Data Loading and Exploration

In [ ]:

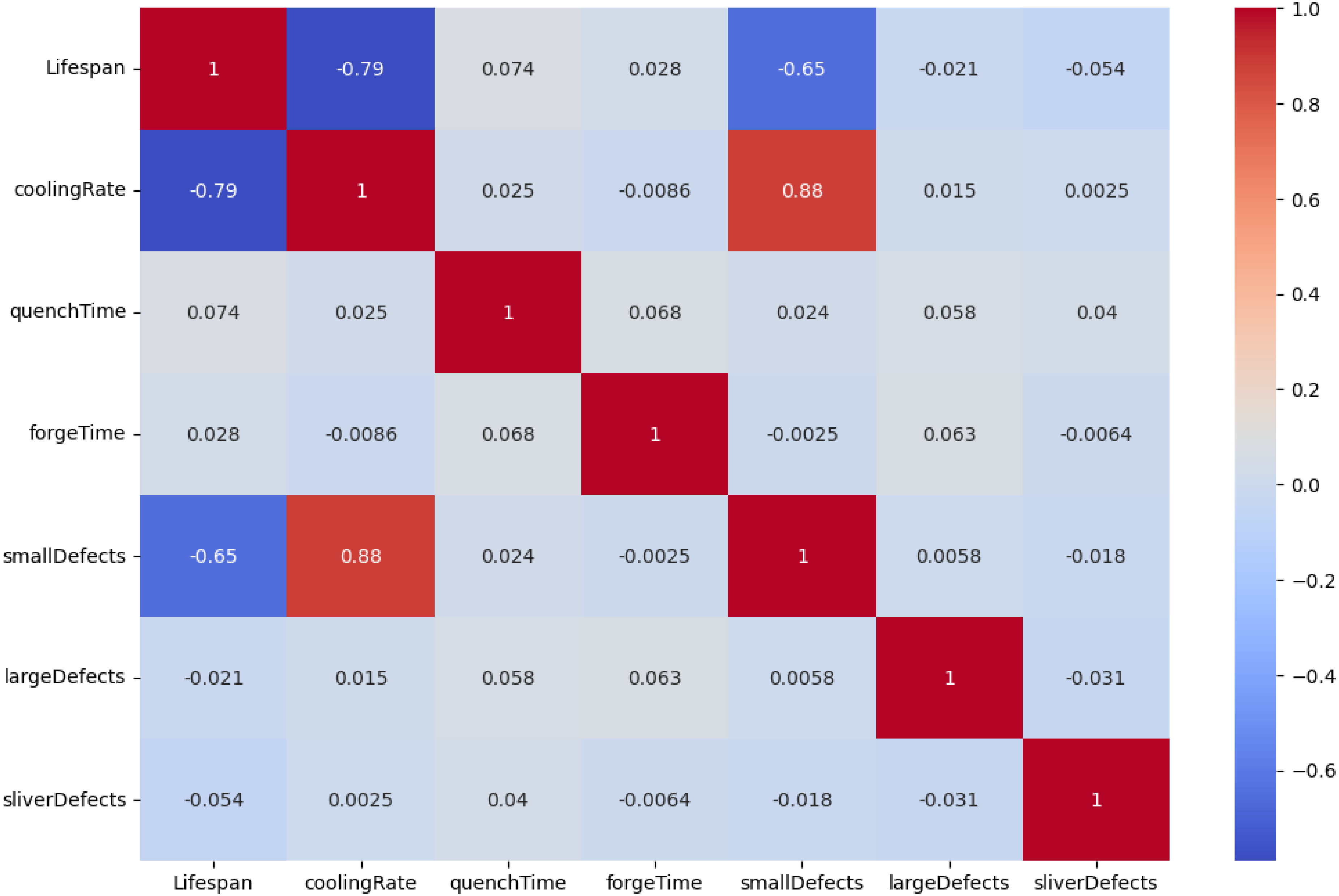
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression , LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
import numpy as np

# Load the dataset
df = pd.read_csv('/content/COMP1801_CourseworkDataset1_tabular (1).csv')

# Display basic information about the dataset
print(df.info())

# Display descriptive statistics
print(df.describe())

# Check for missing values in each column
print(df.isnull().sum())

# Correlation analysis
# Compute the correlation matrix
correlation_matrix = df.corr()

# Plot the correlation matrix as a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
```

```
 ---  ------          --------------  -----
  0   Lifespan        1000 non-null   float64
  1   partType        1000 non-null   object
  2   microstructure  1000 non-null   object
  3   coolingRate     1000 non-null   int64
  4   quenchTime      1000 non-null   float64
  5   forgeTime       1000 non-null   float64
  6   smallDefects    1000 non-null   int64
  7   largeDefects    1000 non-null   int64
  8   sliverDefects   1000 non-null   int64
  9   seedLocation    1000 non-null   object
  10  castType        1000 non-null   object
dtypes: float64(3), int64(4), object(4)
memory usage: 86.1+ KB
None
          Lifespan  coolingRate   quenchTime    forgeTime  smallDefects  \
count  1000.000000  1000.000000  1000.000000  1000.000000    1000.00000
mean   1366.373468    17.480000     2.786059     5.497136      13.37100
std     519.026551     7.557958     1.320935     2.613501       8.07047
min     115.120563     5.000000     0.501046     1.017799       0.00000
25%     960.976320    11.000000     1.608916     3.203739       8.00000
50%    1470.377014    17.000000     2.824488     5.510765      16.00000
75%    1757.165684    24.000000     3.902389     7.735951      20.00000
max    2380.142759    30.000000     4.990795     9.988511      33.00000

       largeDefects  sliverDefects
count   1000.000000    1000.000000
mean       0.117000       0.286000
std        0.565359       1.351307
min        0.000000       0.000000
25%        0.000000       0.000000
50%        0.000000       0.000000
75%        0.000000       0.000000
max        4.000000      10.000000
Lifespan          0
partType          0
microstructure    0
coolingRate       0
quenchTime        0
forgeTime         0
smallDefects      0
largeDefects      0
sliverDefects     0
seedLocation      0
```

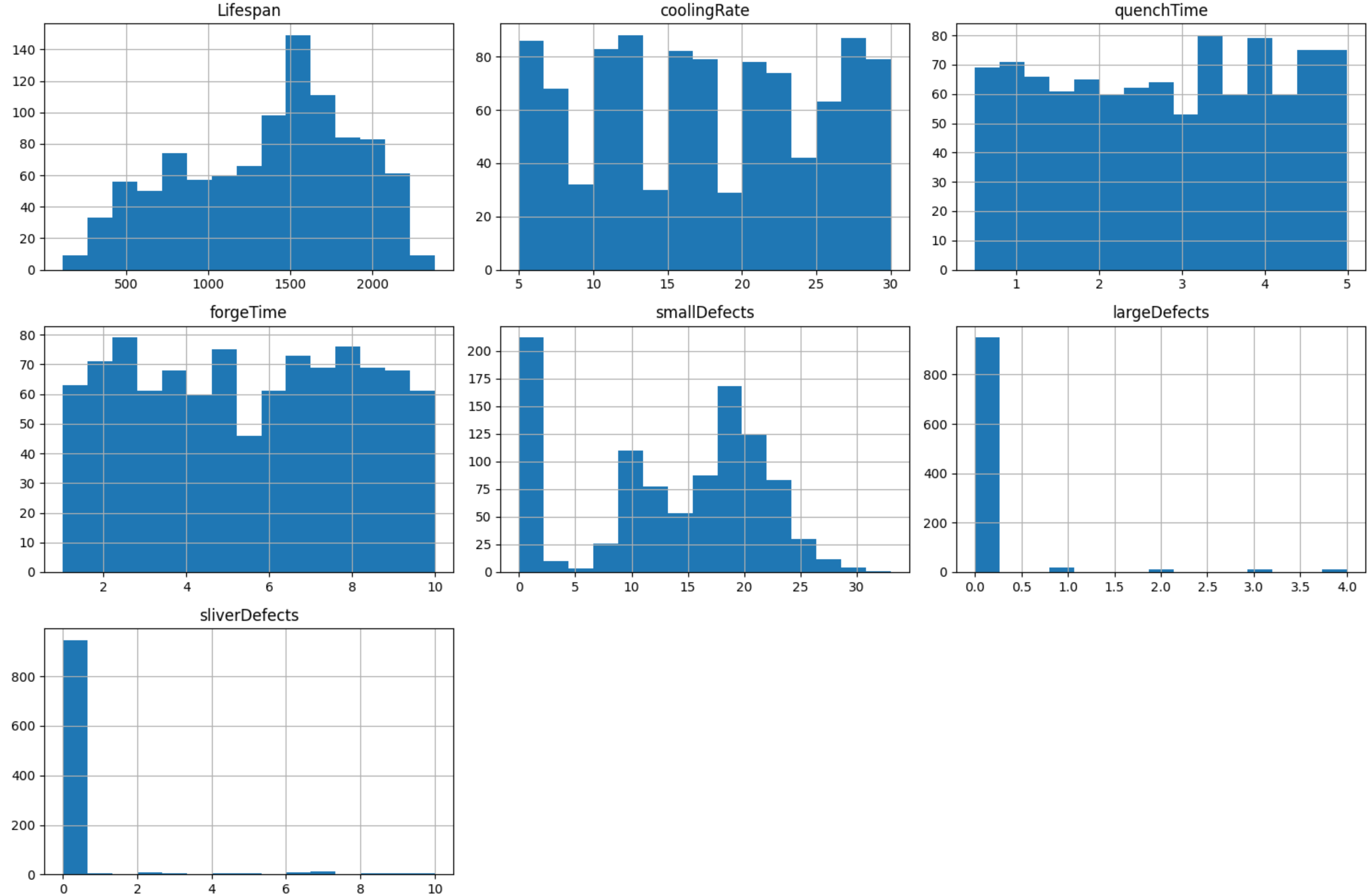
```
castType          0
dtype: int64
```

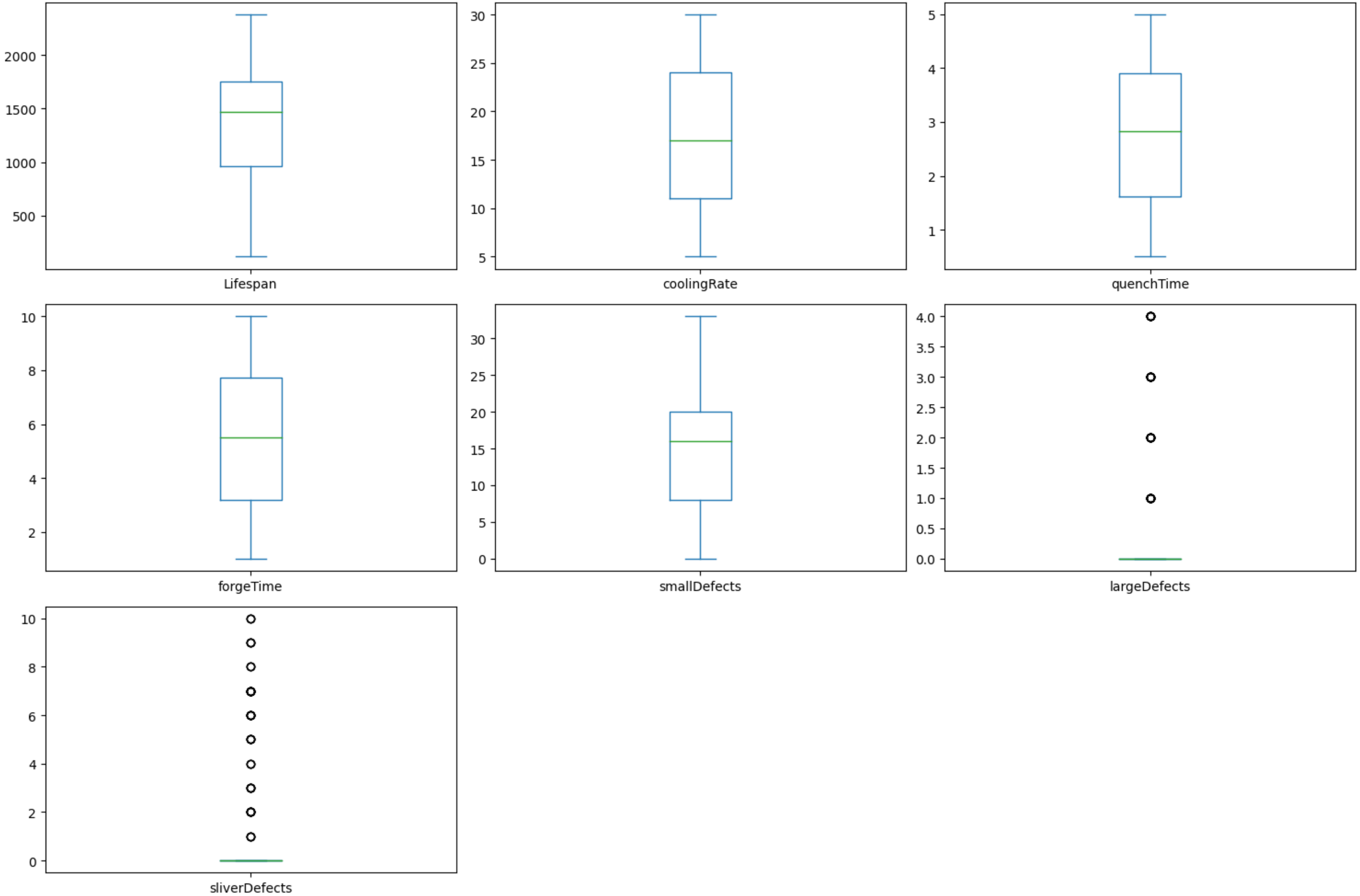
```
<ipython-input-1-9bab57deebee>:30: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
rsion, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  correlation_matrix = df.corr()
```

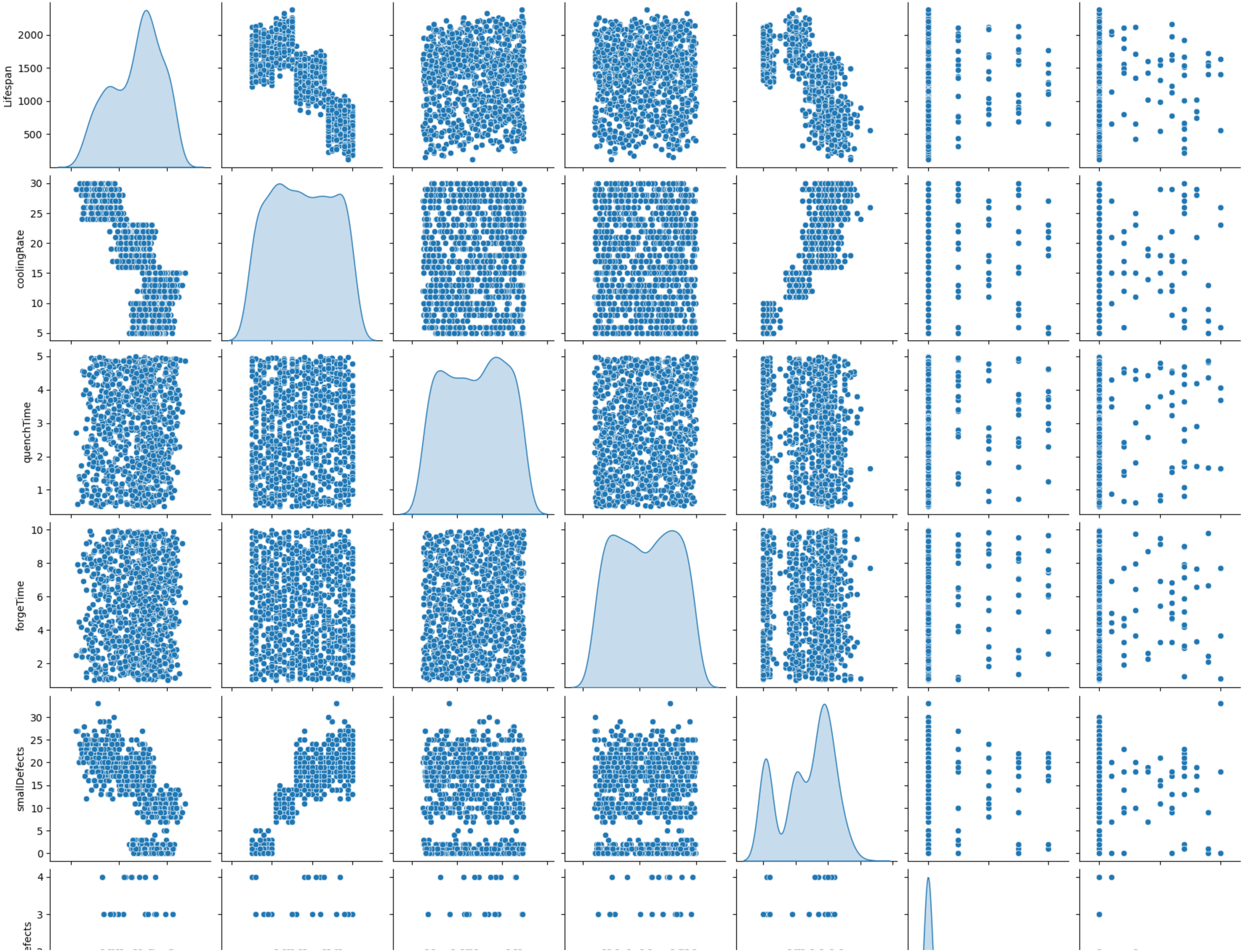


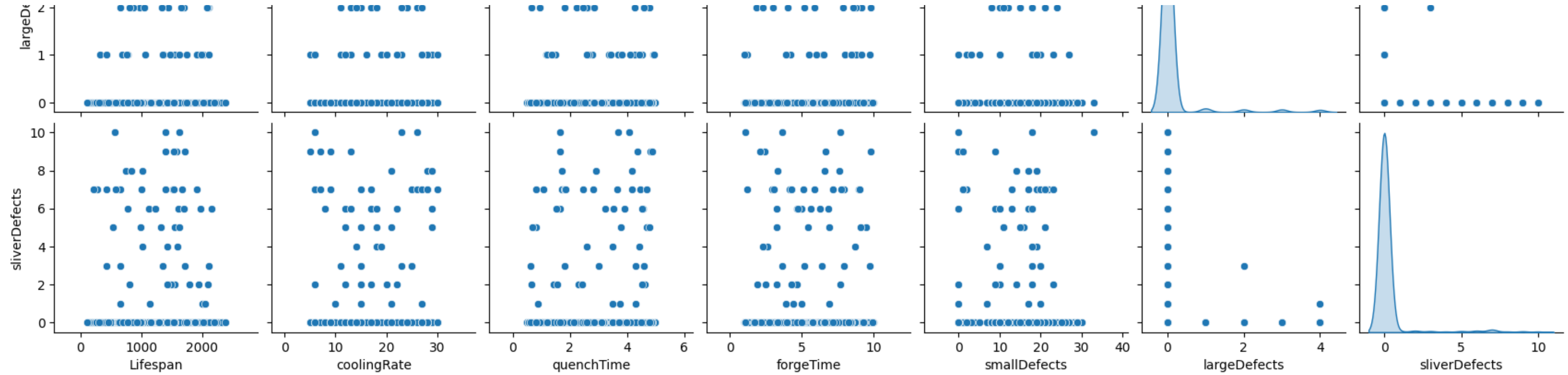
Data Visualization

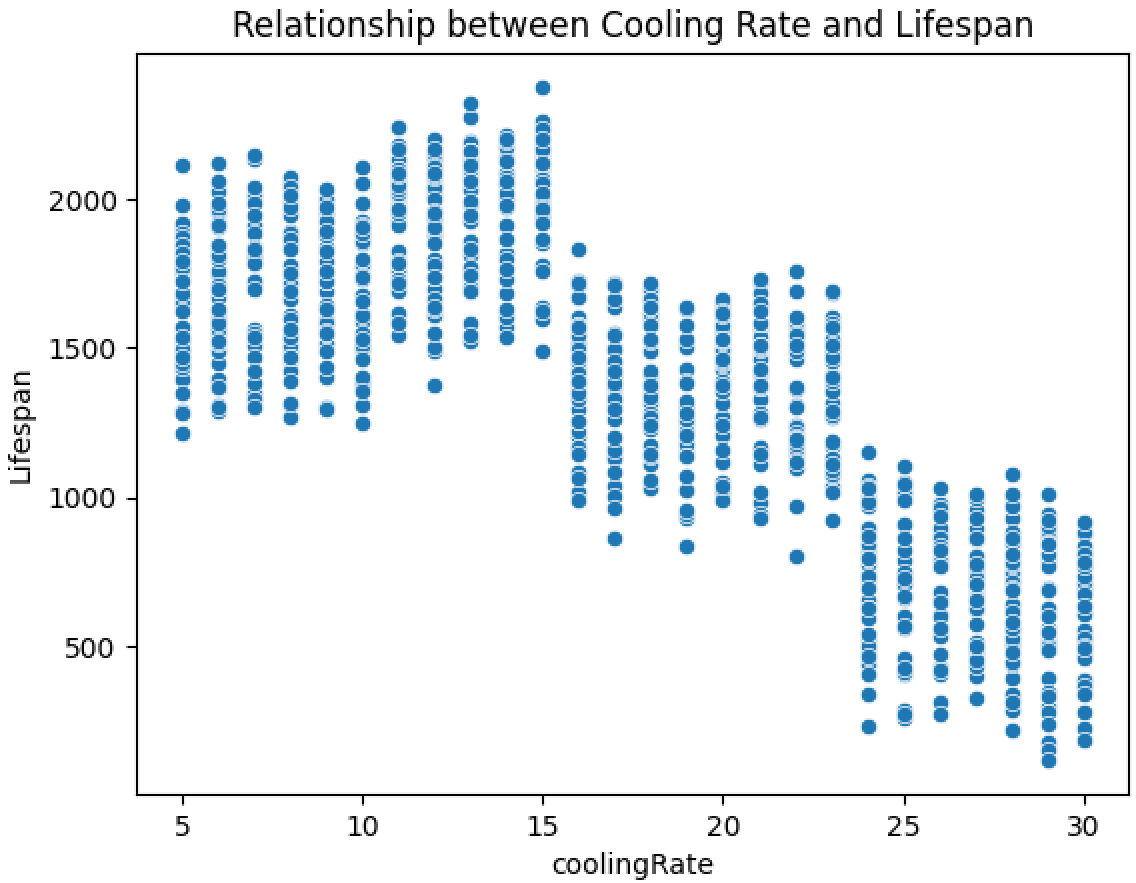
In [ ]:
```
# Plot histograms for all numerical features
df.hist(bins=15, figsize=(15, 10), layout=(3, 3))
plt.tight_layout()
plt.show()

# Plot boxplots for all numerical features
df.plot(kind='box', subplots=True, layout=(3, 3), figsize=(15, 10))
plt.tight_layout()
plt.show()

# Pair plot for a subset of features
sns.pairplot(df, diag_kind='kde')
plt.show()

# Scatter plots showing relationship with Lifespan
sns.scatterplot(data=df, x='coolingRate', y='Lifespan')
plt.title('Relationship between Cooling Rate and Lifespan')
plt.show()

sns.scatterplot(data=df, x='quenchTime', y='Lifespan')
plt.title('Relationship between Quench Time and Lifespan')
plt.show()

sns.scatterplot(data=df, x='forgeTime', y='Lifespan')
plt.title('Relationship between Forge Time and Lifespan')
plt.show()
```

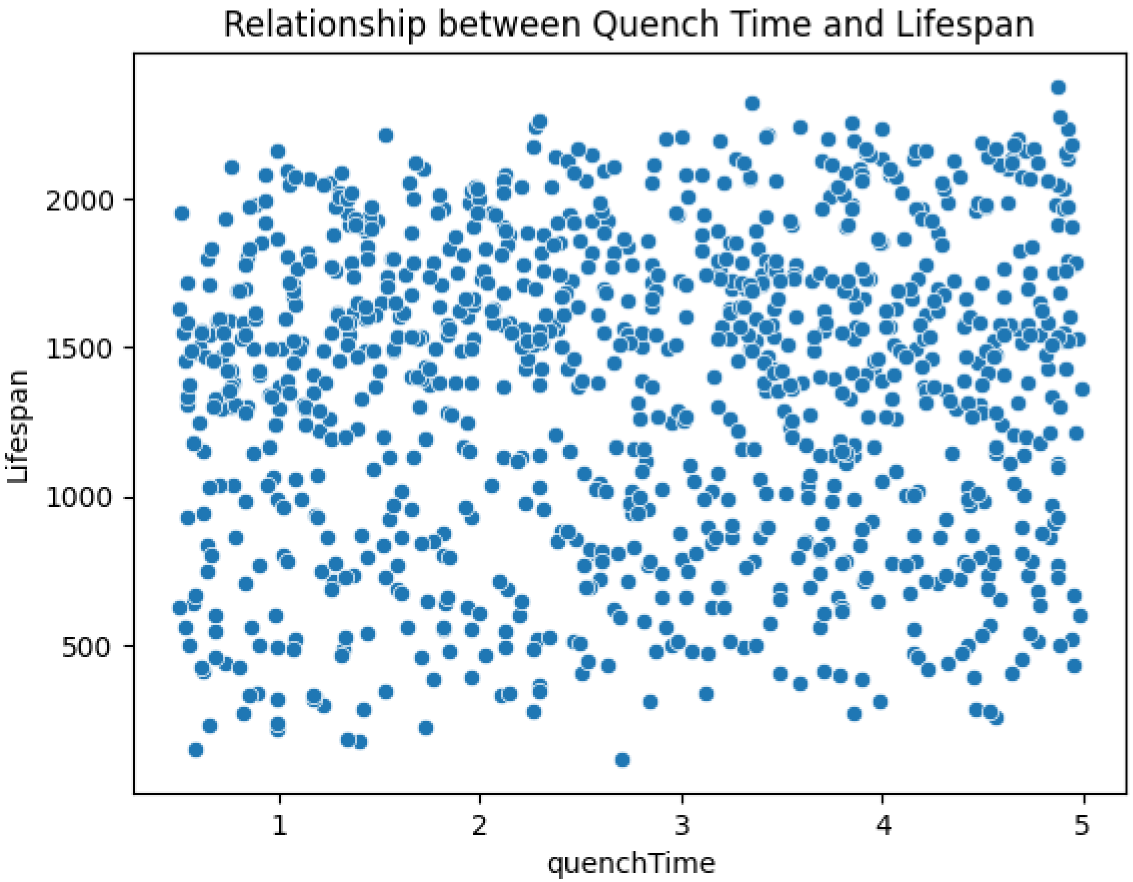

Lifespan
0
20
40
60
80
100
120
140
500
1000
1500
2000
coolingRate
0
20
40
60
80
5
10
15
20
25
30
quenchTime
0
10
20
30
40
50
60
70
80
1
2
3
4
5
forgeTime
0
10
20
30
40
50
60
70
80
2
4
6
8
10
smallDefects
0
25
50
75
100
125
150
175
200
0
5
10
15
20
25
30
largeDefects
0
200
400
600
800
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
sliverDefects
0
200
400
600
800
0
2
4
6
8
10

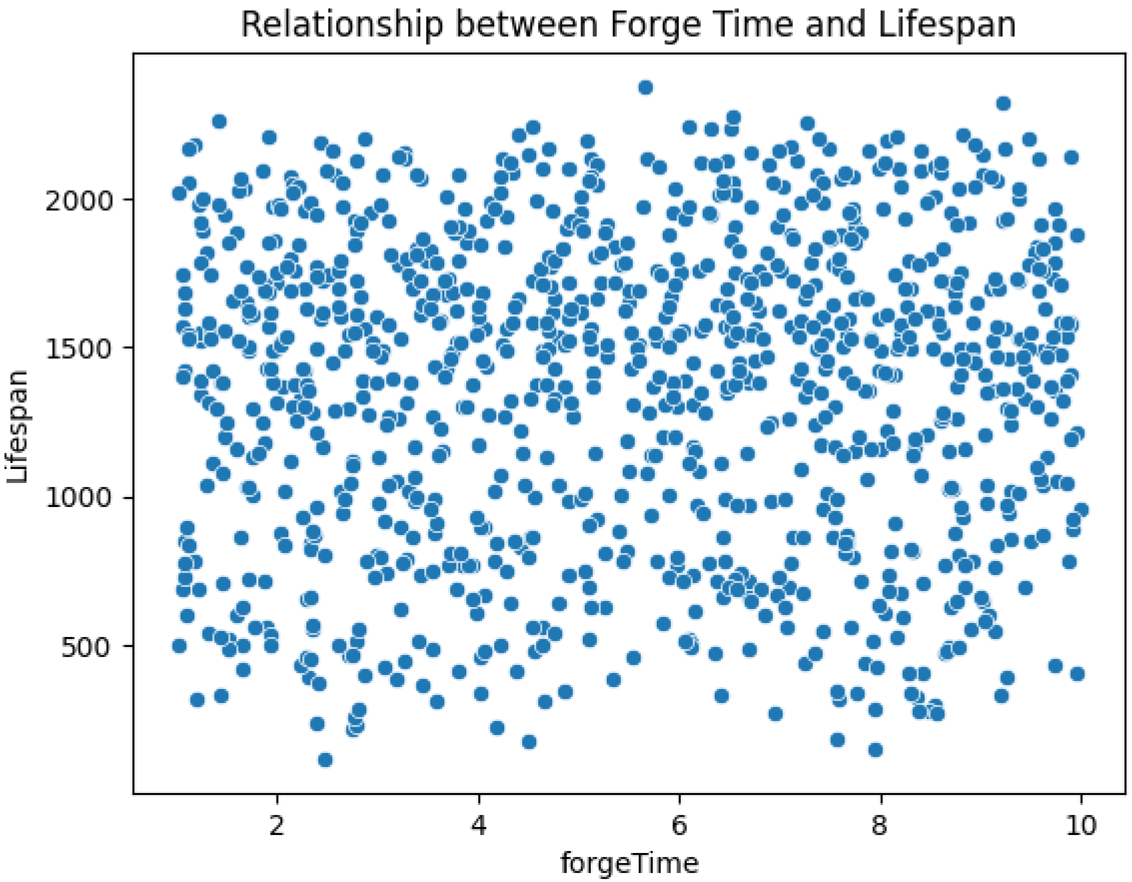

Lifespan
coolingRate
quenchTime
forgeTime
smallDefects
largeDefects
sliverDefects


Lifespan
coolingRate
quenchTime
forgeTime
smallDefects
efects


largeDe
sliverDefects
Lifespan
coolingRate
quenchTime
forgeTime
smallDefects
largeDefects
sliverDefects


Relationship between Cooling Rate and Lifespan
Lifespan
coolingRate


Relationship between Quench Time and Lifespan
Lifespan
2000
1500
1000
500
1
2
3
4
5
quenchTime



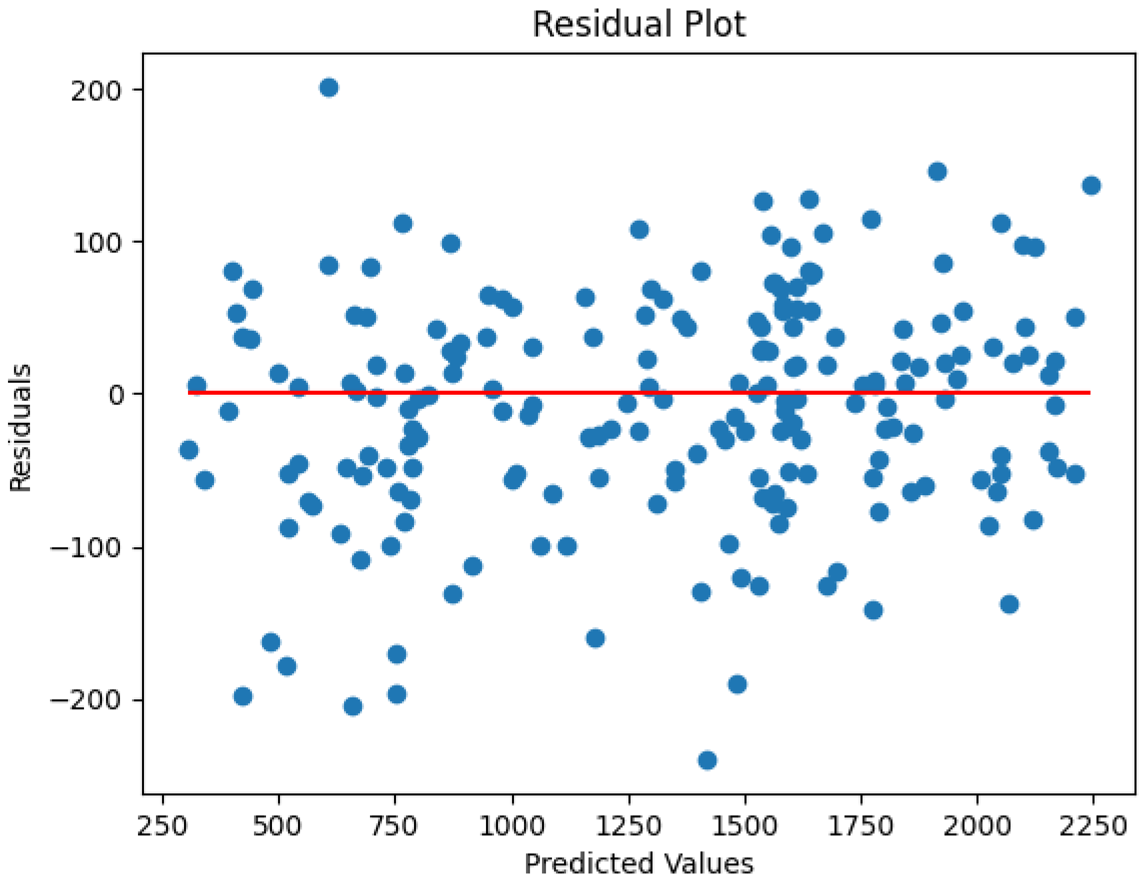
Regression Implementation

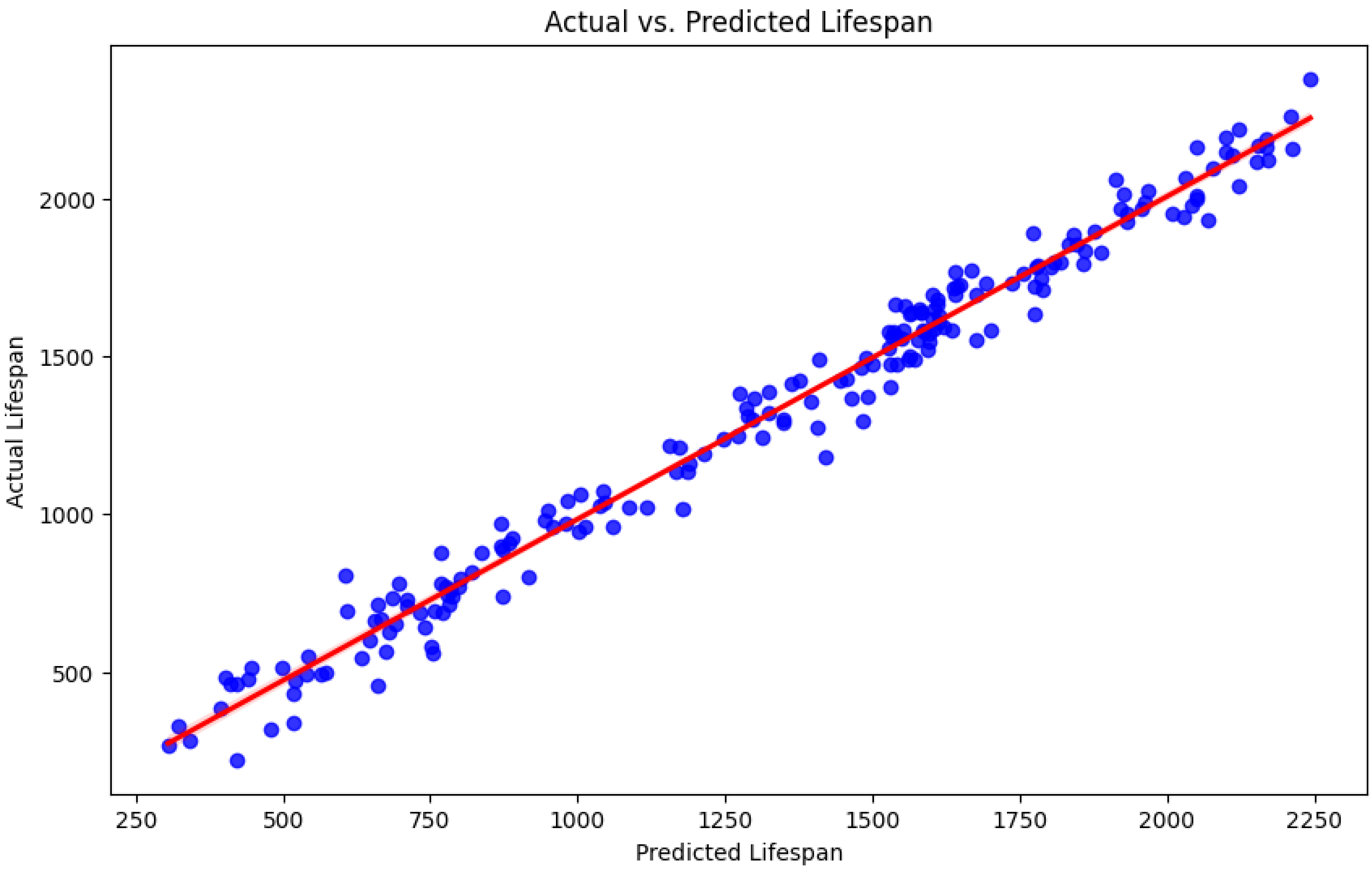
In [ ]:
```
# Feature selection
X = df[['coolingRate', 'quenchTime', 'forgeTime', 'smallDefects', 'largeDefects', 'sliverDefects', 'partType', 'microstructure', '
y = df['Lifespan']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Feature scaling and encoding
numeric_features = ['coolingRate', 'quenchTime', 'forgeTime', 'smallDefects', 'largeDefects', 'sliverDefects']
categorical_features = ['partType', 'microstructure', 'seedLocation', 'castType']

numeric_transformer = Pipeline(steps=[
```

```
    ('scaler', StandardScaler())])

categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)])

# Model selection and training
# Linear Regression
linear_model = Pipeline(steps=[('preprocessor', preprocessor),
                               ('regressor', LinearRegression())])

# Random Forest
rf_model = Pipeline(steps=[('preprocessor', preprocessor),
                           ('regressor', RandomForestRegressor())])

# Decision Tree
dt_model = Pipeline(steps=[('preprocessor', preprocessor),
                           ('regressor', DecisionTreeRegressor())])

# Hyperparameter tuning
param_grid = {
    'regressor__n_estimators': [100, 200],
    'regressor__max_depth': [None, 10, 20],
}

grid_search = GridSearchCV(rf_model, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Best model after tuning
best_model = grid_search.best_estimator_

# Model Evaluation
y_pred = best_model.predict(X_test)
print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("Mean Absolute Error:", mean_absolute_error(y_test, y_pred))
print("R-squared:", r2_score(y_test, y_pred))

# Predicting using the test set
y_pred = best_model.predict(X_test)
```

```
# Calculating residuals
residuals = y_test - y_pred

# Plotting the Residuals
plt.scatter(y_pred, residuals)
plt.hlines(y = 0, xmin = y_pred.min(), xmax = y_pred.max(), color = 'red')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()

plt.figure(figsize=(10,6))
sns.regplot(x=y_pred, y=y_test, fit_reg=True, scatter_kws={"color": "blue"}, line_kws={"color": "red"})
plt.xlabel('Predicted Lifespan')
plt.ylabel('Actual Lifespan')
plt.title('Actual vs. Predicted Lifespan')
plt.show()
```

```
Mean Squared Error: 5505.302189210612
Mean Absolute Error: 57.80574994131826
R-squared: 0.9808131965342906
```


Residual Plot
200
100
0
−100
−200
Residuals
250
500
750
1000
1250
1500
1750
2000
2250
Predicted Values



Binary Classification Implementation

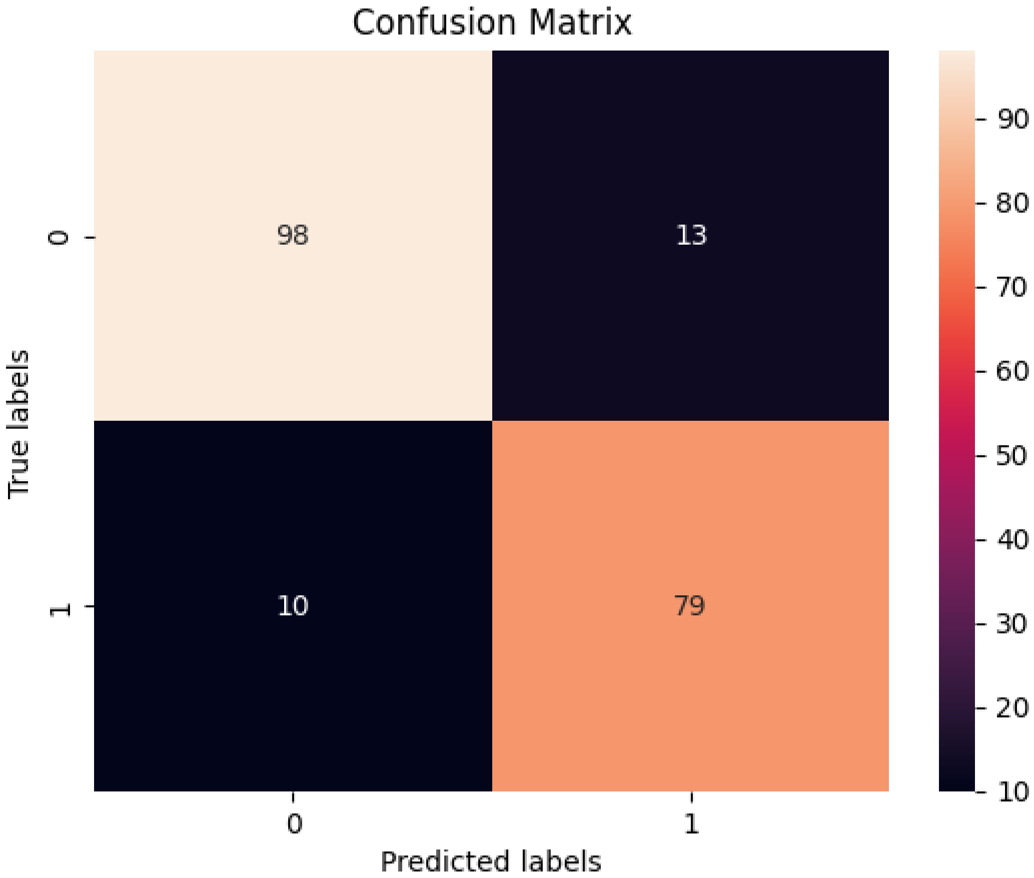
In [ ]:

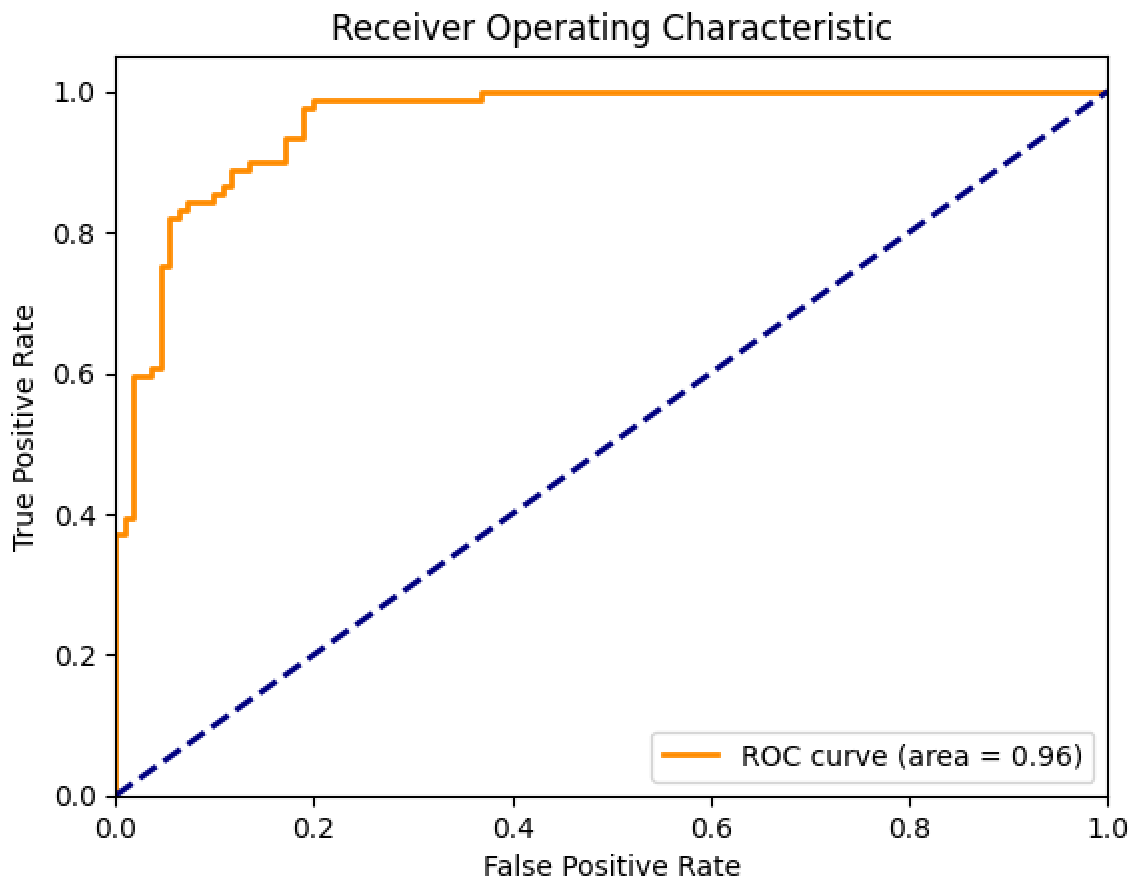
```
from sklearn.ensemble import RandomForestClassifier
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
from sklearn.metrics import classification_report , roc_curve, auc

# Convert 'Lifespan' to binary target
df['is_defective'] = np.where(df['Lifespan'] < 1500, 0, 1)
```

```python
# Features and target
X = df[['coolingRate', 'quenchTime', 'forgeTime', 'smallDefects', 'largeDefects', 'sliverDefects', 'partType', 'microstructure', '
y = df['is_defective']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Feature scaling and encoding
numeric_features = ['coolingRate', 'quenchTime', 'forgeTime', 'smallDefects', 'largeDefects', 'sliverDefects']
categorical_features = ['partType', 'microstructure', 'seedLocation', 'castType']

numeric_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())])

categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)])

# Define SMOTE for resampling
smote = SMOTE()

# Define the classifiers
classifiers = {
    'Logistic Regression': LogisticRegression(),
    'SVM': SVC(probability=True),
    'Random Forest': RandomForestClassifier()
}

# Function to run, evaluate, and visualize a model
def run_model(model_name):
    classifier = classifiers[model_name]
    pipeline = ImbPipeline(steps=[('preprocessor', preprocessor),
                                  ('smote', smote),
                                  ('classifier', classifier)])

    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)
    y_proba = pipeline.predict_proba(X_test)[:, 1]
```

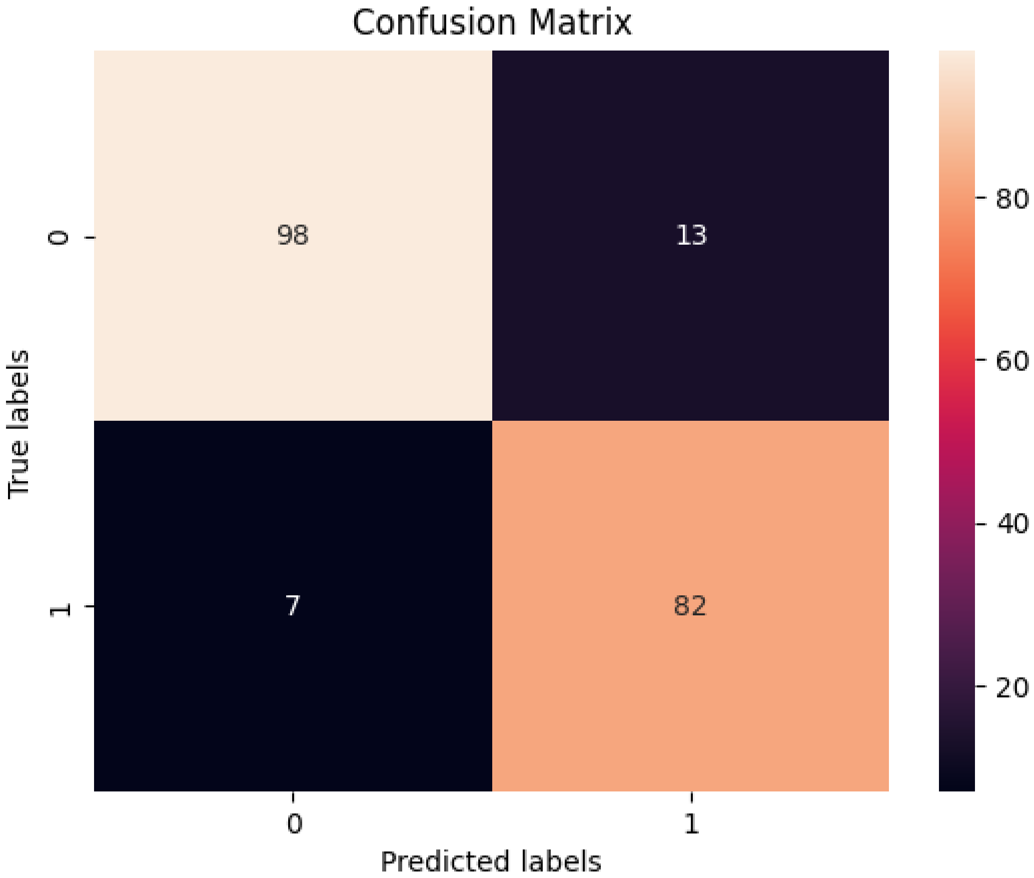
```
    # Evaluation metrics
    print(f"Model: {model_name}")
    print(classification_report(y_test, y_pred))

    # Confusion Matrix
    conf_matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(conf_matrix, annot=True, fmt='g')
    plt.xlabel('Predicted labels')
    plt.ylabel('True labels')
    plt.title('Confusion Matrix')
    plt.show()

    # ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)
    plt.figure()
    plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic')
    plt.legend(loc="lower right")
    plt.show()

# Run and evaluate each model
for model_name in classifiers:
    run_model(model_name)
```

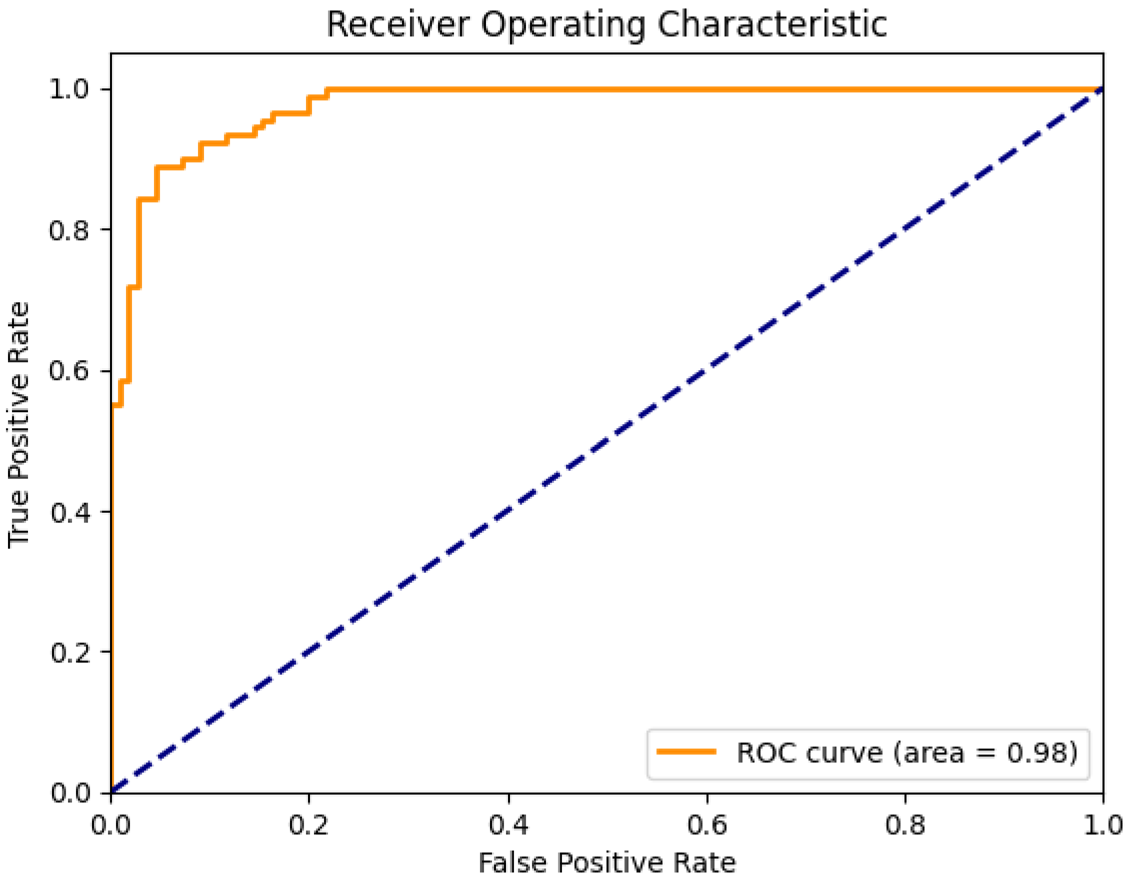
```
Model: Logistic Regression
              precision    recall  f1-score   support

           0       0.91      0.88      0.89       111
           1       0.86      0.89      0.87        89

    accuracy                           0.89       200
   macro avg       0.88      0.89      0.88       200
weighted avg       0.89      0.89      0.89       200
```


Confusion Matrix
98
13
10
79
0
1
True labels
0
1
Predicted labels
90
80
70
60
50
40
30
20
10

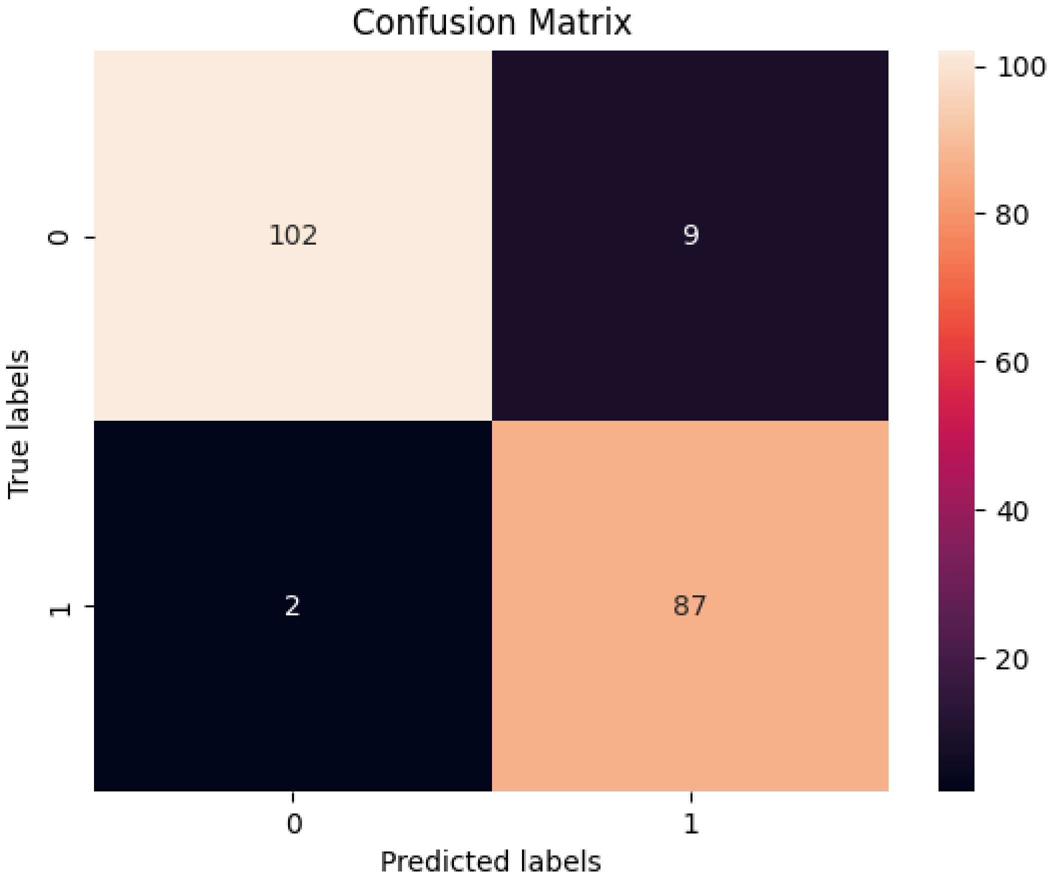


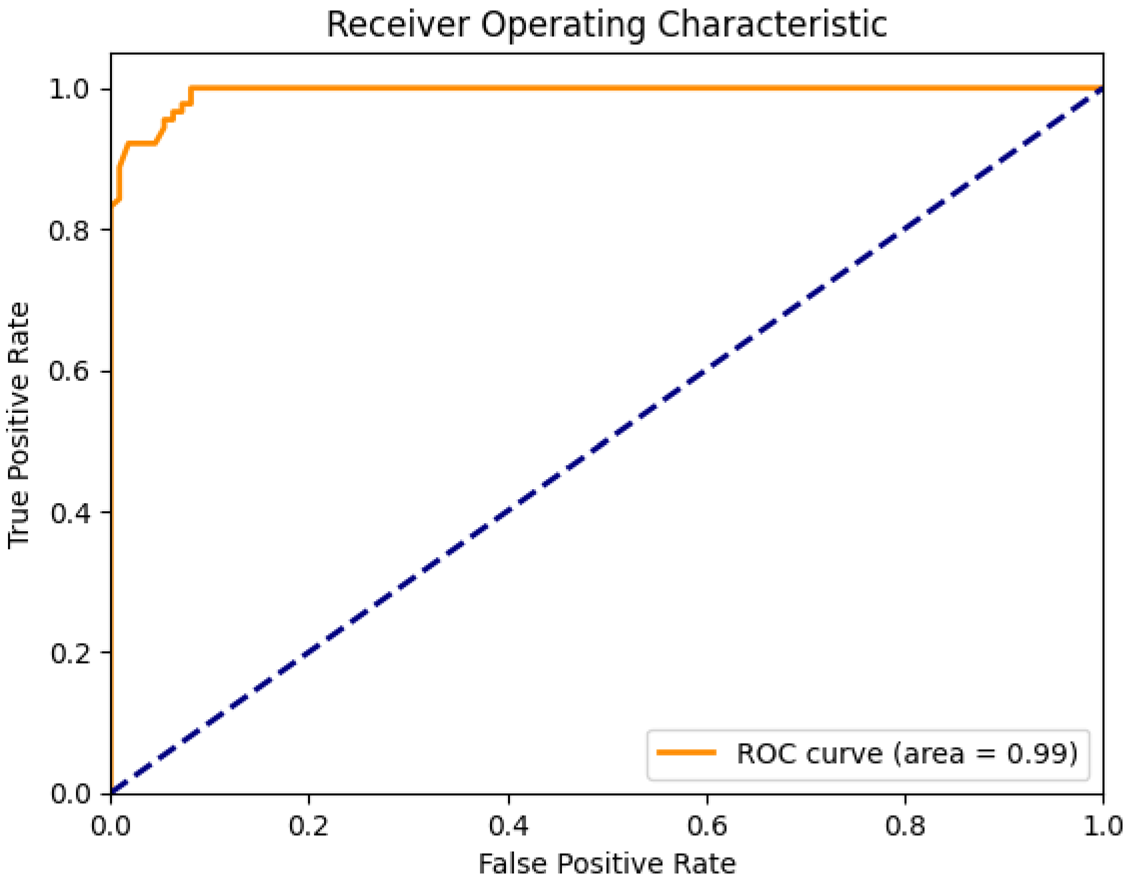

```
Model: SVM
              precision    recall  f1-score   support

           0       0.93      0.88      0.91       111
           1       0.86      0.92      0.89        89

    accuracy                           0.90       200
   macro avg       0.90      0.90      0.90       200
weighted avg       0.90      0.90      0.90       200
```


Confusion Matrix
True labels
Predicted labels
0
1
0
1
98
13
7
82
80
60
40
20




```
Model: Random Forest
              precision    recall  f1-score   support

           0       0.98      0.92      0.95       111
           1       0.91      0.98      0.94        89

    accuracy                           0.94       200
   macro avg       0.94      0.95      0.94       200
weighted avg       0.95      0.94      0.95       200
```


Confusion Matrix
102
9
2
87
True labels
0
1
Predicted labels
0
1
100
80
60
40
20



Convolutional Neural Network Implementation

In [25]:

```
import zipfile
import os

# Path to the zip file and extraction directory
zip_path = '/content/COMP1801_CourseworkDataset2_images (1).zip'
extract_dir = '/content/sample_data/extracted'

# Unzipping the file
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(extract_dir)

print("Dataset unzipped successfully to:", extract_dir)
```

```
Dataset unzipped successfully to: /content/sample_data/extracted
```

In [29]:

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import shutil

# Load the metadata file
metadata_path = '/content/sample_data/extracted/COMP1801_CourseworkDataset2_images/COMP1801_CourseworkDataset2_images_metadata.csv
metadata = pd.read_csv(metadata_path)

# Display the first few rows of the dataframe
print(metadata.head())

# Load the metadata file
metadata_path = '/content/COMP1801_CourseworkDataset2_images/COMP1801_CourseworkDataset2_images/COMP1801_CourseworkDataset2_images_
metadata = pd.read_csv(metadata_path)

# Directory containing the unorganized images
image_dir = '/content/COMP1801_CourseworkDataset2_images/COMP1801_CourseworkDataset2_images'

# Base directory for the organized images
base_dir = '/content/organized_images'
os.makedirs(base_dir, exist_ok=True)

# Iterate over the metadata and organize images
for index, row in metadata.iterrows():
    # Get the defect type (create a 'No Defect' directory for 'None')
    defect_type = row['Type'] if row['Defect'] == 'Yes' else 'No Defect'

    # Create a directory for the defect type if it doesn't exist
    defect_dir = os.path.join(base_dir, defect_type)
    os.makedirs(defect_dir, exist_ok=True)

    # Source and destination paths
    src_path = os.path.join(image_dir, row['Image Filename'])
    dst_path = os.path.join(defect_dir, row['Image Filename'])

    # Copy the image to the new directory
    shutil.copy(src_path, dst_path)

print("Images organized successfully.")
```

```
  Image Filename Defect      Type
0     scan_0.png    Yes  Splinter
1     scan_1.png     No      None
2     scan_2.png    Yes  Multiple
3     scan_3.png     No      None
4     scan_4.png     No      None
Images organized successfully.
```

In [31]:

```
# Base directory where images are currently organized
base_dir = '/content/organized_images'

# New directories for training and validation sets
train_dir = '/content/train'
validation_dir = '/content/validation'
os.makedirs(train_dir, exist_ok=True)
os.makedirs(validation_dir, exist_ok=True)

# Get the list of defect types (subdirectories in base_dir)
defect_types = [d for d in os.listdir(base_dir) if os.path.isdir(os.path.join(base_dir, d))]

# Split images for each defect type into train and validation sets
for defect in defect_types:
    # Paths for defect type in base, train, and validation directories
    defect_base_dir = os.path.join(base_dir, defect)
    defect_train_dir = os.path.join(train_dir, defect)
    defect_validation_dir = os.path.join(validation_dir, defect)

    # Create subdirectories in train and validation directories
    os.makedirs(defect_train_dir, exist_ok=True)
    os.makedirs(defect_validation_dir, exist_ok=True)

    # List of images for this defect type
    images = [f for f in os.listdir(defect_base_dir) if os.path.isfile(os.path.join(defect_base_dir, f))]

    # Splitting images into train and validation sets
    train_imgs, val_imgs = train_test_split(images, test_size=0.2, random_state=42)

    # Copy images to respective directories
    for img in train_imgs:
        shutil.copy(os.path.join(defect_base_dir, img), os.path.join(defect_train_dir, img))
    for img in val_imgs:
        shutil.copy(os.path.join(defect_base_dir, img), os.path.join(defect_validation_dir, img))
```

```
print("Images split into train and validation directories.")
```

```
Images split into train and validation directories.
```

In [32]:
```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Data augmentation for training data and rescaling
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True)

# Rescaling for validation data
validation_datagen = ImageDataGenerator(rescale=1./255)

# Data generators for training and validation sets
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(150, 150),
    batch_size=32,
    class_mode='categorical')

validation_generator = validation_datagen.flow_from_directory(
    validation_dir,
    target_size=(150, 150),
    batch_size=32,
    class_mode='categorical')
```

```
Found 799 images belonging to 4 classes.
Found 201 images belonging to 4 classes.
```

In [33]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

# CNN architecture
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 3)),
    MaxPooling2D(2, 2),
```

```
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D(2, 2),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D(2, 2),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(4, activation='softmax')  # 4 classes
])

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Training the CNN Model
history = model.fit(
    train_generator,
    steps_per_epoch=25,  # 799 images = batch_size * steps
    epochs=20,  # Start with 20 epochs, adjust based on performance
    validation_data=validation_generator,
    validation_steps=6)  # 201 images = batch_size * steps
```

```
Epoch 1/20
25/25 [==============================] - 67s 3s/step - loss: 1.1140 - accuracy: 0.5632 - val_loss: 0.8045 - val_accuracy: 0.6719
Epoch 2/20
25/25 [==============================] - 46s 2s/step - loss: 0.7349 - accuracy: 0.7922 - val_loss: 0.5681 - val_accuracy: 0.8177
Epoch 3/20
25/25 [==============================] - 58s 2s/step - loss: 0.6153 - accuracy: 0.8160 - val_loss: 0.9455 - val_accuracy: 0.6510
Epoch 4/20
25/25 [==============================] - 49s 2s/step - loss: 0.6496 - accuracy: 0.8110 - val_loss: 0.5165 - val_accuracy: 0.8438
Epoch 5/20
25/25 [==============================] - 47s 2s/step - loss: 0.5639 - accuracy: 0.8310 - val_loss: 0.5088 - val_accuracy: 0.8281
Epoch 6/20
25/25 [==============================] - 46s 2s/step - loss: 0.5184 - accuracy: 0.8423 - val_loss: 0.5151 - val_accuracy: 0.8021
Epoch 7/20
25/25 [==============================] - 47s 2s/step - loss: 0.5079 - accuracy: 0.8498 - val_loss: 0.5930 - val_accuracy: 0.7969
Epoch 8/20
25/25 [==============================] - 49s 2s/step - loss: 0.4519 - accuracy: 0.8623 - val_loss: 0.2814 - val_accuracy: 0.9062
Epoch 9/20
25/25 [==============================] - 48s 2s/step - loss: 0.4314 - accuracy: 0.8736 - val_loss: 0.3094 - val_accuracy: 0.8958
Epoch 10/20
25/25 [==============================] - 48s 2s/step - loss: 0.3200 - accuracy: 0.8911 - val_loss: 0.1955 - val_accuracy: 0.9219
Epoch 11/20
25/25 [==============================] - 46s 2s/step - loss: 0.2814 - accuracy: 0.9099 - val_loss: 0.2130 - val_accuracy: 0.9167
Epoch 12/20
25/25 [==============================] - 46s 2s/step - loss: 0.2650 - accuracy: 0.9212 - val_loss: 0.2248 - val_accuracy: 0.9219
```

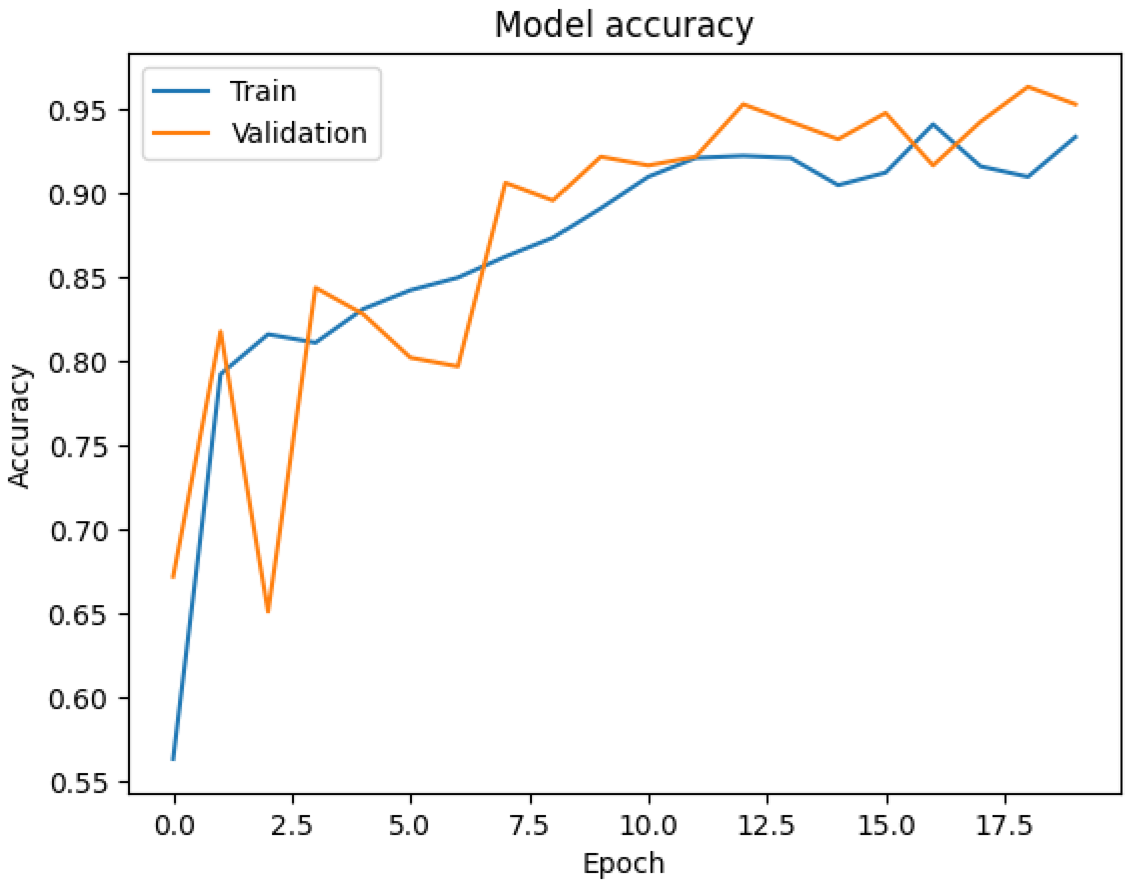
```
Epoch 13/20
25/25 [==============================] - 47s 2s/step - loss: 0.2401 - accuracy: 0.9224 - val_loss: 0.1450 - val_accuracy: 0.9531
Epoch 14/20
25/25 [==============================] - 48s 2s/step - loss: 0.2131 - accuracy: 0.9212 - val_loss: 0.1822 - val_accuracy: 0.9427
Epoch 15/20
25/25 [==============================] - 46s 2s/step - loss: 0.2531 - accuracy: 0.9049 - val_loss: 0.2388 - val_accuracy: 0.9323
Epoch 16/20
25/25 [==============================] - 46s 2s/step - loss: 0.2908 - accuracy: 0.9124 - val_loss: 0.1593 - val_accuracy: 0.9479
Epoch 17/20
25/25 [==============================] - 46s 2s/step - loss: 0.1846 - accuracy: 0.9412 - val_loss: 0.2277 - val_accuracy: 0.9167
Epoch 18/20
25/25 [==============================] - 48s 2s/step - loss: 0.2763 - accuracy: 0.9161 - val_loss: 0.1612 - val_accuracy: 0.9427
Epoch 19/20
25/25 [==============================] - 46s 2s/step - loss: 0.2711 - accuracy: 0.9099 - val_loss: 0.1073 - val_accuracy: 0.9635
Epoch 20/20
25/25 [==============================] - 46s 2s/step - loss: 0.2043 - accuracy: 0.9337 - val_loss: 0.1132 - val_accuracy: 0.9531
```

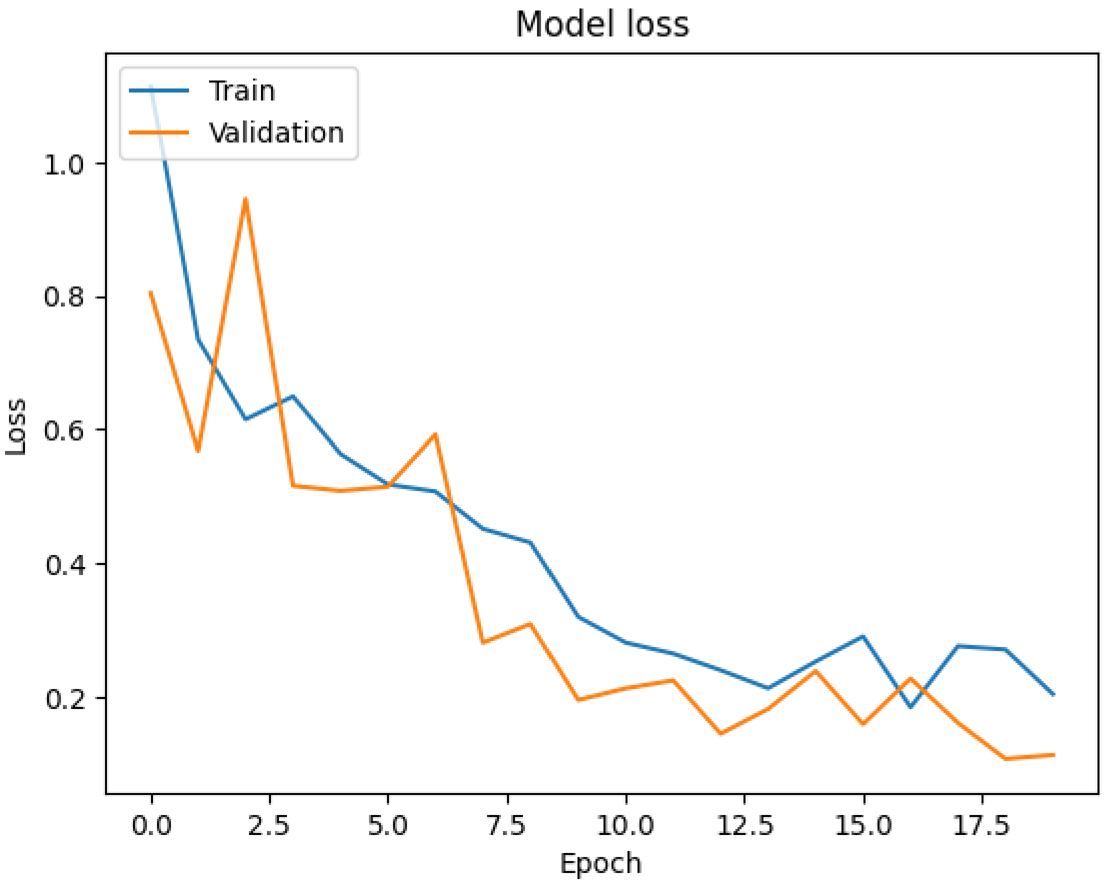
In [34]:

```python
# Evaluate the model
val_loss, val_accuracy = model.evaluate(validation_generator)
print(f'Validation accuracy: {val_accuracy:.2f}')

# Plot training & validation accuracy values
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()

# Plot training & validation loss values
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()

# Predictions
predictions = model.predict(validation_generator)
predicted_classes = np.argmax(predictions, axis=1)
true_classes = validation_generator.classes
```

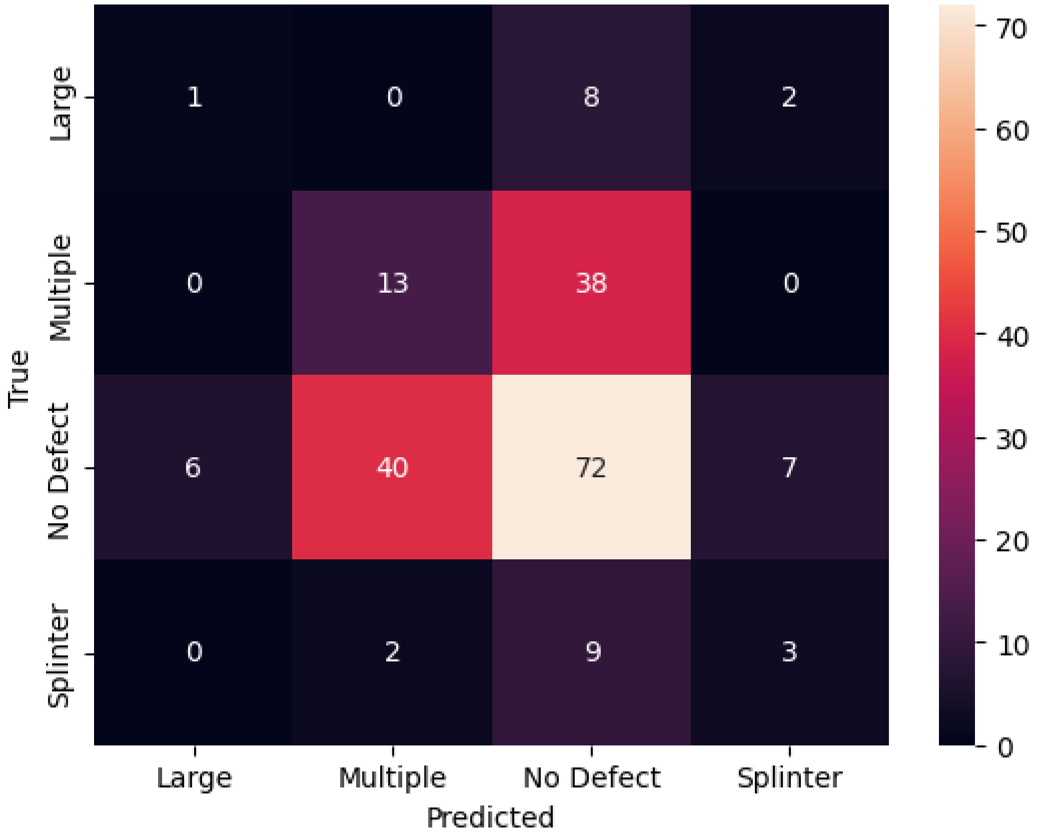
```
class_labels = list(validation_generator.class_indices.keys())

# Classification report
report = classification_report(true_classes, predicted_classes, target_names=class_labels)
print(report)

# Confusion matrix
conf_matrix = confusion_matrix(true_classes, predicted_classes)
sns.heatmap(conf_matrix, annot=True, fmt='g', xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

```
7/7 [==============================] - 3s 343ms/step - loss: 0.1108 - accuracy: 0.9552
Validation accuracy: 0.96
```






```
7/7 [==============================] - 4s 590ms/step
              precision    recall  f1-score   support

       Large       0.14      0.09      0.11        11
    Multiple       0.24      0.25      0.25        51
   No Defect       0.57      0.58      0.57       125
    Splinter       0.25      0.21      0.23        14

    accuracy                           0.44       201
   macro avg       0.30      0.28      0.29       201
weighted avg       0.44      0.44      0.44       201
```



Clustering Implementation

In [36]:

```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Select relevant features for clustering
selected_features = df[['Lifespan', 'coolingRate', 'quenchTime', 'forgeTime']]

# Applying K-Means Clustering
kmeans = KMeans(n_clusters=3, random_state=42)  # Starting with 3 clusters
clusters = kmeans.fit_predict(selected_features)
df['Cluster'] = clusters

# Elbow Method to find the optimal number of clusters
sse = []
for k in range(1, 11):  # Testing k from 1 to 10
```

```python
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(selected_features)
    sse.append(kmeans.inertia_)

plt.plot(range(1, 11), sse)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.show()

# Silhouette Score to validate the cluster number
silhouette_scores = []
for k in range(2, 11):  # Silhouette Score needs at least 2 clusters
    kmeans = KMeans(n_clusters=k, random_state=42)
    cluster_labels = kmeans.fit_predict(selected_features)
    score = silhouette_score(selected_features, cluster_labels)
    silhouette_scores.append(score)

plt.plot(range(2, 11), silhouette_scores)
plt.title('Silhouette Scores')
plt.xlabel('Number of Clusters')
plt.ylabel('Silhouette Score')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
om 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
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```
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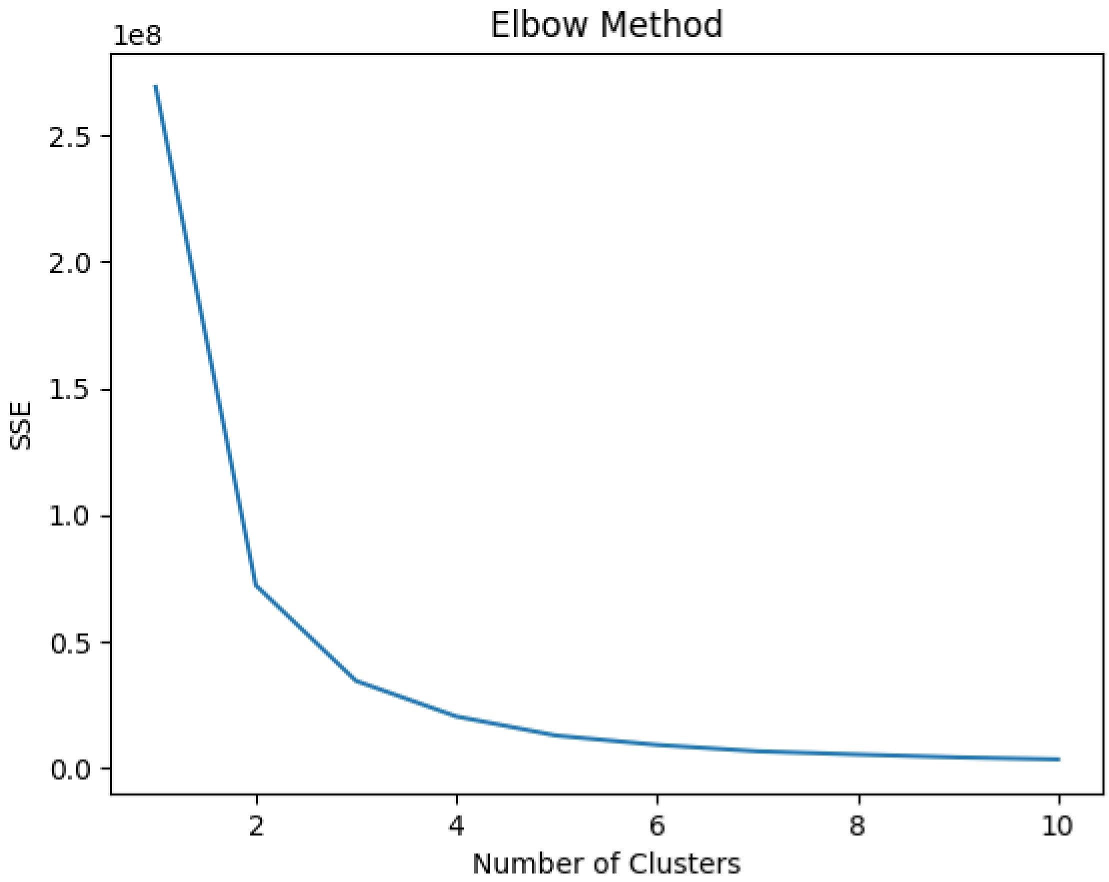
  warnings.warn(
```



```
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om 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

In [37]:

```
# Finding the optimal k based on Silhouette Scores
optimal_k_silhouette = range(2, 11)[silhouette_scores.index(max(silhouette_scores))]
print("Optimal number of clusters based on Silhouette Score:", optimal_k_silhouette)

# Final decision on optimal k
optimal_k = optimal_k_silhouette  # Replace or adjust as necessary
print("Chosen optimal number of clusters:", optimal_k)
```

```
Optimal number of clusters based on Silhouette Score: 2
Chosen optimal number of clusters: 2
```

In [38]:

```
# Re-run K-Means with the optimal number of clusters
optimal_k = 4
```

```
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
clusters = kmeans.fit_predict(selected_features)
df['Cluster'] = clusters

# Scatter plot visualization
sns.scatterplot(data=df, x='coolingRate', y='Lifespan', hue='Cluster', palette='viridis')
plt.title('Clustering of Lifespan against Cooling Rate')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
om 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```