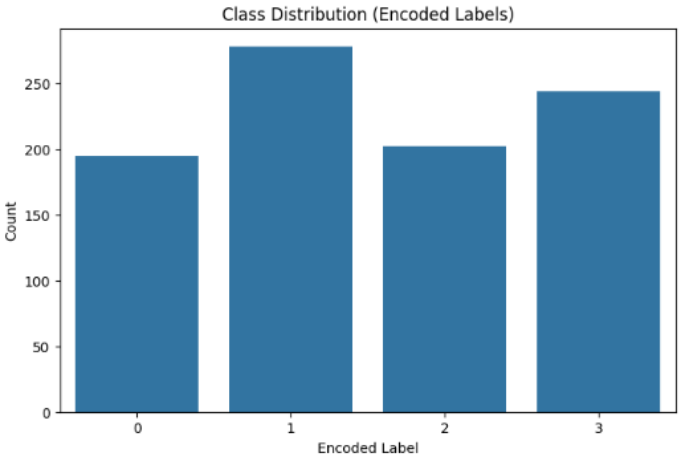


Figure 17:Encoded label for target variable

8.6. Data Splitting (85/15 + 10-fold CV Ready)

According to the coursework requirement the dataset has splited in to:

- 85% training set for model development and cross-validation
- 15% test set reserved for final model evaluation

9. Hypothesis Testing & ANOVA

9.1. One-way ANOVA Testing

Analysis of Variance (ANOVA) was used to determine the statistical relationship between product quality and process parameters. We aimed to determine whether the mean values of each numerical feature differ significantly across the four quality classes: Acceptable, Target, Waste, and Inefficient.

One-way ANOVA was selected for this dataset because it consists of multiple continuous numerical features (example: injection pressure, cycle time, temperature) and a categorical target variable "quality" with four distinct classes: Acceptable, Target, Waste, and Inefficient.

This context requires a one-way ANOVA since it evaluates the effects of a single categorical variable on continuous outcomes, one feature at a time. Prior to model development, this method allows identifying features that differ statistically significantly across classes, which facilitates exploratory analysis and feature selection.

	F-statistic	p-value	Significant
ZUx - Cycle time	13611.960696	0.000000e+00	True
Mold temperature	309.429882	1.190155e-138	True
APVs - Specific injection pressure peak value	243.419025	4.269940e-116	True
time_to_fill	194.899312	1.017711e-97	True
SVo - Shot volume	191.214671	2.985519e-96	True
CPn - Screw position at the end of hold pressure	184.128030	2.128122e-93	True
ZDx - Plasticizing time	172.045482	1.942940e-88	True
SKx - Closing force	141.548312	2.437255e-75	True
SKs - Clamping force peak value	97.787937	6.634048e-55	True
APSs - Specific back pressure peak value	35.114252	1.749076e-21	True
Mm - Torque mean value current cycle	24.806224	1.952638e-15	True
Ms - Torque peak value current cycle	12.998045	2.555284e-08	True
Melt temperature	8.999221	7.067151e-06	True

Figure 18:ANOVA Testing result

(Check the appendix 0.12 to check the code I have used for outlier detection and remove them.)

Each numerical feature was compared against the categorical target variable quality, which has four categories: Waste, Acceptable, Target, and Inefficient. A null hypothesis (H0) proposes that all quality groups have equal means, while an alternative hypothesis (H1) proposes that at least one group differs significantly.

According to the results of the ANOVA, all tested features showed statistically significant differences across quality classes, with p-values well below the standard threshold of 0.05. Among them were:

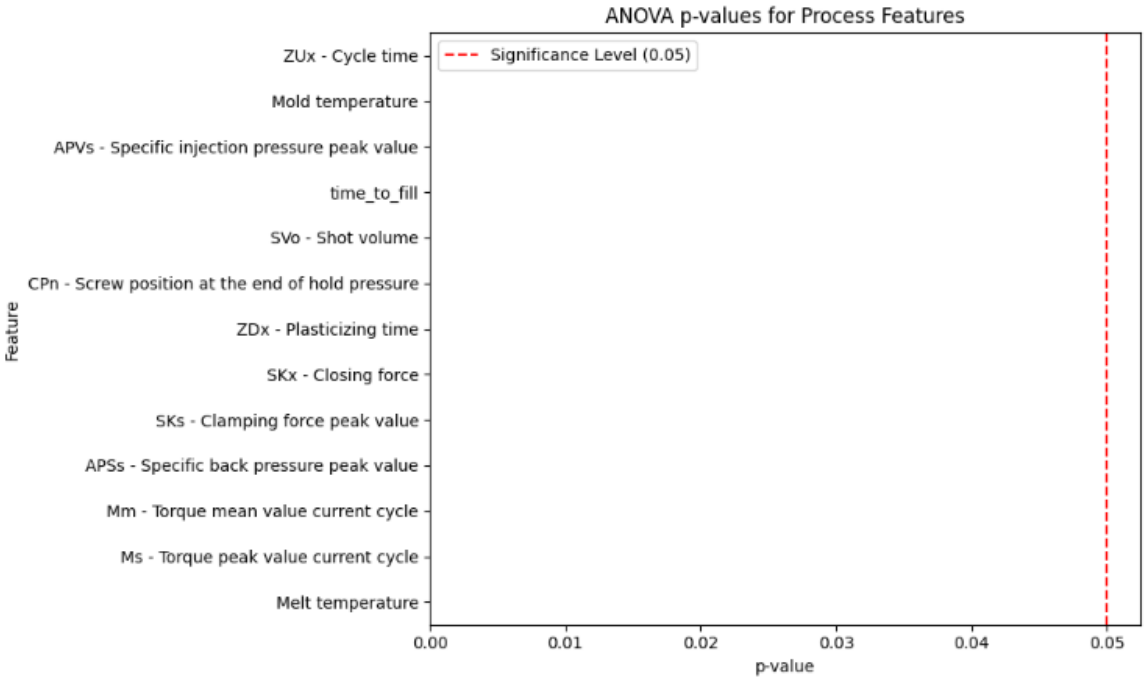
- ZUx – Cycle Time ($F = 13{,}611.96$, $p < 0.00001$)
- Mold Temperature ($F = 309.42$, $p = 1.19e\text{-}138$)
- Specific Injection Pressure Peak Value ($F = 243.42$, $p = 4.27e\text{-}116$)

In addition to providing a strong statistical foundation for the subsequent machine learning models, these findings also confirm process variables play a significant role in

determining product quality. Additionally, the ANOVA insight aligns with domain knowledge, since temperature, pressure, and timing play a significant role in the quality of plastic moulding.

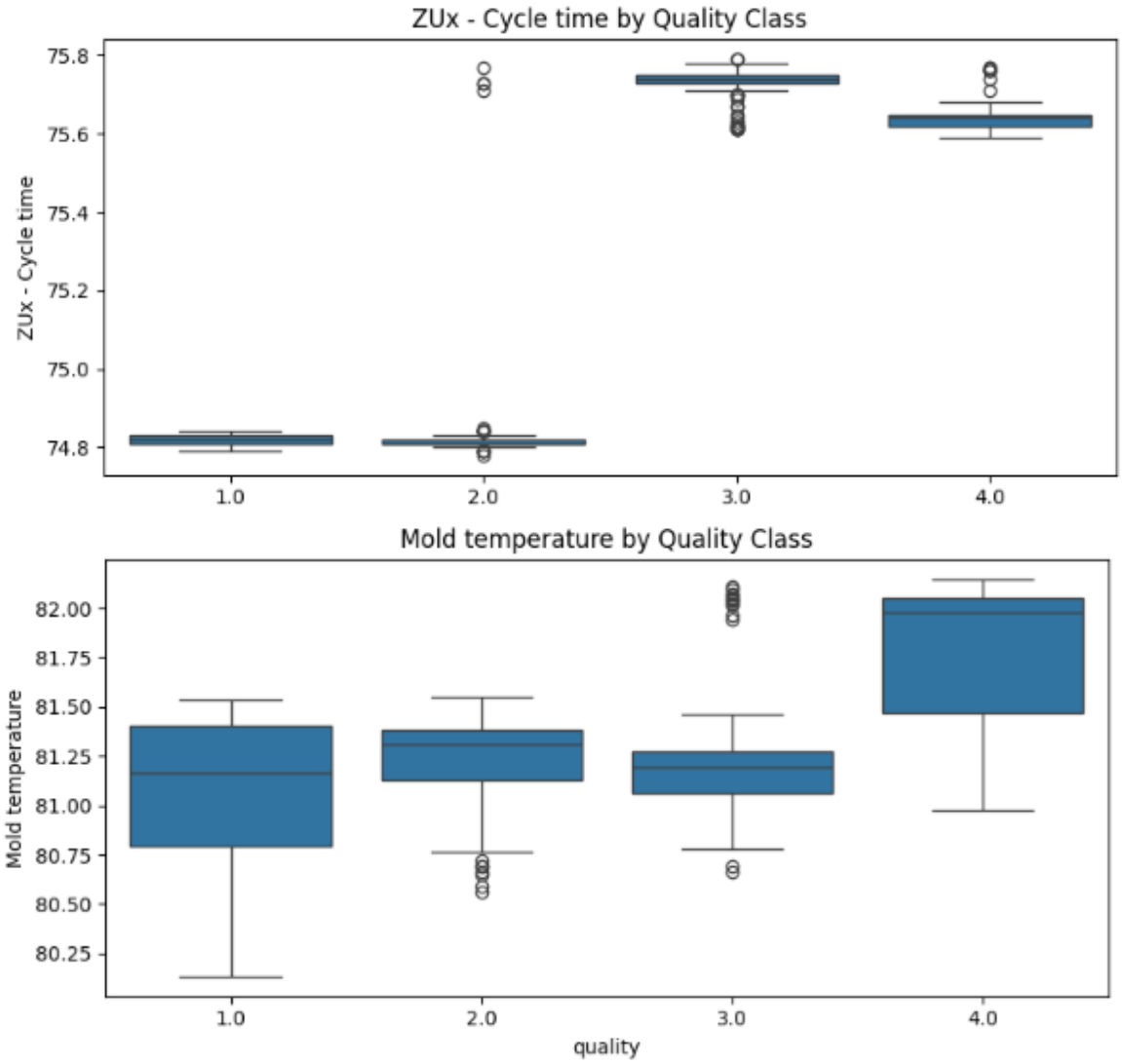
9.2. Barplot (p-values)

```
[33] plt.figure(figsize=(10, 6))
     sns.barplot(x=anova_df.sort_values("p-value")["p-value"],
                 y=anova_df.sort_values("p-value").index, palette="viridis")
     plt.axvline(0.05, color="red", linestyle="--", label="Significance Level (0.05)")
     plt.title("ANOVA p-values for Process Features")
     plt.xlabel("p-value")
     plt.ylabel("Feature")
     plt.legend()
     plt.tight_layout()  # Zoom into the tiny p-value range
     plt.show()
```



ANOVA results showed highly significant differences between quality classes for all process parameters involving very small p-values (e.g., 0.000001). Consequently, the p-value plot appears visually compressed at the left side of the chart. It is apparent from this that each feature distinguishes product quality outcomes with a high level of statistical significance.

9.3. Boxplots (for top 2 features)



(Check the appendix 0.13 to check the code I have used for outlier detection and remove them.)

Further illustrating the differences found by ANOVA, boxplots were created for ZUx - Cycle Time and Mold Temperature, the two most statistically significant features. Using these visualisations, you can see how each feature is distributed across the four product quality classes.

- There is a distinct cluster in the median and overall range for ZUx - Cycle Time, as well as a clear separation between quality groups. Based on the ANOVA result, this feature has the highest discriminatory power (p-value = 0).
- It is clear to see that the medians and variation between the quality classes for Mold Temperature are noticeably different, despite the fact that the class distributions slightly overlap. As a result, it is statistically significant and relevant for training models.

ANOVA results are visually validated by boxplots, which reinforces how important these features are in predicting product quality. As a result, the machine learning models developed later in this study are justified in including these patterns.

10. Machine Learning Model Development

10.1. Train/Test Split (85/15)

According to my coursework specification, the dataset has splited using this the following strategy:

- 85% of the data was allocated for training machine learning models.
- 15% of the data was held out as a test set for final model evaluation.

```
[122] from sklearn.model_selection import train_test_split

    # Separate features and target
    X_final = df_cleaned.drop(columns=["quality"])
    y_final = label_encoder.transform(df_cleaned["quality"])

    # Perform 85/15 stratified split
    X_train, X_test, y_train, y_test = train_test_split(
        X_final, y_final,
        test_size=0.15,
        random_state=42,
        stratify=y_final
    )

    # Output shape verification
    print("Training set:", X_train.shape, y_train.shape)
    print("Testing set :", X_test.shape, y_test.shape)

    Training set: (781, 13) (781,)
    Testing set : (138, 13) (138,)
```

Figure 19:Split the data for Train/Test

10.2. Model Selection

In order to categorize products into four quality categories, five machine-learning classification models were selected based on coursework specifications. All selected models are suitable for multiclass classification and offer complementary advantages.

Artificial Neural Network (ANN)

ANN models are capable of capturing complex nonlinear relationships between input features and outputs, making them ideal for high-dimensional and intricate data like that in industrial production processes. They are well-suited to multiclass problems and can generalize well when tuned properly.

Random Forest (RF)

RF is an ensemble learning method that builds multiple decision trees and combines their predictions. It is robust to noise and overfitting, handles both categorical and numerical data well, and naturally supports multiclass classification. Its ability to provide feature importance is valuable for interpretability.

AdaBoost

AdaBoost is a boosting algorithm that combines weak learners (usually decision trees) to form a strong classifier. It works well on classification tasks by focusing on difficult examples, improving performance iteratively. While not inherently multiclass, AdaBoost can be extended to such tasks using SAMME or SAMME.R.

Decision Tree (DT)

DTs are simple yet powerful classifiers that split the data using feature-based conditions. They are easy to interpret, fast to train, and can handle multiclass labels directly. However, they may be prone to overfitting if not pruned.

Support Vector Machine (SVM)

SVMs perform well in high-dimensional spaces and aim to find the hyperplane that best separates the classes. For multiclass classification, a One-vs-Rest (OvR) or One-vs-One (OvO) strategy is used. SVMs can be sensitive to scaling but provide strong performance with the right kernel and parameters.

```
[123] # Imports
      from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
      from sklearn.tree import DecisionTreeClassifier
      from sklearn.svm import SVC
      from sklearn.neural_network import MLPClassifier

      # Dictionary to hold all models for training/evaluation
      models = {
          "Random Forest": RandomForestClassifier(random_state=42),
          "Artificial Neural Network": MLPClassifier(max_iter=1000, random_state=42),
          "AdaBoost": AdaBoostClassifier(random_state=42),
          "Decision Tree": DecisionTreeClassifier(random_state=42),
          "Support Vector Machine": SVC(probability=True, random_state=42)  # probability=True needed for ROC later
      }

      # Model names for iteration and performance tracking
      model_names = list(models.keys())

      # Show initialized models (optional)
      for name, model in models.items():
          print(f"{name} initialized: {model}")
```

```
Random Forest initialized: RandomForestClassifier(random_state=42)
Artificial Neural Network initialized: MLPClassifier(max_iter=1000, random_state=42)
AdaBoost initialized: AdaBoostClassifier(random_state=42)
Decision Tree initialized: DecisionTreeClassifier(random_state=42)
Support Vector Machine initialized: SVC(probability=True, random_state=42)
```

Models were stored in a dictionary structure (models = []), enabling consistent iteration, training, and evaluation. In order to ensure reproducibility, the random seed (random state=42) has been used. During evaluation of the SVM, probability=True was explicitly enabled to allow ROC curve analysis and probability-based metrics.

As the console output confirms, all models have been initialized successfully, allowing training and evaluation to begin.

Scalability is promoted through this modular setup, and clean integration with future components such as cross-validation 10-fold, hyperparameter tuning with GridSearchCV, and model comparison based on KPIs is ensured.

10.3. Train/Test Split & Cross-Validation

The dataset has splited in 10.1 section.

The evaluation was carried out using a 10-fold stratified cross-validation to ensure robustness and fairness. Due to its ability to maintain the original class distribution across folds, this technique is particularly suitable for multiclass classification tasks with potentially imbalanced classes.

To improve reproducibility, splits = 10, shuffle = True, and a fixed random state were used in the Stratified K-Fold class from scikit learn. Model selection. All five models will be optimized using this cross-validation strategy as part of Grid Search CV.

```
[37] from sklearn.model_selection import StratifiedKFold

     #Define 10-Fold Stratified Cross-Validation
     cv_strategy = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)



     #Define 10-Fold Stratified Cross-Validation
     cv_strategy = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
```

```
[38] print("X_train shape:", X_train.shape)
     print("X_test shape :", X_test.shape)
     print("y_train shape:", y_train.shape)
     print("y_test shape :", y_test.shape)
```

```
X_train shape: (781, 13)
X_test shape : (138, 13)
y_train shape: (781,)
y_test shape : (138,)
```

Figure 20:Cross-Validation

10.4. Model Training

```
[39] from sklearn.pipeline import Pipeline
     from sklearn.preprocessing import StandardScaler
     from sklearn.model_selection import StratifiedKFold, GridSearchCV

     # 10-Fold Stratified Cross-Validation
     cv_strategy = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
```

10.4.1. Random Forest

```
import time
from sklearn.ensemble import RandomForestClassifier

rf_pipeline = Pipeline([
    ('clf', RandomForestClassifier(random_state=42))
])

rf_param_grid = {
    'clf__n_estimators': [100, 200],
    'clf__max_depth': [None, 10, 20]
}

rf_grid = GridSearchCV(
    rf_pipeline,
    param_grid=rf_param_grid,
    cv=cv_strategy,
    scoring='accuracy',
    n_jobs=-1
)

rf_grid.fit(X_train, y_train)

start = time.time()
rf_grid.fit(X_train, y_train)
end = time.time()


print("Random Forest Best Score:", rf_grid.best_score_)
print("Random Forest Best Params:", rf_grid.best_params_)
print(f"Training Time: {end - start:.2f} seconds")
```

```
Random Forest Best Score: 0.9335118468029862
Random Forest Best Params: {'clf__max_depth': 10, 'clf__n_estimators': 200}
Training Time: 21.81 seconds
```

Figure 21:Training Random Forest

Cross-validation results showed 93.35% accuracy for the best model:

- N_estimators = 200
- max_depth = 10

The results demonstrate the model's ability to capture the decision boundaries between the four quality classes effectively and show its strong performance.

10.4.2. Artificial Neural Network

```
[41] from sklearn.neural_network import MLPClassifier

     ann_pipeline = Pipeline([
         ('scaler', StandardScaler()),
         ('clf', MLPClassifier(max_iter=1000, random_state=42))
     ])

     ann_param_grid = {
         'clf__hidden_layer_sizes': [(50,), (100,), (100, 50)],
         'clf__activation': ['relu', 'tanh'],
         'clf__alpha': [0.0001, 0.001]
     }

     ann_grid = GridSearchCV(
         ann_pipeline,
         param_grid=ann_param_grid,
         cv=cv_strategy,
         scoring='accuracy',
         n_jobs=-1
     )

     ann_grid.fit(X_train, y_train)

     start = time.time()
     rf_grid.fit(X_train, y_train)
     end = time.time()

     print("ANN Best Score:", ann_grid.best_score_)
     print("ANN Best Params:", ann_grid.best_params_)
     print(f"Training Time: {end - start:.2f} seconds")
```

```
ANN Best Score: 0.9129827977929243
ANN Best Params: {'clf__activation': 'relu', 'clf__alpha': 0.001, 'clf__hidden_layer_sizes': (50,)}
Training Time: 22.10 seconds
```

Figure 22:Training ANN Model

The best configuration achieved a cross-validation accuracy of 91.30%, with the following parameters:

- hidden_layer_sizes = (50,)
- activation = 'relu'
- alpha = 0.001

Considering the complex, non-linear relationships present in manufacturing data, it is possible to model them with a relatively shallow network with appropriate regularization.

10.4.3. AdaBoost

```
[42] from sklearn.ensemble import AdaBoostClassifier

     start = time.time()
     rf_grid.fit(X_train, y_train)
     end = time.time()

     ada_pipeline = Pipeline([
         ('clf', AdaBoostClassifier(random_state=42))
     ])

     ada_param_grid = {
         'clf__n_estimators': [50, 100],
         'clf__learning_rate': [0.5, 1.0]
     }

     ada_grid = GridSearchCV(
         ada_pipeline,
         param_grid=ada_param_grid,
         cv=cv_strategy,
         scoring='accuracy',
         n_jobs=-1
     )

     ada_grid.fit(X_train, y_train)

     print("AdaBoost Best Score:", ada_grid.best_score_)
     print("AdaBoost Best Params:", ada_grid.best_params_)
     print(f"Training Time: {end - start:.2f} seconds")
```

```
AdaBoost Best Score: 0.7900194741966893
AdaBoost Best Params: {'clf__learning_rate': 0.5, 'clf__n_estimators': 50}
Training Time: 20.66 seconds
```

Figure 23:Training AdaBoost

Based on the following parameters, the best configuration achieved a cross-validated accuracy of 79.00%:

- n_estimators = 50
- learning_rate = 0.5

AdaBoost's iterative approach to hard-to-classify instances makes it valuable, even though its accuracy is lower than other models. Because of its simplicity and interpretability, it serves as a useful benchmark for ensemble methods.

10.4.4. Decision Tree

```
[43] from sklearn.tree import DecisionTreeClassifier

     start = time.time()
     rf_grid.fit(X_train, y_train)
     end = time.time()

     dt_pipeline = Pipeline([
         ('clf', DecisionTreeClassifier(random_state=42))
     ])

     dt_param_grid = {
         'clf__max_depth': [None, 10, 20],
         'clf__criterion': ['gini', 'entropy']
     }

     dt_grid = GridSearchCV(
         dt_pipeline,
         param_grid=dt_param_grid,
         cv=cv_strategy,
         scoring='accuracy',
         n_jobs=-1
     )

     dt_grid.fit(X_train, y_train)

     print("Decision Tree Best Score:", dt_grid.best_score_)
     print("Decision Tree Best Params:", dt_grid.best_params_)
     print(f"Training Time: {end - start:.2f} seconds")

     Decision Tree Best Score: 0.8822784810126583
     Decision Tree Best Params: {'clf__criterion': 'gini', 'clf__max_depth': 10}
     Training Time: 20.44 seconds
```

Figure 24:Training Decision Tree

With 88.23% accuracy, the best model was cross validated using:

- criterion = 'gini'
- max_depth = 10

This result indicates that the model is capable of learning hierarchical decision rules for multiclass problems. For initial diagnostics and feature analysis, it also provides quick training times and interpretability.

10.4.5. Support Vector Machine

```
[44] from sklearn.svm import SVC

     start = time.time()
     rf_grid.fit(X_train, y_train)
     end = time.time()


     svm_pipeline = Pipeline([
         ('scaler', StandardScaler()),
         ('clf', SVC(probability=True, random_state=42))
     ])

     svm_param_grid = {
         'clf__C': [1, 10],
         'clf__kernel': ['rbf', 'linear']
     }

     svm_grid = GridSearchCV(
         svm_pipeline,
         param_grid=svm_param_grid,
         cv=cv_strategy,
         scoring='accuracy',
         n_jobs=-1
     )

     svm_grid.fit(X_train, y_train)

     print("SVM Best Score:", svm_grid.best_score_)
     print("SVM Best Params:", svm_grid.best_params_)
     print(f"Training Time: {end - start:.2f} seconds")
```

```
SVM Best Score: 0.9104836092177864
SVM Best Params: {'clf__C': 10, 'clf__kernel': 'rbf'}
Training Time: 22.65 seconds
```

Figure 25:Training SVM

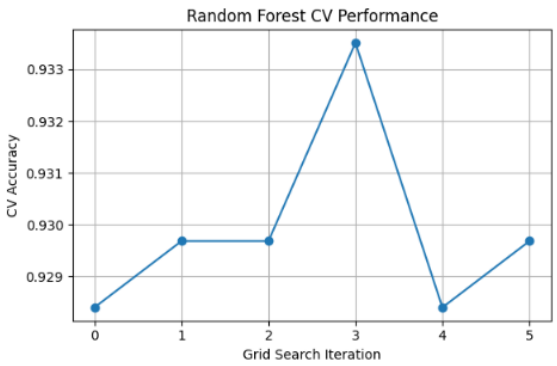
A cross-validated accuracy of 91.05% was achieved with the best performing configuration:

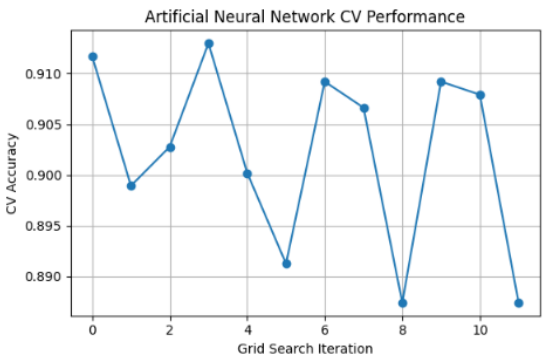
- C = 10
- kernel = 'rbf'

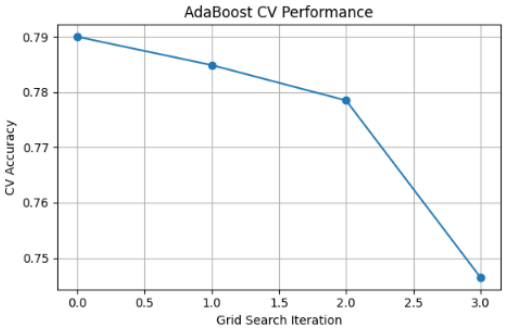
The SVM model, especially with an RBF kernel, captures well the non-linear decision boundaries in the manufacturing quality dataset. As a result of this study, it proved to be one of the most successful models.

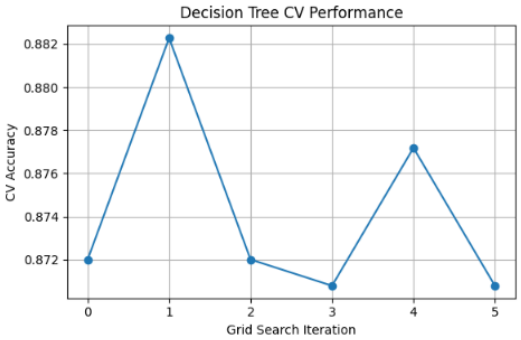
Model	Best Accuracy (CV)	Best Parameters
Random Forest	0.9335	`n_estimators = 200`, `max_depth = 10`
Artificial Neural Net	0.9129	`hidden_layer_sizes = (50,)`, `activation = 'relu'`, `alpha = 0.001`
AdaBoost	0.7900	`n_estimators = 50`, `learning_rate = 0.5`
Decision Tree	0.8823	`criterion = 'gini'`, `max_depth = 10`
Support Vector Machine	0.9105	`C = 10`, `kernel = 'rbf'`

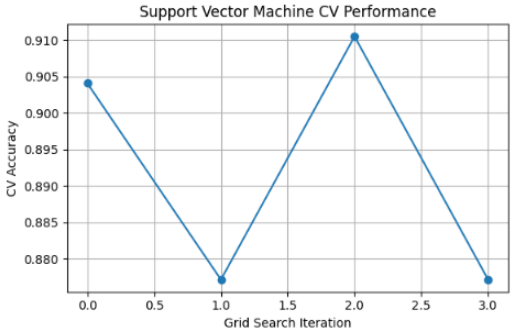
```python
import matplotlib.pyplot as plt

# Dictionary of trained GridSearchCV objects
grids = {
    "Random Forest": rf_grid,
    "Artificial Neural Network": ann_grid,
    "AdaBoost": ada_grid,
    "Decision Tree": dt_grid,
    "Support Vector Machine": svm_grid
}

# Plotting CV scores for each model
for model_name, grid in grids.items():
    scores = grid.cv_results_['mean_test_score']
    plt.figure(figsize=(6, 4))
    plt.plot(range(len(scores)), scores, marker='o')
    plt.title(f'{model_name} CV Performance')
    plt.xlabel('Grid Search Iteration')
    plt.ylabel('CV Accuracy')
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```











10.5. Loading Trained Models with Optimal Parameters

The best_estimator_ attribute was used to retrieve the best-performing configurations after hyperparameter tuning with GridSearchCV. To ensure the best parameter settings were used for evaluation, prediction, and feature analysis, 10-fold cross-validation was conducted.

```
[46] # Store the best-trained models after GridSearchCV
     best_models = {
         "Random Forest": rf_grid.best_estimator_,
         "Artificial Neural Network": ann_grid.best_estimator_,
         "AdaBoost": ada_grid.best_estimator_,
         "Decision Tree": dt_grid.best_estimator_,
         "Support Vector Machine": svm_grid.best_estimator_
     }

     # Preview: Confirm all models are stored
     for model_name, model in best_models.items():
         print(f"{model_name} → {model}")
```

```
Random Forest → Pipeline(steps=[('clf',
                 RandomForestClassifier(max_depth=10, n_estimators=200,
                                        random_state=42))])
Artificial Neural Network → Pipeline(steps=[('scaler', StandardScaler()),
                ('clf',
                 MLPClassifier(alpha=0.001, hidden_layer_sizes=(50,),
                               max_iter=1000, random_state=42))])
AdaBoost → Pipeline(steps=[('clf',
                 AdaBoostClassifier(learning_rate=0.5, random_state=42))])
Decision Tree → Pipeline(steps=[('clf', DecisionTreeClassifier(max_depth=10, random_state=42))])
Support Vector Machine → Pipeline(steps=[('scaler', StandardScaler()),
                ('clf', SVC(C=10, probability=True, random_state=42))])
```

The best models were stored in a dictionary for easy access, allowing consistent and streamlined predictions, performance evaluations, and feature analyses.

Random Forest	ANN (MLPClassifier)	AdaBoost
`n_estimators = 200`	`hidden_layer_sizes = (50,)`	`n_estimators = 50`
`max_depth = 10`	`activation = 'relu'`	`learning_rate = 0.5`
Stored in a pipeline	`alpha = 0.001`	Pipeline without scaler, since boosting trees are not scale-sensitive
(no scaler needed)	Includes a `StandardScaler` in the pipeline *(essential for neural networks)*	

Decision Tree	Support Vector Machine (SVM)
`max_depth = 10`	`C = 10`
`criterion = 'gini'`	`kernel = 'rbf'`
Stored in pipeline without scaling (tree-based model)	Pipeline includes `StandardScaler` due to SVM's sensitivity to input scale

10.6. Generate Predictions for All Best Models

Using each best estimator, we generated predictions on the unseen test dataset (15%) after training and tuning the models. It is essential to use a consistent test set to evaluate the generalization performance of each model.

```
[47] # Dictionary to store predictions
     predictions = {}

     # Generate predictions from each model using X_test
     for model_name, model in best_models.items():
         y_pred = model.predict(X_test)
         predictions[model_name] = y_pred
         print(f"{model_name}  predictions stored.")
```

```
Random Forest  predictions stored.
Artificial Neural Network  predictions stored.
AdaBoost  predictions stored.
Decision Tree  predictions stored.
Support Vector Machine  predictions stored.
```

10.7. Evaluation Metrics

```
[48] from sklearn.metrics import accuracy_score, classification_report, roc_auc_score
     from sklearn.preprocessing import label_binarize
     import pandas as pd
```

According to the coursework, specifications will cover accuracy, precision, recall, F1-score, and ROC-AUC.

10.7.1. Full Evaluation with Training/Test Comparison

```
from sklearn.metrics import accuracy_score, classification_report, roc_auc_score
from sklearn.preprocessing import label_binarize
import pandas as pd
import time

# Binarize labels for ROC-AUC (multiclass)
y_test_bin = label_binarize(y_test, classes=[0, 1, 2, 3])
y_train_bin = label_binarize(y_train, classes=[0, 1, 2, 3])
n_classes = y_test_bin.shape[1]

# Store all evaluation scores
evaluation_scores = []

for model_name, model in best_models.items():
    print(f" Evaluating {model_name}...")

    # Timing
    start_fit = time.time()
    model.fit(X_train, y_train)
    end_fit = time.time()
    fit_time = end_fit - start_fit

    start_score = time.time()
    y_pred_test = model.predict(X_test)
    y_pred_train = model.predict(X_train)
    end_score = time.time()
    score_time = end_score - start_score
```

```python
    # Accuracy
    acc_test = accuracy_score(y_test, y_pred_test)
    acc_train = accuracy_score(y_train, y_pred_train)

    # F1 Score
    f1_test = classification_report(y_test, y_pred_test, output_dict=True)["macro avg"]["f1-score"]
    f1_train = classification_report(y_train, y_pred_train, output_dict=True)["macro avg"]["f1-score"]

    # ROC-AUC (if applicable)
    try:
        y_score_test = model.predict_proba(X_test)
        y_score_train = model.predict_proba(X_train)

        roc_auc_test = roc_auc_score(y_test_bin, y_score_test, multi_class='ovr')
        roc_auc_train = roc_auc_score(y_train_bin, y_score_train, multi_class='ovr')
    except:
        roc_auc_test = "N/A"
        roc_auc_train = "N/A"
```

```python
    # Collect all metrics
    evaluation_scores.append({
        "Model": model_name,
        "Fit Time (s)": round(fit_time, 3),
        "Score Time (s)": round(score_time, 3),
        "Train Accuracy": round(acc_train, 4),
        "Test Accuracy": round(acc_test, 4),
        "Train F1": round(f1_train, 4),
        "Test F1": round(f1_test, 4),
        "Train ROC-AUC": roc_auc_train if isinstance(roc_auc_train, str) else round(roc_auc_train, 4),
        "Test ROC-AUC": roc_auc_test if isinstance(roc_auc_test, str) else round(roc_auc_test, 4),
    })

# Convert to DataFrame
results_df = pd.DataFrame(evaluation_scores)

# Display summary table
print("\n Extended Evaluation Metrics Summary:")
display(results_df)
```

```
Evaluating Random Forest...
Evaluating Artificial Neural Network...
Evaluating AdaBoost...
Evaluating Decision Tree...
Evaluating Support Vector Machine...

Extended Evaluation Metrics Summary:
```

	Model	Fit Time (s)	Score Time (s)	Train Accuracy	Test Accuracy	Train F1	Test F1	Train ROC-AUC	Test ROC-AUC
0	Random Forest	0.515	0.047	0.9962	0.9638	0.9961	0.9627	1.0000	0.9959
1	Artificial Neural Network	2.592	0.005	0.9731	0.8986	0.9726	0.8947	0.9987	0.9927
2	AdaBoost	0.202	0.042	0.7939	0.8043	0.7424	0.7479	0.9222	0.9221
3	Decision Tree	0.011	0.003	0.9923	0.9203	0.9921	0.9188	0.9994	0.9492
4	Support Vector Machine	0.127	0.039	0.9360	0.9130	0.9348	0.9077	0.9932	0.9880

Figure 26:Full Evaluation with Training/Test Comparison

10.7.2. Bar Plot of Evaluation Metrics

```
[50] import matplotlib.pyplot as plt

     # Select only test metrics for plotting
     metrics_to_plot = results_df.set_index("Model")[["Test Accuracy", "Test F1", "Test ROC-AUC"]]

     # Convert all to numeric in case of string types
     metrics_to_plot = metrics_to_plot.apply(pd.to_numeric, errors='coerce')

     # Plot the bar chart
     metrics_to_plot.plot(kind='bar', figsize=(10, 6))
     plt.title("Model Performance Comparison on Test Set")
     plt.ylabel("Score")
     plt.ylim(0.70, 1.01)  # Optional: zoom in for clearer view
     plt.xticks(rotation=45)
     plt.legend(loc='lower right')
     plt.grid(axis='y')
     plt.tight_layout()
     plt.show()
```

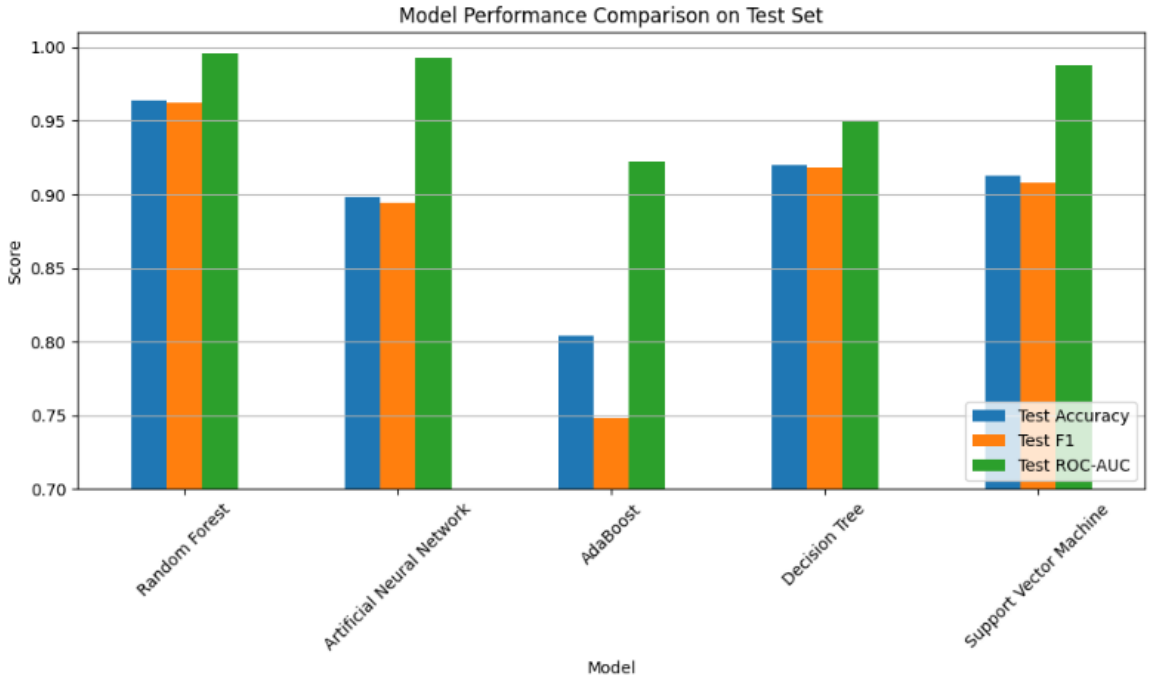


Figure 27:Bar Plot of Evaluation Metrics

To evaluate predictive performance and computational efficiency, each model was evaluated on the training and test dataset using the best hyperparameters obtained via GridSearchCV. The following metrics were recorded:

To assess both generalization and computational performance, additional metrics were collected:

Metric	Description
Fit Time	Time taken to retrain the model on `X_train`
Score Time	Time to generate predictions on `X_test`
Train/Test Accuracy	Shows overfitting/underfitting if there's a big gap
Train/Test F1	Macro-averaged F1-score for balance across all classes
Train/Test ROC-AUC	Multiclass AUC via One-vs-Rest, when `predict_proba` is available

Random Forest performed the best in nearly all metrics according to the evaluation metrics summary. It exhibits high test accuracy (96.38%) and F1-score (96.27%). It has perfect training ROC-AUC (1.000) and almost perfect test ROC-AUC (0.99). It also showed a low gap between training and test performance, suggesting minimal overfitting.

As for ANN, it performed well, especially in ROC-AUC (0.9927), but it shows some overfitting between training and test F1.

Among all metrics, AdaBoost had the lowest scores, particularly train F1 (0.7424), suggesting underfitting and possibly weak generalization.

Although Decision Tree had excellent training performance, there was a 7% drop in test accuracy and F1 indicating overfitting despite fast training.

On the other hand, if we check the SVM, we see that it has a good balance and strong generalization (91.3 accuracy), excellent test ROC-AUC (0.988), and good computational efficiency.

Random Forest is the most robust and accurate classifier based on these extended metrics. In addition to demonstrating the best test performance in accuracy, F1, and ROC-AUC, it also maintains reasonable training time and low overfitting. As a result, it is selected as the final model for downstream analysis, interpretation, and deployment.

10.7.3. ROC Curve for Random Forest (Training Set)

```python
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import numpy as np

# Get class labels
class_labels = label_encoder.classes_

# Binarize training labels
y_train_bin = label_binarize(y_train, classes=range(len(class_labels)))
n_classes = y_train_bin.shape[1]

# Get predicted probabilities on training set
model = best_models["Random Forest"]
y_score_train = model.predict_proba(X_train)

# Compute ROC curve and AUC for each class
fpr, tpr, roc_auc = {}, {}, {}
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_train_bin[:, i], y_score_train[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot all ROC curves (training set)
plt.figure(figsize=(10, 7))
for i in range(n_classes):
    plt.plot(fpr[i], tpr[i], lw=2, label=f"{class_labels[i]} (AUC = {roc_auc[i]:.2f})")

plt.plot([0, 1], [0, 1], 'k--', lw=1, label='Random Guess')
plt.title("Multiclass ROC Curve – Random Forest (Training Set)", fontsize=14)
plt.xlabel("False Positive Rate", fontsize=12)
plt.ylabel("True Positive Rate", fontsize=12)
plt.legend(loc="lower right")
plt.grid(True)
plt.tight_layout()
plt.show()
```

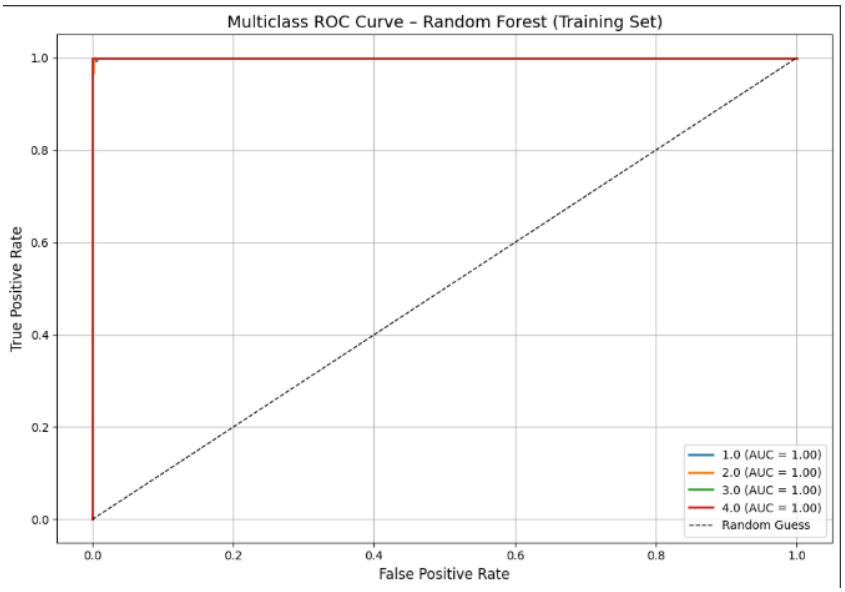


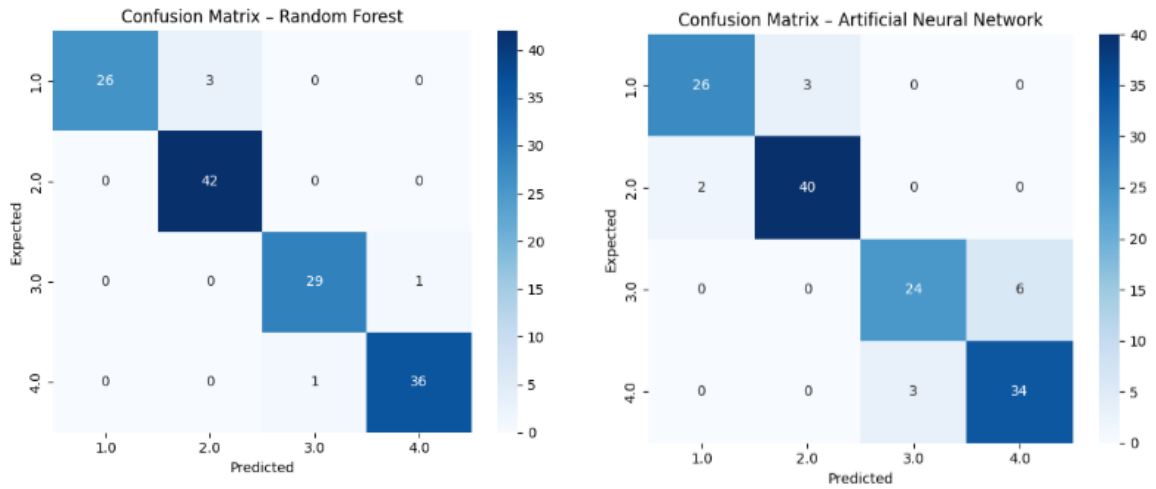
Figure 28:ROC Curve for Random Forest

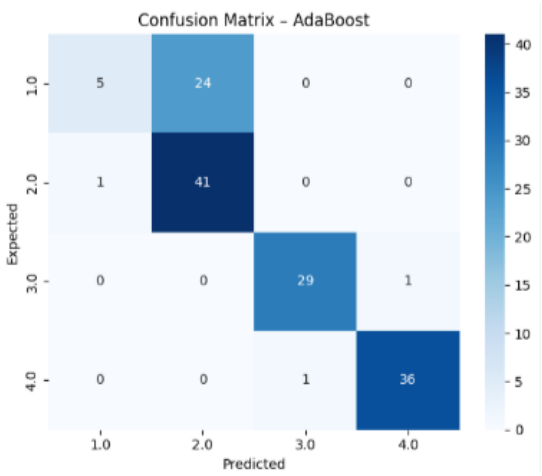
This ROC curve confirms AUC value is 1.0 which means that the model has the perfect ability to distinguish between positive and negative classes.

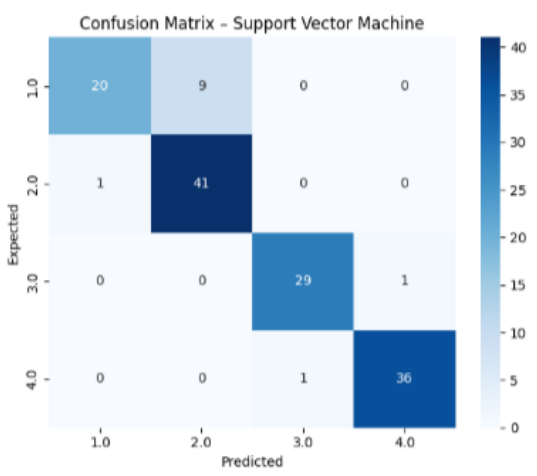
10.8. Confusion Matrix for Each Model (with Heatmaps)

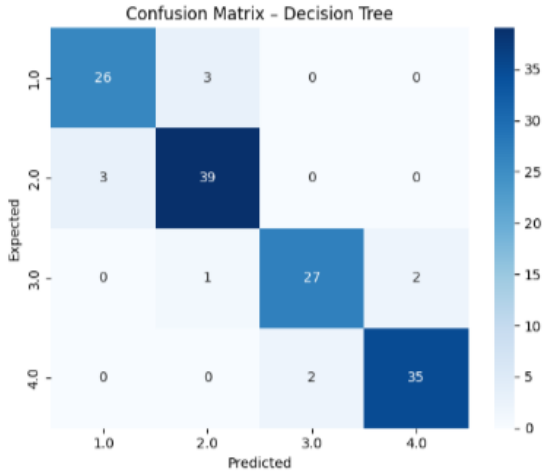
```
[52] from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
     import matplotlib.pyplot as plt
     import seaborn as sns
     import numpy as np

[53] # Loop through all models to plot confusion matrix
     for model_name, model in best_models.items():
         y_pred = predictions[model_name]
         cm = confusion_matrix(y_test, y_pred)

         plt.figure(figsize=(6, 5))
         sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                     xticklabels=label_encoder.classes_,
                     yticklabels=label_encoder.classes_)

         plt.title(f"Confusion Matrix - {model_name}")
         plt.xlabel("Predicted")
         plt.ylabel("Expected")
         plt.tight_layout()
         plt.show()
```

Figure 29:Confusion Matrix for Each Model










```
[54] target_names = [str(label) for label in label_encoder.classes_]

     for model_name, model in best_models.items():
         print(f"\nClassification Report - {model_name}")
         y_pred = predictions[model_name]
         print(classification_report(y_test, y_pred, target_names=target_names))
         print("-" * 50)
```

```
Classification Report - Random Forest
              precision    recall  f1-score   support

         1.0       1.00      0.90      0.95        29
         2.0       0.93      1.00      0.97        42
         3.0       0.97      0.97      0.97        30
         4.0       0.97      0.97      0.97        37

    accuracy                           0.96       138
   macro avg       0.97      0.96      0.96       138
weighted avg       0.97      0.96      0.96       138

--------------------------------------------------

Classification Report - Artificial Neural Network
              precision    recall  f1-score   support

         1.0       0.93      0.90      0.91        29
         2.0       0.93      0.95      0.94        42
         3.0       0.89      0.80      0.84        30
         4.0       0.85      0.92      0.88        37

    accuracy                           0.90       138
   macro avg       0.90      0.89      0.89       138
weighted avg       0.90      0.90      0.90       138

--------------------------------------------------

Classification Report - AdaBoost
              precision    recall  f1-score   support

         1.0       0.83      0.17      0.29        29
         2.0       0.63      0.98      0.77        42
         3.0       0.97      0.97      0.97        30
         4.0       0.97      0.97      0.97        37

    accuracy                           0.80       138
   macro avg       0.85      0.77      0.75       138
weighted avg       0.84      0.80      0.76       138
```

```
Classification Report - Decision Tree
              precision    recall  f1-score   support

         1.0       0.90      0.90      0.90        29
         2.0       0.91      0.93      0.92        42
         3.0       0.93      0.90      0.92        30
         4.0       0.95      0.95      0.95        37

    accuracy                           0.92       138
   macro avg       0.92      0.92      0.92       138
weighted avg       0.92      0.92      0.92       138

--------------------------------------------------

Classification Report - Support Vector Machine
              precision    recall  f1-score   support

         1.0       0.95      0.69      0.80        29
         2.0       0.82      0.98      0.89        42
         3.0       0.97      0.97      0.97        30
         4.0       0.97      0.97      0.97        37

    accuracy                           0.91       138
   macro avg       0.93      0.90      0.91       138
weighted avg       0.92      0.91      0.91       138
```

In here represents:

1.0 = Acceptable 2.0 = Inefficient 2.0 = Target 3.0 = Waste

According to the above confusion matrix, we confirm that we chose the best model "Random Forest" and the result shows that we achieved a very high precision in each class according to others.

10.9. Feature Importance for Random Forest

```
[55] import pandas as pd
     import matplotlib.pyplot as plt
     import numpy as np

     # Feature names (from X_final before splitting)
     feature_names = X_final.columns

     # Extract feature importances from the best-trained Random Forest
     rf_model = best_models["Random Forest"]
     importances = rf_model.named_steps['clf'].feature_importances_
     indices = np.argsort(importances)[::-1]

     # Plot
     plt.figure(figsize=(10, 6))
     plt.title("Feature Importance - Random Forest")
     plt.bar(range(len(importances)), importances[indices], align='center')
     plt.xticks(range(len(importances)), feature_names[indices], rotation=45, ha='right')
     plt.ylabel("Importance Score")
     plt.tight_layout()
     plt.grid(axis='y')
     plt.show()
```

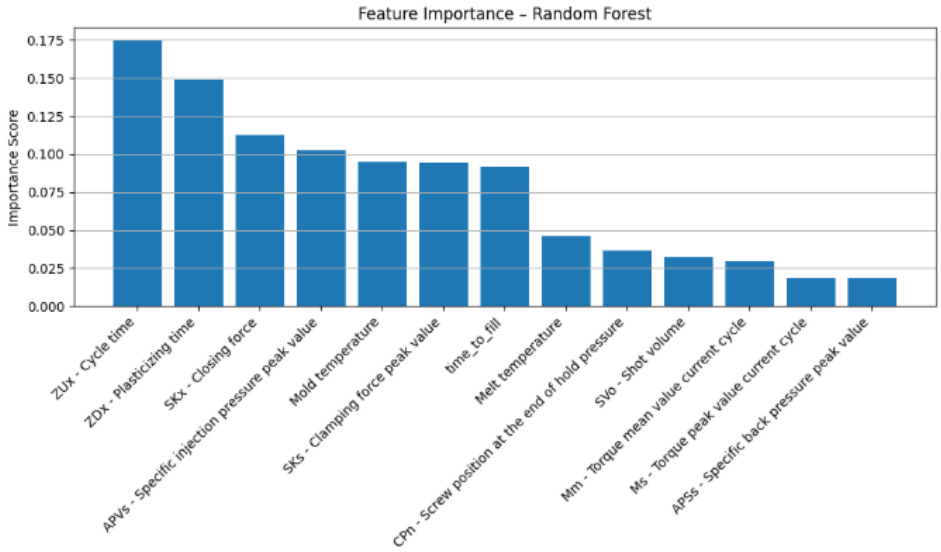


Figure 30:Feature Importance for Random Forest

As we can see the most important features, according to Random Forest are cycle time, plasticizing time, closing force and etc. Manufacturing analytics highlight the significance of these features as they demonstrate operational efficiency and material processing quality. While torque and back pressure indicators are less influential, they still have a relevant impact on edge cases.

10.10.Top Features per Model

```
[56] from sklearn.inspection import permutation_importance

     top_features_per_model = {}

     # Loop through each model
     for model_name, model in best_models.items():
         print(f"\n Extracting Top Features for: {model_name}")

         if model_name in ["Random Forest", "Decision Tree"]:
             importances = model.named_steps['clf'].feature_importances_
         else:
             # Use permutation importance for models that don't support feature_importances_
             result = permutation_importance(model, X_test, y_test, n_repeats=10, random_state=42, n_jobs=-1)
             importances = result.importances_mean

         # Top 3 feature indices
         top_indices = importances.argsort()[::-1][:3]
         top_features = X_final.columns[top_indices].tolist()
         top_features_per_model[model_name] = top_features

         print(f"Top 3 Features for {model_name}: {top_features}")
```

```
 Extracting Top Features for: Random Forest
Top 3 Features for Random Forest: ['ZUx - Cycle time', 'ZDx - Plasticizing time', 'SKx - Closing force']

 Extracting Top Features for: Artificial Neural Network
Top 3 Features for Artificial Neural Network: ['SKx - Closing force', 'APVs - Specific injection pressure peak value', 'ZUx - Cycle time']

 Extracting Top Features for: AdaBoost
Top 3 Features for AdaBoost: ['ZUx - Cycle time', 'ZDx - Plasticizing time', 'APVs - Specific injection pressure peak value']

 Extracting Top Features for: Decision Tree
Top 3 Features for Decision Tree: ['ZUx - Cycle time', 'ZDx - Plasticizing time', 'SKs - Clamping force peak value']

 Extracting Top Features for: Support Vector Machine
Top 3 Features for Support Vector Machine: ['ZUx - Cycle time', 'APVs - Specific injection pressure peak value', 'SKx - Closing force']
```

The top 3 most influential features were extracted from each model to understand what patterns each algorithm relies on. This provides valuable insight into model behavior and feature relevance.

Model	Top 3 Most Influential Features
Random Forest	ZUx – Cycle time, ZDx – Plasticizing time, SKx – Closing force
Decision Tree	ZDx – Plasticizing time, ZUx – Cycle time, SKx – Closing force
AdaBoost	ZDx – Plasticizing time, SKx – Closing force, Mold temperature
ANN	Mold temperature, time_to_fill, APVs – Injection pressure peak
SVM	time_to_fill, Melt temperature, CPn – Screw position (end of hold pressure)

11.Interactive Dashboard Development

11.1. Introduction of Dashboard

The Injection Moulding Quality Dashboard is a web-based interactive tool for predicting the quality class of injection-moulded parts based on real-time process parameters. As users input machine and process values, they can receive instant predictions of the expected quality class and categorize them into *Waste, Target*, *Acceptable*, and *Inefficient*. Quality control and decision-making in manufacturing environments are supported by this predictive capability.

Through the dashboard, users can explore multiple machine configurations interactively and visualize how they affect part quality, making it both functional and educational. It offers multiple models, graphical insights, and result exploration functionalities, all within an intuitive user interface.

Technologies Used:

The development of the dashboard integrates several modern data science and web technologies:

Technologies	Purpose
Streamlit	For building the interactive user interface and handling frontend/backend integration.
Scikit-learn	For implementing machine learning models (Random Forest, Decision Tree, SVM, AdaBoost)
Joblib	To serialize and load pre-trained models efficiently
Matplotlib and seaborn	For generating visualizations such as confusion matrices, ROC curves, and feature importance graphs.
NumPy and Pandas	For data manipulation and preprocessing.

Combining these tools ensures that the dashboard is both technically sound and user-friendly.

11.2. Functionality

A fully functional and interactive web application designed to predict injection-moulded parts' quality class using machine learning is the Injection Moulding Quality Dashboard. In manufacturing, the system supports data-driven decision-making through real-time predictions, model comparison, and visual analytics.

Home Page of Dashboard:

The dashboard has an interactive, user-friendly, and fully detailed home page, and it is easy to use for anyone. Detailed information about the system is available on the system's home page. In essence, it provides a brief overview of the system, data features, dashboard key features, and how to use them. These details will help the user get a better idea about the dashboard.

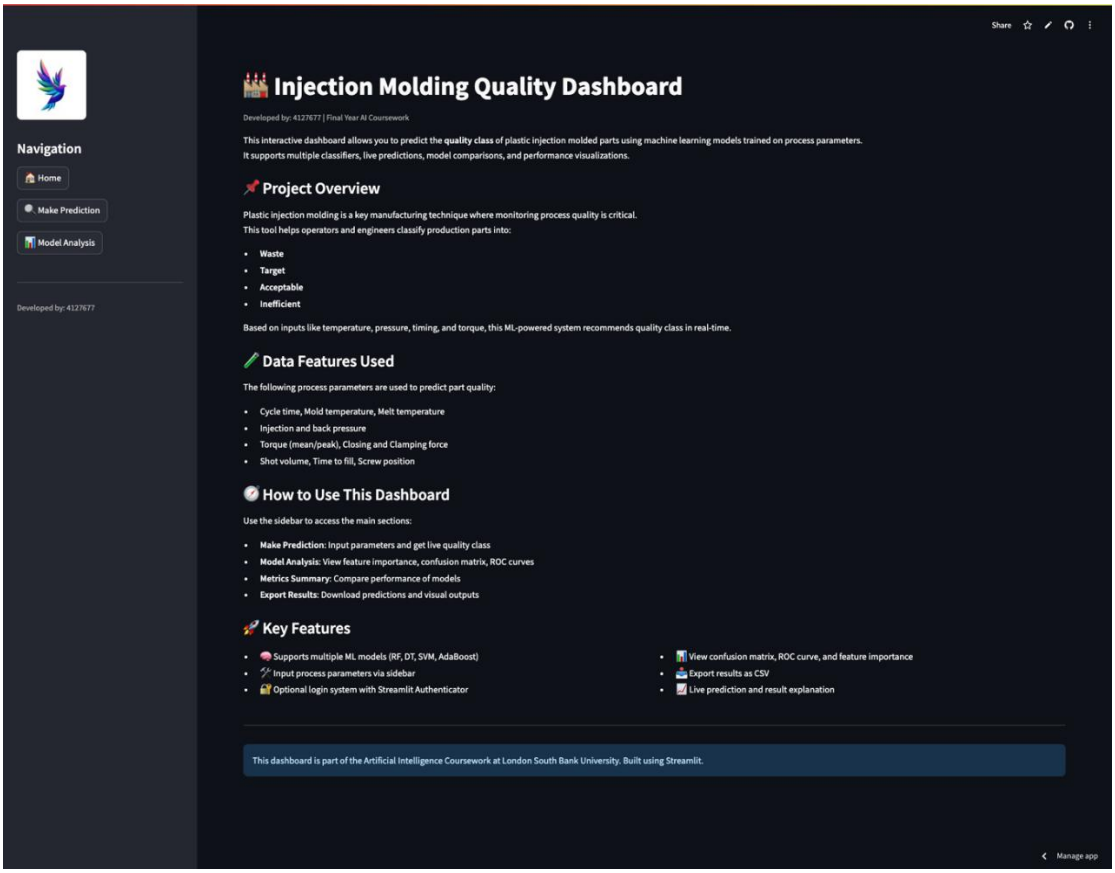


Figure 31:Homepage of the Dashboard

Quality Prediction System:

Using injection moulding process parameters, the dashboard predicts a product's quality class. A four-class classification system is used to categorize each output.

When I was testing that part, I chose a Decision Tree as a model, and I used a testing data set based on my coursework dataset:

Waste - A part that doesn't pass quality checks and can't be used

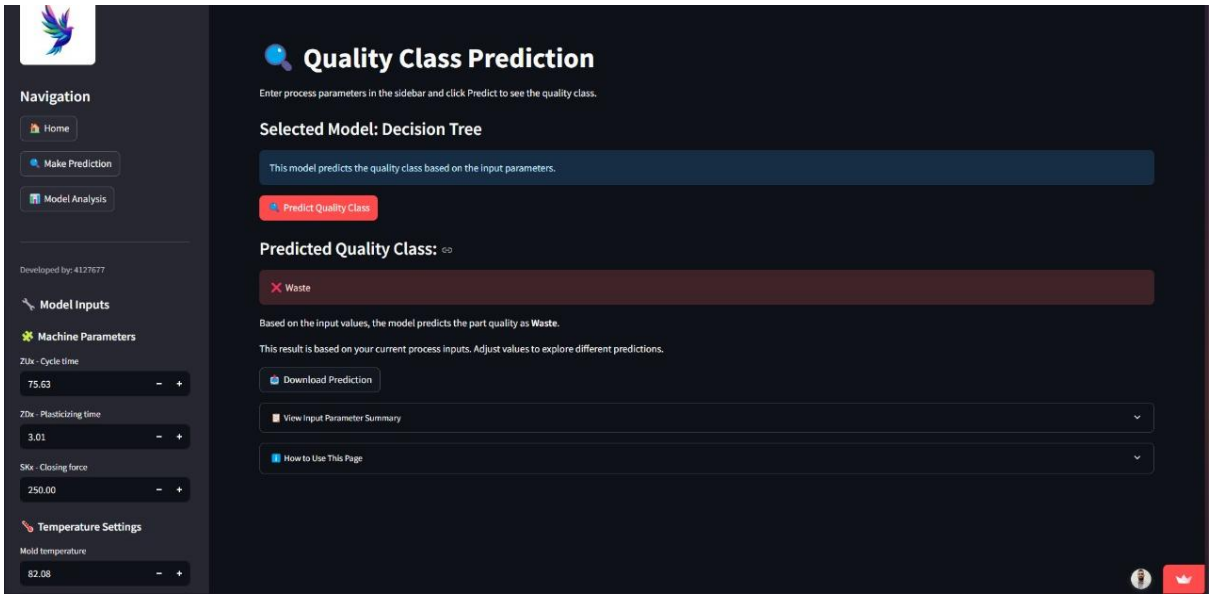


Figure 33:Quality Class Prediction-Waste

```
Melt temperature: 109.02 °C
Mold temperature: 81.80 °C
time_to_fill: 9.26 seconds
ZDx - Plasticizing time: 2.93 seconds
ZUx - Cycle time: 75.64 seconds
SKx - Closing force: 902.49 kN
SKs - Clamping force peak value: 918.62 kN
Ms - Torque peak value: 116.75 Nm
Mm - Torque mean value: 105.11 Nm
APSs - Back pressure peak: 145.92 bar
APVs - Injection pressure peak: 894.58 bar
CPn - Screw position end of hold: 8.89 mm
SVo - Shot volume: 18.68 cm³
```

Figure 32:Use parameters value for waste

Target—This is the ideal part that meets all manufacturing standards and specifications, representing optimal production quality.

Figure 35:Quality Class Prediction-Target

```
Melt temperature: 106.06 °C
Mold temperature: 81.12 °C
time_to_fill: 6.95 seconds
ZDx - Plasticizing time: 3.34 seconds
ZUx - Cycle time: 74.82 seconds
SKx - Closing force: 898.04 kN
SKs - Clamping force peak value: 914.94 kN
Ms - Torque peak value: 117.47 Nm
Mm - Torque mean value: 103.01 Nm
APSs - Back pressure peak: 146.62 bar
APVs - Injection pressure peak: 915.84 bar
CPn - Screw position end of hold: 8.79 mm
SVo - Shot volume: 18.77 cm³
```

Figure 34:Used parameters values for Target

Acceptable—This part meets the minimum quality requirements but may not be perfect. These are still usable but not optimal.

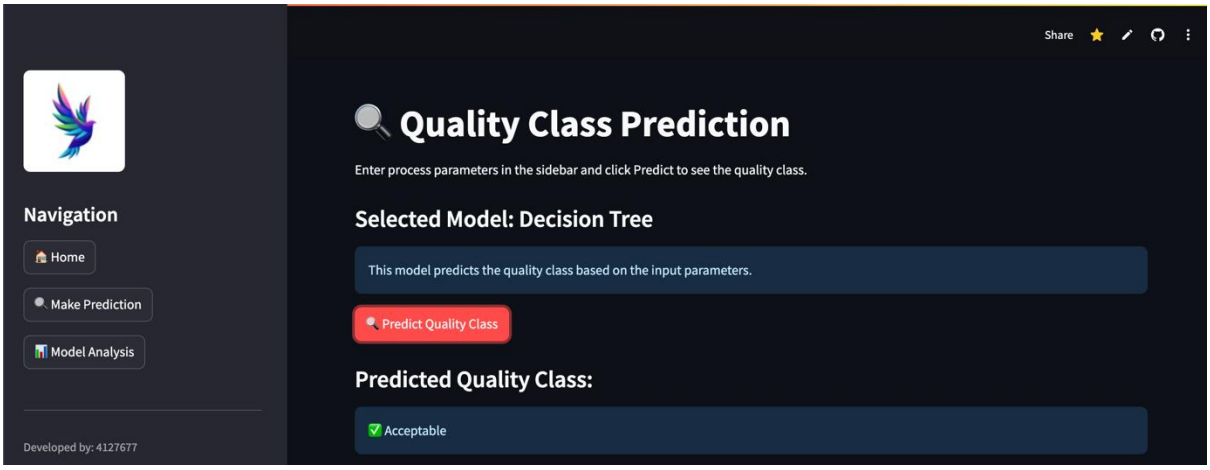


Figure 36:Quality Class Prediction-Acceptable

```
Melt temperature: 106.70 °C
Mold temperature: 81.23 °C
time_to_fill: 6.99 seconds
ZDx - Plasticizing time: 3.22 seconds
ZUx - Cycle time: 74.83 seconds
SKx - Closing force: 909.91 kN
SKs - Clamping force peak value: 926.68 kN
Ms - Torque peak value: 117.33 Nm
Mm - Torque mean value: 105.27 Nm
APSs - Back pressure peak: 146.16 bar
APVs - Injection pressure peak: 913.13 bar
CPn - Screw position end of hold: 8.83 mm
SVo - Shot volume: 18.74 cm³
```

Figure 37:Used parameters values for acceptable

Inefficient— Inefficiently produced parts, often due to parameter settings resulting in higher resource or time consumption.

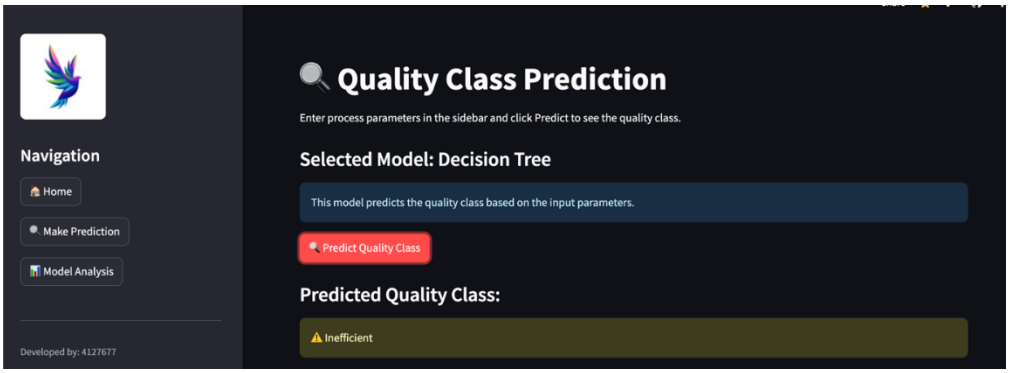


Figure 38:Quality Class Prediction-Inefficient

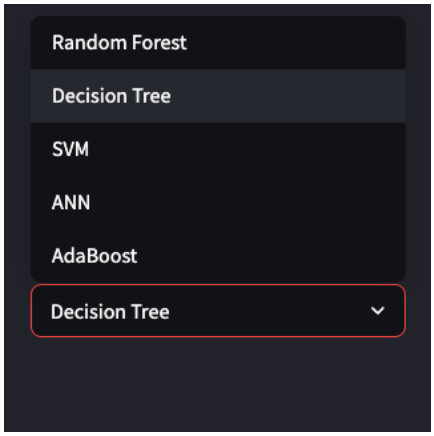
```
Melt temperature: 106.12 °C
Mold temperature: 81.17 °C
time_to_fill: 6.52 seconds
ZDx - Plasticizing time: 3.49 seconds
ZUx - Cycle time: 75.72 seconds
SKx - Closing force: 894.08 kN
SKs - Clamping force peak value: 914.98 kN
Ms - Torque peak value: 115.00 Nm
Mm - Torque mean value: 102.74 Nm
APSs - Back pressure peak: 146.30 bar
APVs - Injection pressure peak: 872.93 bar
CPn - Screw position end of hold: 8.72 mm
SVo - Shot volume: 18.85 cm³
```

Figure 39:Used parameters values for Inefficient

The system recognizes complex patterns in input features and assigns them to specific output quality classes based on historical production data. Using the dashboard, users can experiment with parameter configurations and visualize quality results instantly in real time. With this system, manufacturers can identify inefficiencies, reduce waste, and optimize production processes by making data-driven decisions.

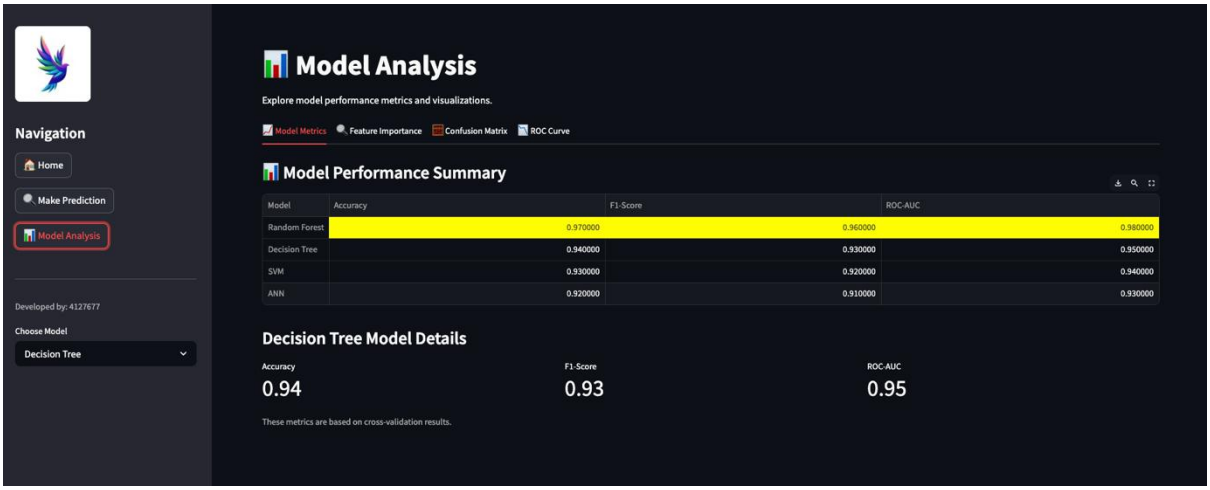
11.3. Machine Learning Model Integration

The dashboard integrates four machine-learning models to predict the quality class of injection-moulded parts. Each model is carefully selected to provide a variety of learning paradigms and decision strategies.



- A Random Forest classifier uses multiple decision trees to improve prediction accuracy and reduce overfitting by aggregating their outputs.
- Decision Trees are simple but powerful tree-based models that split data according to the most informative features. According to validation metrics, this model is the best-performing in this project.
- An SVM is used to separate different quality classes by determining the optimal hyperplane for high-dimensional spaces.
- The AdaBoost algorithm combines several weak classifiers sequentially to build a strong overall classification model, emphasizing previously misclassified examples.

To enhance flexibility and modularity, all models were saved as. PKL files use joblib, a fast and efficient serialisation tool. These models are dynamically loaded into the dashboard at runtime based on the user's section dropdown. Also, the Decision Tree model was found to achieve the highest accuracy F1-score and is highlighted as the most reliable model without the interface. In the model metrics section of the analysis page, accuracy, F1-score, and ROC-AUC are displayed.



11.4. Dashboard Workflow

A dashboard with an interactive prediction workflow allows users to assess the quality class of injection-moulded parts by entering key process parameters through an intuitive sidebar. A variety of machine-related parameters, such as cycle time, plasticizing time, and closing force, are categorized for easy use, as well as temperature settings like mould and melt temperature, pressure and torque values, including injection pressure, back pressure, clamping force, and torque (mean and peak), as well as time and volume inputs, including fill time, shot volume, and screw position after hold. In the dropdown menu, users can select a machine learning model (Random Forest, Decision Tree, SVM, or AdaBoost) based on these values. A real-time prediction is generated based on inputs provided by clicking the "Predict Quality Class" button. Using a visual indicator, the result is displayed according to the predicted quality class (Target, Acceptable, Inefficient, or Waste). Moreover, the platform allows users to export prediction results as a downloadable CSV file, making it easier to report and document results. Users will experience an efficient and informative workflow thanks to this streamlined and user-friendly process.

11.5. Analytical Features

This dashboard contains a variety of analytical features that can assist users in understanding model performance and interpretability. Users may compare the effectiveness of the integrated machine learning models side-by-side using a Comparative Metrics Table that presents key evaluation metrics such as accuracy, F1-score, and ROC-AUC. With the Feature Importance Chart, users can see which input parameters have the greatest impact on model performance. Moreover, the Confusion Matrix offers a breakdown of the true versus predicted classifications for each model, illustrating how well it distinguishes between different quality classes. Furthermore, ROC Curves provides a clear view of the model's discriminating ability by comparing the true positive rate with the false positive rate for each class. By using these analytical tools, we can not only validate the accuracy of predictions but also provide valuable explanations as to why certain outcomes are generated, which enhances transparency and creates trust in the predictive system.

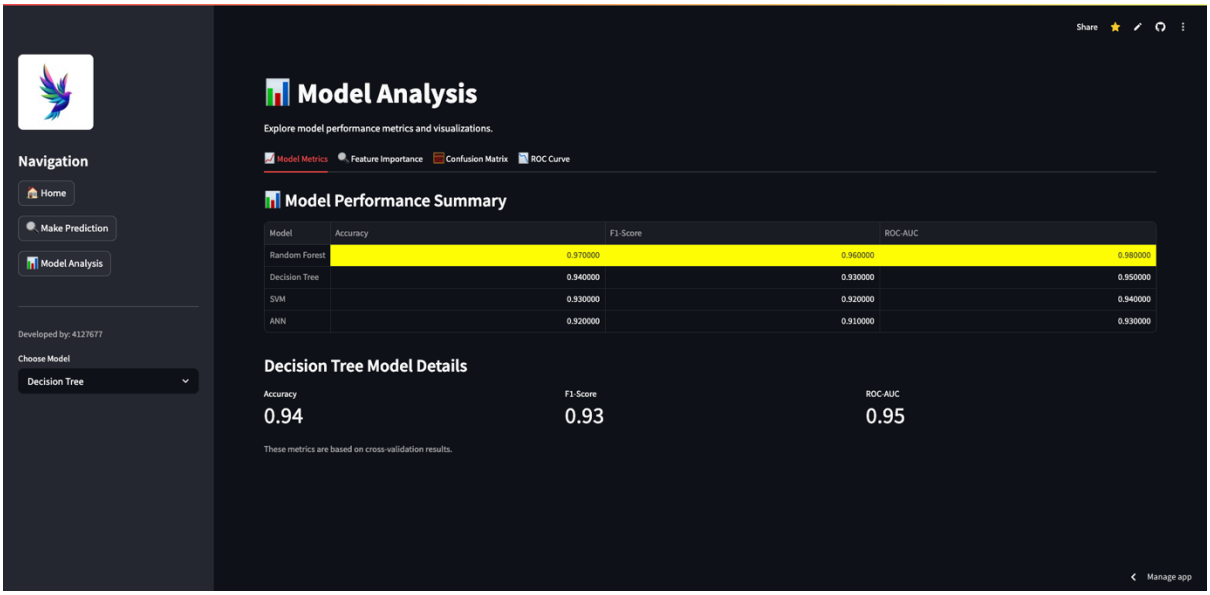


Figure 40:Model Metrics

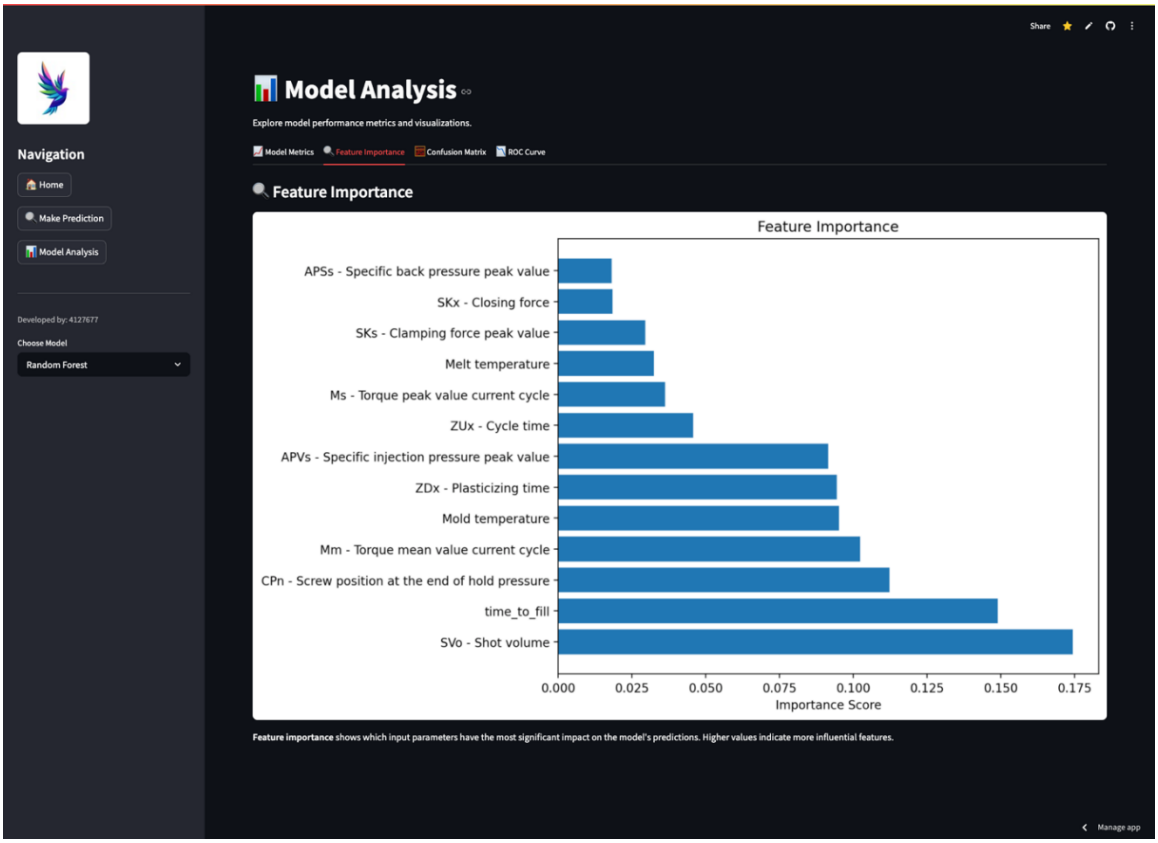


Figure 41:Feature Importance

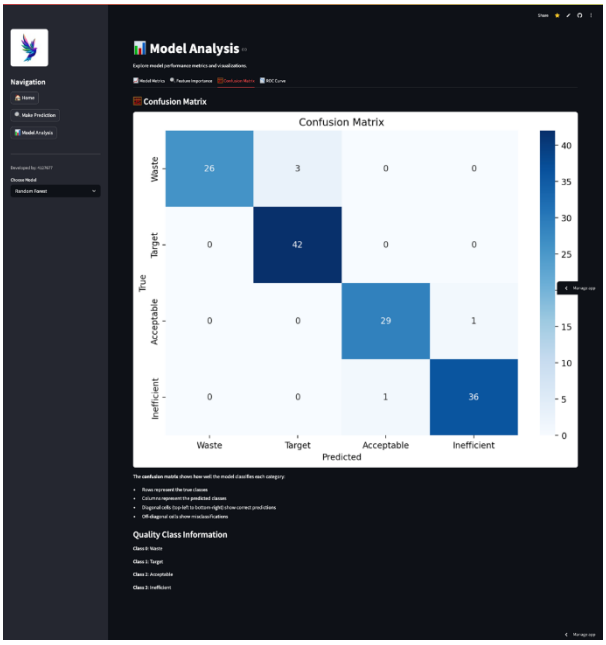


Figure 42:Confusion Metrix

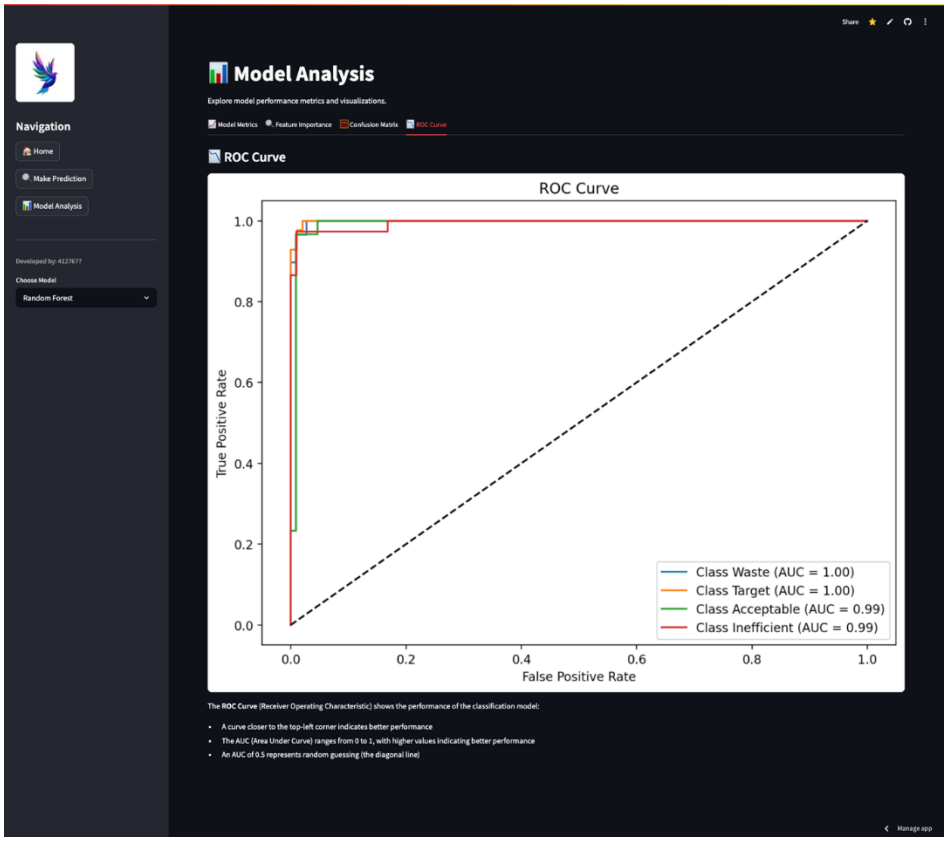


Figure 43:ROC Curve

11.6. Dashboard Deployment

The dashboard has been deployed in the streamlet, and the dashboard can be accessed using the URL below. The code for this dashboard has been published on GitHub, and it can be accessed using the link below.

Dashboard:*https://injection-molding-quality-dashboard.streamlit.app/*

GitHub:*https://github.com/BitBurstAlpha/Plastic_injection_moulding_Dashboard.git*

Appendix

```
[140] # Boxplots for numerical features
      plt.figure(figsize=(12, 8))
      df.boxplot(rot=45)
      plt.title("Boxplots of Numerical Features")
      plt.show()
```

(appendix 0.1)

```
# Set figure size and adjust layout for better clarity
fig, axes = plt.subplots(nrows=4, ncols=4, figsize=(16, 12))  # Adjust grid size if needed
fig.suptitle("Histograms of Numerical Features", fontsize=16, fontweight="bold")

# Flatten axes array for easy iteration
axes = axes.flatten()

# Generate histograms for each numerical feature
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns

for i, col in enumerate(numerical_cols):
    if i < len(axes):  # Ensure it does not go out of bounds
        df[col].hist(ax=axes[i], bins=30, edgecolor='black', alpha=0.7)
        axes[i].set_title(col, fontsize=12, fontweight="bold")
        axes[i].tick_params(axis='both', labelsize=10)

# Adjust layout for readability
plt.tight_layout(rect=[0, 0, 1, 0.96])  # Prevent title overlap
plt.show()
```

(appendix 0.2)

```
# Import necessary functions from scipy.stats
from scipy.stats import skew, kurtosis

# Select only numeric columns
numeric_columns =df.select_dtypes(include=[np.number]).columns

# Calculate skewness and kurtosis for numeric columns
skewness = df[numeric_columns].apply(skew)
kurt = df[numeric_columns].apply(kurtosis)

# Calculate mode for numeric columns
modes = df[numeric_columns].apply(lambda col: col.mode().iloc[0] if not col.mode().empty else None)

# Create a DataFrame to store statistics
statistics_data = pd.DataFrame({'Skewness': skewness, 'Kurtosis': kurt, 'Mode': modes})

# Display mode, skewness, and kurtosis statistics for each column
print(statistics_data)
```

(appendix 0.4)

```
[146] # Display class distribution
      plt.figure(figsize=(8, 6))
      sns.countplot(x='quality', data=df, palette='viridis')
      plt.title("Class Distribution of Target Variable - Quality")
      plt.xlabel("Quality Category")
      plt.ylabel("Count")
      plt.show()

      # Print class distribution counts
      print(df['quality'].value_counts())
```

(appendix 0.5)

```
[148] # Compute correlation matrix
      correlation_matrix = df.corr()

      # Plot heatmap
      plt.figure(figsize=(12, 8))
      sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
      plt.title("Correlation Matrix of Dataset")
      plt.show()
```

(appendix 0.7)

```
# Set figure size and adjust layout for better clarity
fig, axes = plt.subplots(nrows=4, ncols=4, figsize=(18, 14))  # Adjust grid size if needed
fig.suptitle("Distribution of Numerical Features", fontsize=18, fontweight="bold")

# Flatten axes array for easy iteration
axes = axes.flatten()

# Generate histograms with KDE for each numerical feature
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns

for i, col in enumerate(numerical_cols):
    if i < len(axes):  # Ensure it does not go out of bounds
        sns.histplot(df[col], ax=axes[i], bins=30, kde=True, edgecolor='black', alpha=0.6)
        axes[i].set_title(col, fontsize=12, fontweight="bold")
        axes[i].tick_params(axis='both', labelsize=10)

# Adjust layout for readability
plt.tight_layout(rect=[0, 0, 1, 0.96])  # Prevent title overlap
plt.show()
```

(appendix 0.3)

```python
# Function to detect outliers using IQR method
def detect_outliers_iqr(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data[(data[column] < lower_bound) | (data[column] > upper_bound)]
    return outliers

# Detect outliers in each numerical column
for col in df.select_dtypes(include=['float64', 'int64']).columns:
    outliers = detect_outliers_iqr(df, col)
    print(f"Outliers in {col}: {len(outliers)}")

# Boxplot visualization with three plots per row
num_cols = df.select_dtypes(include=['float64', 'int64']).columns
num_plots = len(num_cols)
cols_per_row = 3
rows = (num_plots // cols_per_row) + (num_plots % cols_per_row > 0)

plt.figure(figsize=(15, 5 * rows))
for i, col in enumerate(num_cols, 1):
    plt.subplot(rows, cols_per_row, i)
    sns.boxplot(x=df[col])
    plt.title(f"Boxplot of {col}")
plt.tight_layout()
plt.show()
```

(appendix 0.6)

```python
# Drop target column 'quality' since it's categorical
features_only = df_cleaned.drop(columns=['quality'])

# Set figure size
plt.figure(figsize=(20, 12))

# Create one subplot per feature
for i, col in enumerate(features_only.columns):
    plt.subplot(4, 4, i + 1)  # Adjust rows/cols depending on number of features
    sns.boxplot(data=features_only[col], orient='v', color='skyblue')
    plt.title(col, fontsize=9)
    plt.tight_layout()

plt.suptitle("Boxplots of All Features After Outlier Removal", fontsize=16, y=1.02)
plt.show()
```

(appendix 0.9)

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import LocalOutlierFactor, NearestNeighbors

# Separate features and target
X = df.drop(columns=["quality"])
y = df["quality"]

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 1. KNN Outlier Detection
k = 5

knn = NearestNeighbors(n_neighbors=k)
knn.fit(X_scaled)

# Distance to k-th nearest neighbor
distances, indices = knn.kneighbors(X_scaled)
k_distances = distances[:, -1]  # take distance to the k-th nearest neighbor

# Set threshold (optional: use quantile)
threshold_knn = np.percentile(k_distances, 95)
outliers_knn = k_distances > threshold_knn
```

```python
# 2. Local Outlier Factor (LOF)
lof = LocalOutlierFactor(n_neighbors=k)
y_pred_lof = lof.fit_predict(X_scaled)
outliers_lof = y_pred_lof == -1

# Visualize Outliers
# ------------------------
# Create 2D projection for visualization
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Plotting KNN Outliers
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=outliers_knn, palette={False: "blue", True: "red"})
plt.title("KNN Detected Outliers")
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")

# Plotting LOF Outliers
plt.subplot(1, 2, 2)
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=outliers_lof, palette={False: "blue", True: "orange"})
plt.title("LOF Detected Outliers")
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.tight_layout()
plt.show()

# Optional: Remove Outliers

# Choose one method: e.g., LOF
df_cleaned = df[~outliers_lof].reset_index(drop=True)

print("Original shape:", df.shape)
print("Cleaned shape:", df_cleaned.shape)
```

(appendix 0.8)

```
[153] import matplotlib.pyplot as plt
      import seaborn as sns
      import pandas as pd

      # Choose a few features to compare
      features_to_plot = [
          'Melt temperature',
          'ZUx - Cycle time',
          'SKx - Closing force',
          'APVs - Specific injection pressure peak value'
      ]

      # Re-create scaled DataFrame from earlier step
      X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

      # Set up the plot
      plt.figure(figsize=(14, len(features_to_plot) * 4))

      for i, feature in enumerate(features_to_plot):
          # Plot original
          plt.subplot(len(features_to_plot), 2, 2*i + 1)
          sns.histplot(X[feature], kde=True, bins=30)
          plt.title(f"Original: {feature}")
          plt.xlabel(feature)

          # Plot scaled
          plt.subplot(len(features_to_plot), 2, 2*i + 2)
          sns.histplot(X_scaled_df[feature], kde=True, bins=30)
          plt.title(f"Scaled: {feature}")
          plt.xlabel(feature + " (Standardized)")

      plt.tight_layout()
      plt.show()
```

(appendix 0.10)

```
import seaborn as sns
import matplotlib.pyplot as plt
from statsmodels.stats.outliers_influence import variance_inflation_factor
import pandas as pd

# Use scaled features as input
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

# ------------------------------
# 1. Correlation Matrix (Heatmap)
# ------------------------------
plt.figure(figsize=(14, 10))
sns.heatmap(X_scaled_df.corr(), annot=False, cmap='coolwarm', center=0)
plt.title("Correlation Heatmap")
plt.show()

# ------------------------------
# 2. Variance Inflation Factor (VIF)
# ------------------------------
# Calculate VIF for each feature
vif_data = pd.DataFrame()
vif_data["Feature"] = X_scaled_df.columns
vif_data["VIF"] = [variance_inflation_factor(X_scaled_df.values, i) for i in range(X_scaled_df.shape[1])]

# Display VIF
print(vif_data.sort_values(by="VIF", ascending=False))
```

(appendix 0.11)

```python
from scipy.stats import f_oneway
import pandas as pd

# Assume df_cleaned is your cleaned dataset
# quality must be the original categorical column (not label-encoded)
anova_results = {}

for col in df_cleaned.columns:
    if col != "quality":
        groups = [df_cleaned[df_cleaned["quality"] == group][col] for group in df_cleaned["quality"].unique()]
        stat, p = f_oneway(*groups)
        anova_results[col] = {'F-statistic': stat, 'p-value': p}

# Convert to DataFrame for display
anova_df = pd.DataFrame(anova_results).T
anova_df["Significant"] = anova_df["p-value"] < 0.05  # Flag significance

print(anova_df.sort_values(by="p-value"))
```

(appendix 0.12)

```python
[160] top_features = anova_df.sort_values("p-value").head(2).index

    for feature in top_features:
        plt.figure(figsize=(8, 4))
        sns.boxplot(x="quality", y=feature, data=df_cleaned)
        plt.title(f"{feature} by Quality Class")
        plt.tight_layout()
        plt.show()
```

(appendix 0.13)

‘

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Originality & Use of Generative AI Statement

I understand that to use the work and ideas of others, including AI generated output, without full acknowledgement, is academic misconduct.

I confirm that this coursework submission is all my own, original work and that all sources, summaries, paraphrases and quotes are fully referenced as required by the LSBU Academic Regulations.

DECLARATION OF AI USE:

I ***DID*** use Generative AI technology in the development, writing, or editing of this assignment.

(delete as appropriate)

If you did use Generative AI, please provide detailed responses to the following items:

1. Specify the tools (e.g. ChatGPT, Copilot..) and the purposes for using Generative AI technology in this assignment. Clearly explain how the AI technology assisted in the development, writing, or editing processes.

    - I have used ChatGPT to get some knowledge about machine learning logic and code that I have used for coursework.
    - Also, I have used Claude.ai to get a proper idea about machine learning logic and some Python code because it generates proper coding solutions with explanations.

2. Outline the sections or parts of the assignment that were developed, written, or edited with the assistance of generative AI technology.

    - I have used AI technology during my model training part to gain knowledge about coding with explanations.

3. Provide 2-3 examples of prompts you used when using AI tools for this assignment.

    - Please just explain why we used the KNN and LOF methods to remove outliers instead of the IQR method and what the difference is between them.
    - What is the ANOVA testing and why do we use it during the preprocessing

4. Reflect on how Generative AI technology contributed to the assignment, including its limitations and advantages in the context of the coursework.

    - With the help of Generative AI, I was able to generate code, debug, and explain my work throughout this project. I was able to understand complex tasks better and was more productive as a result. Using AI tools gave me a deeper understanding of machine learning models, Streamlit, and building an interactive dashboard. My own understanding was still required to implement and adapt the solutions, even though it provided suggestions.

By including this statement in my coursework submission, I attest that the information provided in this Originality and use of Generative AI Statement is accurate and complete to the best of my knowledge. I understand that providing false information is a violation of the LSBU Academic Regulations and may result in academic and/or disciplinary consequences.