Testing

November 7, 2024

1 COMP1801 - Machine Learning Coursework Solution

Let's start by importing the essential Python libraries for data analysis and machine learning.

[151]:
```
# Import libraries
try:
    # Importing general libraries
    import os
    import glob
    import pandas as pd
    import joblib

    # Importing libraries for data visualization
    import matplotlib.pyplot as plt
    import numpy as np

    # Importing libraries for model building
    from sklearn.preprocessing import LabelEncoder
    from sklearn.model_selection import train_test_split, GridSearchCV,␣
 ↪RandomizedSearchCV
    from sklearn.ensemble import RandomForestRegressor
    from sklearn.metrics import root_mean_squared_error, r2_score,␣
 ↪mean_absolute_error, mean_squared_log_error

    # Importing libraries for data preprocessing
    from scipy.stats import randint

except Exception as e:
    print(f"Error : {e}")
```

[152]:
```
# Find the CSV file in the Datasets directory
data_path = '../Datasets/*.csv'
file_list = glob.glob(data_path)

for file in file_list:
    print(f"Found file: {file}")

# Ensure there is exactly one file
```

```python
if len(file_list) == 1:
    # Load the dataset
    df = pd.read_csv(file_list[0])
    print(f"Loaded dataset: {file_list[0]}")
else:
    raise FileNotFoundError("No CSV file found or multiple CSV files found in
 ↪the Datasets directory.")
```

```
Found file: ../Datasets/Dataset.csv
Loaded dataset: ../Datasets/Dataset.csv
```

[153]:
```python
# File path to save the trained model
destination = '../Models/'
os.makedirs(destination, exist_ok=True)
```

[154]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 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   HeatTreatTime   1000 non-null   float64
 7   Nickel%         1000 non-null   float64
 8   Iron%           1000 non-null   float64
 9   Cobalt%         1000 non-null   float64
 10  Chromium%       1000 non-null   float64
 11  smallDefects    1000 non-null   int64
 12  largeDefects    1000 non-null   int64
 13  sliverDefects   1000 non-null   int64
 14  seedLocation    1000 non-null   object
 15  castType        1000 non-null   object
dtypes: float64(8), int64(4), object(4)
memory usage: 125.1+ KB
```

[155]:
```python
# Check for missing values
df.isnull().sum()
```

[155]:
```
Lifespan          0
partType          0
microstructure    0
coolingRate       0
```

```
quenchTime        0
forgeTime         0
HeatTreatTime     0
Nickel%           0
Iron%             0
Cobalt%           0
Chromium%         0
smallDefects      0
largeDefects      0
sliverDefects     0
seedLocation      0
castType          0
dtype: int64
```

[156]:
```
df.head()
```

[156]:
```
   Lifespan partType microstructure  coolingRate  quenchTime  forgeTime  \
0   1469.17   Nozzle      equiGrain           13        3.84       6.47
1   1793.64    Block    singleGrain           19        2.62       3.48
2    700.60    Blade      equiGrain           28        0.76       1.34
3   1082.10   Nozzle       colGrain            9        2.01       2.19
4   1838.83    Blade       colGrain           16        4.13       3.87

   HeatTreatTime  Nickel%  Iron%  Cobalt%  Chromium%  smallDefects  \
0          46.87    65.73  16.52    16.82       0.93            10
1          44.70    54.22  35.38     6.14       4.26            19
2           9.54    51.83  35.95     8.81       3.41            35
3          20.29    57.03  23.33    16.86       2.78             0
4          16.13    59.62  27.37    11.45       1.56            10

   largeDefects  sliverDefects seedLocation    castType
0             0              0       Bottom         Die
1             0              0       Bottom  Investment
2             3              0       Bottom  Investment
3             1              0          Top  Continuous
4             0              0          Top         Die
```

[157]:
```
df.describe()
```

[157]:
```
          Lifespan  coolingRate   quenchTime    forgeTime  HeatTreatTime  \
count  1000.000000  1000.000000  1000.000000  1000.000000    1000.000000
mean   1298.556320    17.639000     2.764230     5.464600      30.194510
std     340.071434     7.491783     1.316979     2.604513      16.889415
min     417.990000     5.000000     0.500000     1.030000       1.030000
25%    1047.257500    11.000000     1.640000     3.170000      16.185000
50%    1266.040000    18.000000     2.755000     5.475000      29.365000
75%    1563.050000    24.000000     3.970000     7.740000      44.955000
```

```
max    2134.530000    30.000000     4.990000    10.000000      59.910000

           Nickel%        Iron%      Cobalt%    Chromium%  smallDefects  \
count  1000.000000  1000.000000  1000.000000  1000.000000   1000.000000
mean     60.243080    24.553580    12.434690     2.768650     17.311000
std       5.790475     7.371737     4.333197     1.326496     12.268365
min      50.020000     6.660000     5.020000     0.510000      0.000000
25%      55.287500    19.387500     8.597500     1.590000      7.000000
50%      60.615000    24.690000    12.585000     2.865000     18.000000
75%      65.220000    29.882500    16.080000     3.922500     26.000000
max      69.950000    43.650000    19.990000     4.990000     61.000000

       largeDefects  sliverDefects
count   1000.000000    1000.000000
mean       0.550000       0.292000
std        1.163982       1.199239
min        0.000000       0.000000
25%        0.000000       0.000000
50%        0.000000       0.000000
75%        0.000000       0.000000
max        4.000000       8.000000
```

[158]:

```python
# Using nunique()
num_parts = df['partType'].nunique()
print(f"Number of unique parts types: {num_parts}")

# Or using value_counts() to see the distribution
parts_distribution = df['partType'].value_counts()
print("\nDistribution of parts types:")
print(parts_distribution)
```

```
Number of unique parts types: 4

Distribution of parts types:
partType
Valve     265
Block     253
Nozzle    245
Blade     237
Name: count, dtype: int64
```

[159]:

```python
categorical_cols_unified = ['partType', 'microstructure', 'seedLocation',␣
 ↪'castType']

# Create a DataFrame to display unique values and their counts
unique_values_df = pd.DataFrame({
    'Column': categorical_cols_unified,
```

```
    'Unique Values': [df[col].unique().tolist() for col in␣
↪categorical_cols_unified],
    'Count of Unique Values': [df[col].nunique() for col in␣
↪categorical_cols_unified]
})

print(unique_values_df)
```

```
           Column                        Unique Values  Count of Unique Values
0        partType       [Nozzle, Block, Blade, Valve]                       4
1  microstructure  [equiGrain, singleGrain, colGrain]                       3
2    seedLocation                       [Bottom, Top]                       2
3        castType       [Die, Investment, Continuous]                       3
```

[160]:

```
# Creating a copy of the dataframe to ensure we maintain the original intact
df_label_encoded = df.copy()
encoder = "Label Encoding"

# Apply Label Encoding to each categorical column
label_encoders = {}
for col in categorical_cols_unified:
    le = LabelEncoder()
    df_label_encoded[col] = le.fit_transform(df_label_encoded[col])
    label_encoders[col] = le  # Store the encoder for inverse transformation if␣
↪needed later

# Display the first few rows to verify
display(df_label_encoded.head())
```

```
   Lifespan  partType  microstructure  coolingRate  quenchTime  forgeTime  \
0   1469.17         2               1           13        3.84       6.47
1   1793.64         1               2           19        2.62       3.48
2    700.60         0               1           28        0.76       1.34
3   1082.10         2               0            9        2.01       2.19
4   1838.83         0               0           16        4.13       3.87

   HeatTreatTime  Nickel%  Iron%  Cobalt%  Chromium%  smallDefects  \
0          46.87    65.73  16.52    16.82       0.93            10
1          44.70    54.22  35.38     6.14       4.26            19
2           9.54    51.83  35.95     8.81       3.41            35
3          20.29    57.03  23.33    16.86       2.78             0
4          16.13    59.62  27.37    11.45       1.56            10

   largeDefects  sliverDefects  seedLocation  castType
0             0              0             0         1
1             0              0             0         2
2             3              0             0         2
3             1              0             1         0
```

```
4            0              0             1         1
```

[161]:
```
df_label_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Lifespan        1000 non-null   float64
 1   partType        1000 non-null   int64
 2   microstructure  1000 non-null   int64
 3   coolingRate     1000 non-null   int64
 4   quenchTime      1000 non-null   float64
 5   forgeTime       1000 non-null   float64
 6   HeatTreatTime   1000 non-null   float64
 7   Nickel%         1000 non-null   float64
 8   Iron%           1000 non-null   float64
 9   Cobalt%         1000 non-null   float64
 10  Chromium%       1000 non-null   float64
 11  smallDefects    1000 non-null   int64
 12  largeDefects    1000 non-null   int64
 13  sliverDefects   1000 non-null   int64
 14  seedLocation    1000 non-null   int64
 15  castType        1000 non-null   int64
dtypes: float64(8), int64(8)
memory usage: 125.1 KB
```

[162]:
```
# Define the target variable and feature set
X = df_label_encoded.drop(columns=['Lifespan'])  # Features
y = df_label_encoded['Lifespan']  # Target

# Split the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Display the shapes of the training and testing sets to verify
print(f'--- {encoder} Shape ---\n')
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)
```

```
--- Label Encoding Shape ---

X_train shape: (800, 15)
X_test shape: (200, 15)
y_train shape: (800,)
y_test shape: (200,)
```

[163]:
```python
# Initialize the Random Forest Regressor with default parameters
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Fit the model to the training data
rf_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = rf_model.predict(X_test)

# Evaluate the model using RMSE, R² Score, and MAE
rmse = root_mean_squared_error(y_test, y_pred)  # Root Mean Squared Error
r2 = r2_score(y_test, y_pred)  # R² Score
mae = mean_absolute_error(y_test, y_pred)  # Mean Absolute Error
msle = mean_squared_log_error(y_test, y_pred)  # Mean Squared Log Error

print(f'--- {encoder} Performance ---\n')
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R\u00b2 Score: {r2:.2f}")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Log Error (MSLE): {msle:.2f}")
```

```
--- Label Encoding Performance ---

Root Mean Squared Error (RMSE): 90.95
R² Score: 0.92
Mean Absolute Error (MAE): 72.50
Mean Squared Log Error (MSLE): 0.01
```

[164]:
```python
print(f"\nFeatures saved with {encoder}\n")
for col in X.columns:
    print(f"- {col}")
```

```

Features saved with Label Encoding

- partType
- microstructure
- coolingRate
- quenchTime
- forgeTime
- HeatTreatTime
- Nickel%
- Iron%
- Cobalt%
- Chromium%
- smallDefects
- largeDefects
- sliverDefects
```

```
- seedLocation
- castType
```

[165]:
```python
# Features to drop based on low importance for Label Encoding
low_importance_features = ['seedLocation', 'microstructure', 'castType',␣
↪'smallDefects', 'sliverDefects']
```

[166]:
```python
print(f"--- {encoder} Shape Reduction ---")

# Split the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Display the shapes of the training and testing sets to verify
print("\nOriginal Shapes")
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)

# Features to drop based on low importance
low_importance_features = ['seedLocation', 'microstructure', 'castType',␣
↪'smallDefects', 'sliverDefects']

# Create a new DataFrame excluding these features
X_train_reduced = X_train.drop(columns=low_importance_features)
X_test_reduced = X_test.drop(columns=low_importance_features)

# Display the shapes of the training and testing sets to verify
print("\nUpdated Shapes")
print("X_train_reduced shape:", X_train_reduced.shape)
print("X_test_reduced shape:", X_test_reduced.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
```

```
--- Label Encoding Shape Reduction ---

Original Shapes
X_train shape: (800, 15)
X_test shape: (200, 15)
y_train shape: (800,)
y_test shape: (200,)

Updated Shapes
X_train_reduced shape: (800, 10)
X_test_reduced shape: (200, 10)
y_train shape: (800,)
y_test shape: (200,)
```

[167]:
```python
# Initialize the Random Forest Regressor with best parameters
rf_model = RandomForestRegressor(
    max_depth=15,
    n_estimators=387,
    random_state=42
)

# Fit the model to the training data
rf_model.fit(X_train_reduced, y_train)

# Make predictions on the test set
y_pred = rf_model.predict(X_test_reduced)

# Evaluate the model using RMSE, R² Score, and MAE
rmse = root_mean_squared_error(y_test, y_pred)  # Root Mean Squared Error
r2 = r2_score(y_test, y_pred)  # R² Score
mae = mean_absolute_error(y_test, y_pred)  # Mean Absolute Error
msle = mean_squared_log_error(y_test, y_pred)  # Mean Squared Log Error

print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R\u00b2 Score: {r2:.2f}")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Log Error (MSLE): {msle:.2f}")
```

```
Root Mean Squared Error (RMSE): 88.10
R² Score: 0.93
Mean Absolute Error (MAE): 70.68
Mean Squared Log Error (MSLE): 0.01
```

[168]:
```python
# Creating a copy of the dataframe to ensure we maintain the original intact
df_onehot_encoded = df.copy()
encoder = "One-Hot Encoding"

# Apply one-hot encoding to the categorical columns
df_onehot_encoded = pd.get_dummies(df_onehot_encoded,␣
 ↪columns=categorical_cols_unified, drop_first=False)

# Display the first few rows to verify
display(df_onehot_encoded.head())
```

```
   Lifespan  coolingRate  quenchTime  forgeTime  HeatTreatTime  Nickel%  \
0   1469.17           13        3.84       6.47          46.87    65.73
1   1793.64           19        2.62       3.48          44.70    54.22
2    700.60           28        0.76       1.34           9.54    51.83
3   1082.10            9        2.01       2.19          20.29    57.03
4   1838.83           16        4.13       3.87          16.13    59.62

   Iron%  Cobalt%  Chromium%  smallDefects  …  partType_Nozzle  \
```

```
0  16.52    16.82       0.93             10  …             True
1  35.38     6.14       4.26             19  …            False
2  35.95     8.81       3.41             35  …            False
3  23.33    16.86       2.78              0  …             True
4  27.37    11.45       1.56             10  …            False

   partType_Valve  microstructure_colGrain  microstructure_equiGrain  \
0           False                    False                      True
1           False                    False                     False
2           False                    False                      True
3           False                     True                     False
4           False                     True                     False

   microstructure_singleGrain  seedLocation_Bottom  seedLocation_Top  \
0                       False                 True             False
1                        True                 True             False
2                       False                 True             False
3                       False                False              True
4                       False                False              True

   castType_Continuous  castType_Die  castType_Investment
0                False          True                False
1                False         False                 True
2                False         False                 True
3                 True         False                False
4                False          True                False

[5 rows x 24 columns]
```

[169]:

```
df_onehot_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 24 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Lifespan                     1000 non-null   float64
 1   coolingRate                  1000 non-null   int64
 2   quenchTime                   1000 non-null   float64
 3   forgeTime                    1000 non-null   float64
 4   HeatTreatTime                1000 non-null   float64
 5   Nickel%                      1000 non-null   float64
 6   Iron%                        1000 non-null   float64
 7   Cobalt%                      1000 non-null   float64
 8   Chromium%                    1000 non-null   float64
 9   smallDefects                 1000 non-null   int64
 10  largeDefects                 1000 non-null   int64
 11  sliverDefects                1000 non-null   int64
```

```
 12  partType_Blade              1000 non-null   bool
 13  partType_Block              1000 non-null   bool
 14  partType_Nozzle             1000 non-null   bool
 15  partType_Valve              1000 non-null   bool
 16  microstructure_colGrain     1000 non-null   bool
 17  microstructure_equiGrain    1000 non-null   bool
 18  microstructure_singleGrain  1000 non-null   bool
 19  seedLocation_Bottom         1000 non-null   bool
 20  seedLocation_Top            1000 non-null   bool
 21  castType_Continuous         1000 non-null   bool
 22  castType_Die                1000 non-null   bool
 23  castType_Investment         1000 non-null   bool
dtypes: bool(12), float64(8), int64(4)
memory usage: 105.6 KB
```

[170]:
```python
# Define the target variable and feature set
X = df_onehot_encoded.drop(columns=['Lifespan'])  # Features
y = df_onehot_encoded['Lifespan']  # Target

# Split the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Display the shapes of the training and testing sets to verify
print(f'--- {encoder} Shape ---\n')
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)
```

```
--- One-Hot Encoding Shape ---

X_train shape: (800, 23)
X_test shape: (200, 23)
y_train shape: (800,)
y_test shape: (200,)
```

[171]:
```python
# Initialize the Random Forest Regressor with default parameters
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Fit the model to the training data
rf_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = rf_model.predict(X_test)

# Evaluate the model using RMSE, R² Score, and MAE
rmse = root_mean_squared_error(y_test, y_pred)  # Root Mean Squared Error
```

```
r2 = r2_score(y_test, y_pred)  # R² Score
mae = mean_absolute_error(y_test, y_pred)  # Mean Absolute Error
msle = mean_squared_log_error(y_test, y_pred)  # Mean Squared Log Error

print(f'--- {encoder} Performance ---\n')
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R\u00b2 Score: {r2:.2f}")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Log Error (MSLE): {msle:.2f}")
```

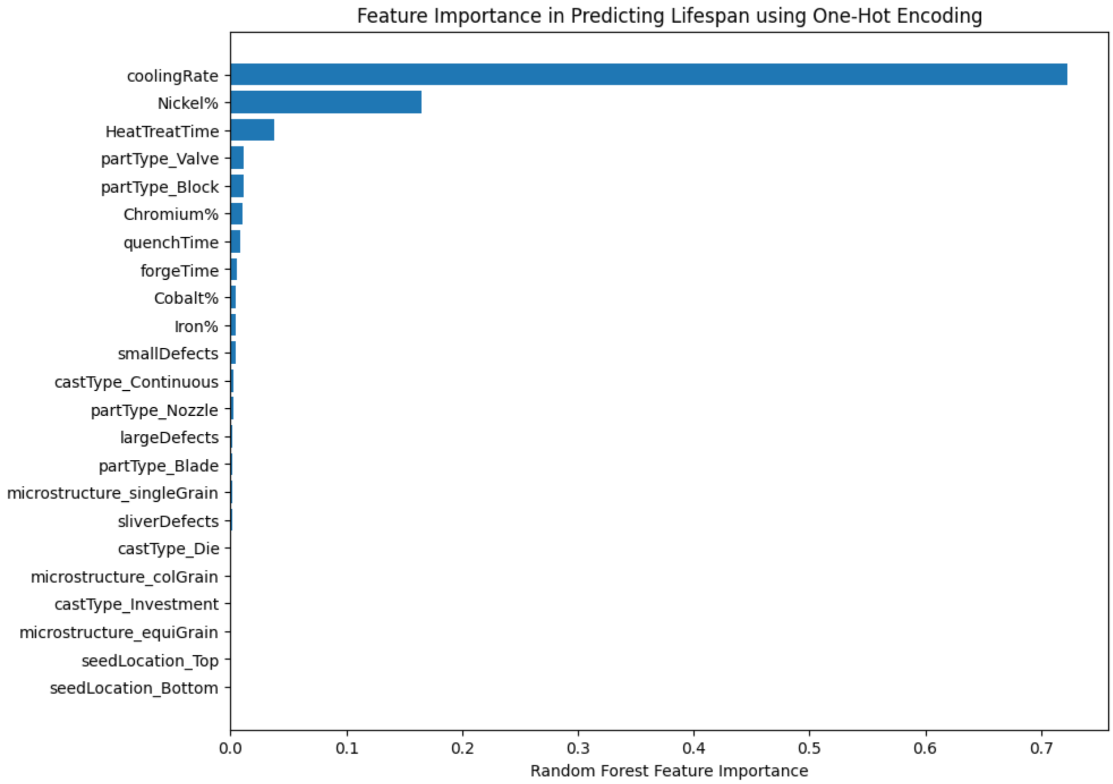
```
--- One-Hot Encoding Performance ---

Root Mean Squared Error (RMSE): 85.15
R² Score: 0.93
Mean Absolute Error (MAE): 67.46
Mean Squared Log Error (MSLE): 0.01
```

[174]:
```
# Train the final model with the best parameters with the best parameters
final_rf_model = RandomForestRegressor(
    max_depth=15,
    n_estimators=387,
    random_state=42
)

print(f'--- Generating model with {encoder} ---')

# Fit the model to the training data
final_rf_model.fit(X_train, y_train)

# Save the trained model
joblib.dump(final_rf_model, f'{destination}Final-RFModel.pkl')
```

```
--- Generating model with One-Hot Encoding ---
```

[174]:
```
['../Models/Final-RFModel.pkl']
```

[175]:
```
# Feature importance analysis
feature_importances = final_rf_model.feature_importances_
feature_names = X_train.columns

# Sort features by importance
sorted_idx = np.argsort(feature_importances)
plt.figure(figsize=(10, 8))
plt.barh(feature_names[sorted_idx], feature_importances[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
plt.title(f"Feature Importance in Predicting Lifespan using {encoder}")
plt.show()
```



[176]:

```
print(f"\nFeatures saved with {encoder}\n")
for col in X.columns:
    print(f"- {col}")
```

```
Features saved with One-Hot Encoding

- coolingRate
- quenchTime
- forgeTime
- HeatTreatTime
- Nickel%
- Iron%
- Cobalt%
- Chromium%
- smallDefects
- largeDefects
- sliverDefects
- partType_Blade
- partType_Block
- partType_Nozzle
- partType_Valve
```

```
- microstructure_colGrain
- microstructure_equiGrain
- microstructure_singleGrain
- seedLocation_Bottom
- seedLocation_Top
- castType_Continuous
- castType_Die
- castType_Investment
```

[177]:

```python
# Selecting only the most important features (those with non-zero or␣
↪significant importance)
important_features = ['partType_Blade', 'partType_Block', 'partType_Nozzle',␣
↪'partType_Valve', 'coolingRate', 'Nickel%', 'HeatTreatTime', 'Chromium%' ,␣
↪'quenchTime']
X_important = df_onehot_encoded[important_features]

print(f'--- {encoder} Updated Performance ---\n')

# Split the dataset and retrain the model
X_train_imp, X_test_imp, y_train_imp, y_test_imp =␣
↪train_test_split(X_important, y, test_size=0.2, random_state=42)

# Initialize and train the Random Forest Regressor with reduced features with␣
↪the best parameters
rf_model_imp = RandomForestRegressor(
    max_depth=15,
    n_estimators=387,
    random_state=42
)
rf_model_imp.fit(X_train_imp, y_train_imp)

# Evaluate the model
y_pred_imp = rf_model_imp.predict(X_test_imp)
rmse_imp = root_mean_squared_error(y_test_imp, y_pred_imp)
r2_imp = r2_score(y_test_imp, y_pred_imp)
mae_imp = mean_absolute_error(y_test_imp, y_pred_imp)
msle_imp = mean_squared_log_error(y_test_imp, y_pred_imp)

print(f"Reduced Features RMSE: {rmse_imp:.2f}")
print(f"Reduced Features R² Score: {r2_imp:.2f}")
print(f"Reduced Features MAE: {mae_imp:.2f}")
print(f"Reduced Features MSLE: {msle_imp:.2f}")
```

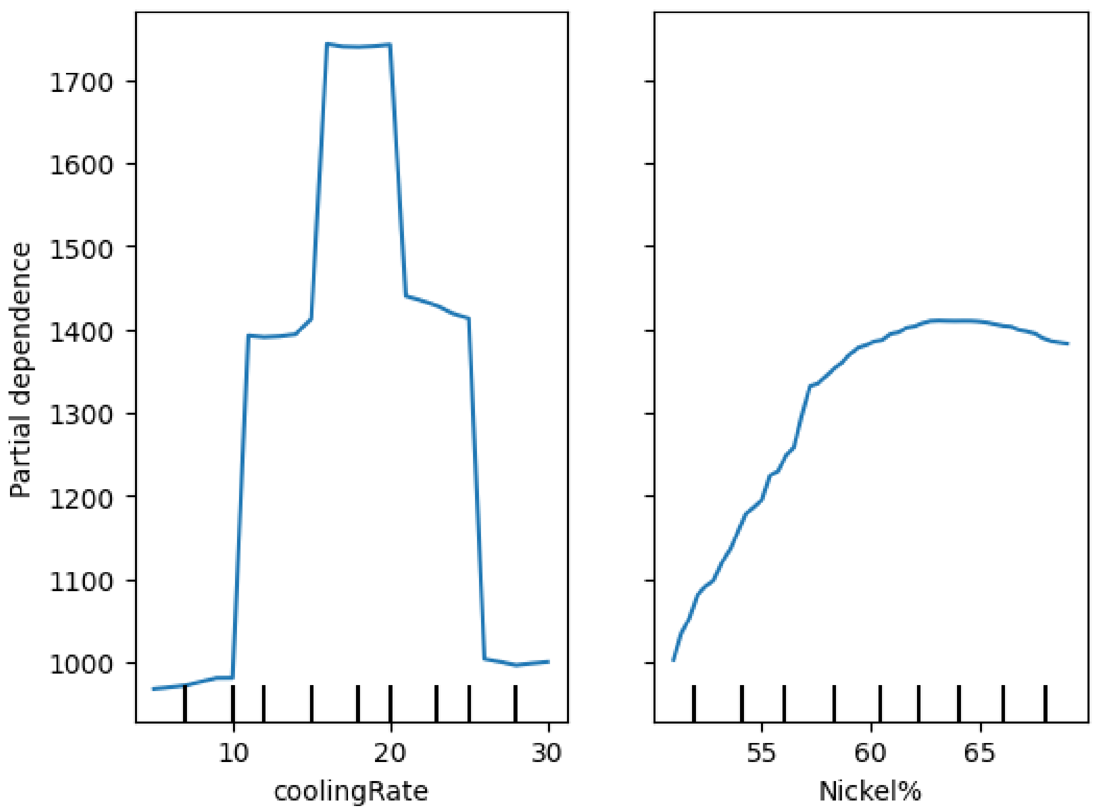
```
--- One-Hot Encoding Updated Performance ---

Reduced Features RMSE: 78.70
Reduced Features R² Score: 0.94
Reduced Features MAE: 61.14
```

```
Reduced Features MSLE: 0.01
```

[178]:
```python
import sklearn
print(sklearn.__version__)
```

```
1.5.2
```

[179]:
```python
from sklearn.inspection import PartialDependenceDisplay

# Plot partial dependence for important features using the new API
features_to_plot = ['coolingRate', 'Nickel%']
PartialDependenceDisplay.from_estimator(rf_model_imp, X_train_imp,␣
 ↪features_to_plot, grid_resolution=50)
plt.show()
```



[180]:
```python
from sklearn.model_selection import cross_val_score
from sklearn.metrics import make_scorer, root_mean_squared_error

# Define the model with best-found hyperparameters
rf_model_cv = RandomForestRegressor(
    max_depth=15,
    n_estimators=387,
```

```
    min_samples_leaf=2,
    min_samples_split=3,
    random_state=42
)

# Define the scoring metric: RMSE
scorer = make_scorer(root_mean_squared_error)

# Perform 5-Fold Cross-Validation
cv_scores = cross_val_score(rf_model_cv, X_important, y, cv=5, scoring=scorer)

# Print results
print("Cross-Validation RMSE scores for each fold: ", cv_scores)
print(f"Mean CV RMSE: {cv_scores.mean():.2f}")
print(f"Standard Deviation of CV RMSE: {cv_scores.std():.2f}")
```

```
Cross-Validation RMSE scores for each fold:  [77.55548306 74.97658535
77.56023918 82.12528196 81.38495862]
Mean CV RMSE: 78.72
Standard Deviation of CV RMSE: 2.66
```

[181]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestRegressor

# Separate features for encoding
onehot_features = ['microstructure', 'seedLocation', 'castType']
label_features = ['partType']

# Custom transformers
label_encoder = LabelEncoder()
df['partType'] = label_encoder.fit_transform(df['partType'])  # Apply label␣
↪encoding directly

# Create a ColumnTransformer for One-Hot Encoding
preprocessor = ColumnTransformer(
    transformers=[
        # To match the output of One-Hot Encoding with the Label Encoding
        ('onehot', OneHotEncoder(dtype=int), onehot_features)
    ],
    remainder='passthrough'  # Keeps all other features as they are
)

# Define pipeline with preprocessing and model
pipeline = Pipeline([
    ('preprocessor', preprocessor),
```

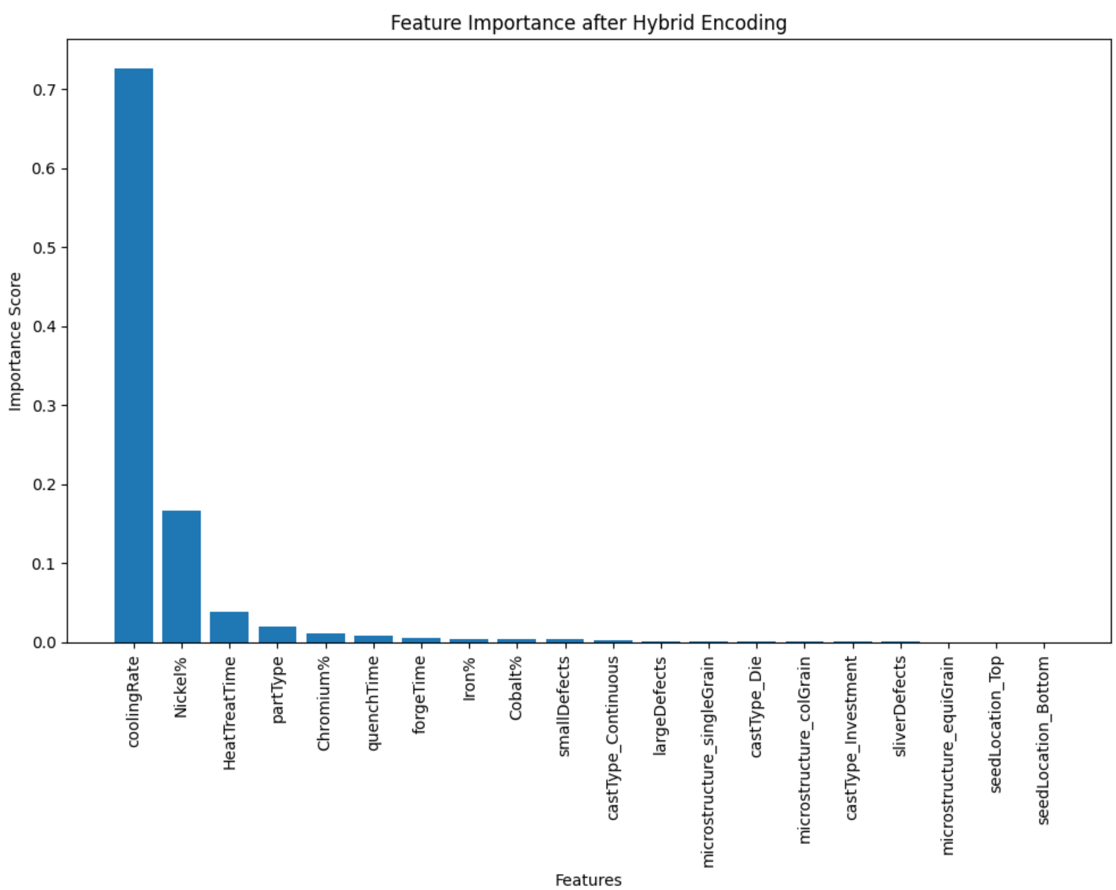
```
    ('model', RandomForestRegressor(
        max_depth=15,
        n_estimators=387,
        min_samples_leaf=2,
        min_samples_split=3,
        random_state=42
    ))
])

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(df.
 ↪drop(columns=['Lifespan']), df['Lifespan'], test_size=0.2, random_state=42)

# Fit the pipeline
pipeline.fit(X_train, y_train)

# Evaluate the model
y_pred = pipeline.predict(X_test)
rmse = root_mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
msle = mean_squared_log_error(y_test, y_pred)

print(f"RMSE: {rmse:.2f}")
print(f"R² Score: {r2:.2f}")
print(f"MAE: {mae:.2f}")
print(f"MSLE: {msle:.2f}")
```

```
RMSE: 89.91
R² Score: 0.92
MAE: 71.64
MSLE: 0.01
```

[182]:

```
import matplotlib.pyplot as plt
import numpy as np

# Step 1: Access the trained Random Forest model from the pipeline
rf_model_imp = pipeline.named_steps['model']

# Step 2: Retrieve the feature names from the preprocessor
# Get the One-Hot Encoder categories and append label encoded features
onehot_encoder = pipeline.named_steps['preprocessor'].
 ↪named_transformers_['onehot']
onehot_feature_names = onehot_encoder.get_feature_names_out(onehot_features)

# Combine One-Hot Encoded feature names with label-encoded and numerical␣
 ↪feature names
```

```
all_feature_names = list(onehot_feature_names) + label_features + [col for col␣
 ↪in X_train.columns if col not in onehot_features + label_features]

# Step 3: Extract the feature importances from the RandomForestRegressor
importances = rf_model_imp.feature_importances_

# Sort feature importances in descending order
indices = np.argsort(importances)[::-1]

# Step 4: Plot the feature importances
plt.figure(figsize=(10, 8))
plt.title("Feature Importance after Hybrid Encoding")
plt.bar(range(len(importances)), importances[indices], align="center")
plt.xticks(range(len(importances)), np.array(all_feature_names)[indices],␣
 ↪rotation=90)
plt.xlabel("Features")
plt.ylabel("Importance Score")
plt.tight_layout()
plt.show()
```



[183]:
```python
# Important features
important_features = ['partType', 'coolingRate', 'Nickel%', 'HeatTreatTime',␣
↪'Chromium%' , 'quenchTime']

# Subset the dataset to include only the important features
X_important = df[important_features]

# Split the dataset
X_train_imp, X_test_imp, y_train_imp, y_test_imp =␣
↪train_test_split(X_important, df['Lifespan'], test_size=0.2, random_state=42)

# Initialize the Random Forest Regressor with the best parameters obtained from␣
↪previous tuning
rf_model_imp = RandomForestRegressor(
    max_depth=15,
    n_estimators=387,
    random_state=42
)

# Train the model with reduced features
rf_model_imp.fit(X_train_imp, y_train_imp)

# Evaluate the model
y_pred_imp = rf_model_imp.predict(X_test_imp)
rmse_imp = root_mean_squared_error(y_test_imp, y_pred_imp)
r2_imp = r2_score(y_test_imp, y_pred_imp)
mae_imp = mean_absolute_error(y_test_imp, y_pred_imp)
msle_imp = mean_squared_log_error(y_test_imp, y_pred_imp)

print(f"Reduced Features RMSE: {rmse_imp:.2f}")
print(f"Reduced Features R² Score: {r2_imp:.2f}")
print(f"Reduced Features MAE: {mae_imp:.2f}")
print(f"Reduced Features MSLE: {msle_imp:.2f}")
```

```
Reduced Features RMSE: 84.17
Reduced Features R² Score: 0.93
Reduced Features MAE: 66.48
Reduced Features MSLE: 0.01
```