

```
In [1]: # Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer # Advanced imputation
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.svm import SVR
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import accuracy_score, classification_report, mean_squared_
```

```
In [4]: # Clean column names (remove unwanted characters and strip whitespace)
df.columns = df.columns.str.replace('Â', '', regex=False)
df.columns = df.columns.str.strip()
```

```
In [5]: # Step 2: Initial inspection & EDA
print(df.info())
print(df.describe())
print("Missing values in each column:\n", df.isna().sum())
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 368341 entries, 0 to 368340
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Time              368341 non-null   object  
 1   Engine Coolant Temperature [°C] 368341 non-null   int64   
 2   Intake Manifold Absolute Pressure [kPa] 368329 non-null   float64 
 3   Engine RPM [RPM]        368317 non-null   float64 
 4   Vehicle Speed Sensor [km/h]      368305 non-null   float64 
 5   Intake Air Temperature [°C]      368293 non-null   float64 
 6   Air Flow Rate from Mass Flow Sensor [g/s] 368281 non-null   float64 
 7   Absolute Throttle Position [%]    368269 non-null   float64 
 8   Ambient Air Temperature [°C]      368257 non-null   float64 
 9   Accelerator Pedal Position D [%] 368245 non-null   float64 
 10  Accelerator Pedal Position E [%] 368233 non-null   float64 
dtypes: float64(9), int64(1), object(1)
memory usage: 30.9+ MB
None
    Engine Coolant Temperature [°C] \
count          368341.000000
mean           84.588770
std            14.872193
min            24.000000
25%           90.000000
50%           91.000000
75%           91.000000
max            97.000000

    Intake Manifold Absolute Pressure [kPa]  Engine RPM [RPM] \
count          368329.000000          368317.000000
mean           123.747424          1431.849087
std             31.450095          546.891641
min            36.000000           0.000000
25%           103.000000          1013.000000
50%           113.000000          1487.000000
75%           133.000000          1776.000000
max            242.000000          3563.000000

    Vehicle Speed Sensor [km/h]  Intake Air Temperature [°C] \
count          368305.000000          368293.000000
mean           58.062880           33.27672
std            44.482831           17.59453
min            0.000000           -8.00000
25%           16.000000           26.00000
50%           55.000000           30.00000
75%           94.000000           35.00000
max            211.000000          150.00000

    Air Flow Rate from Mass Flow Sensor [g/s] \
count          368281.000000
mean           21.384516
std            16.466133
min            0.000000
25%           10.190000
50%           17.020000
75%           27.270000
max            121.080000

    Absolute Throttle Position [%]  Ambient Air Temperature [°C] \

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count	368269.000000	368257.000000
mean	80.802209	22.723587
std	12.488784	4.350579
min	13.700000	16.000000
25%	83.500000	19.000000
50%	83.500000	22.000000
75%	83.500000	26.000000
max	89.000000	33.000000

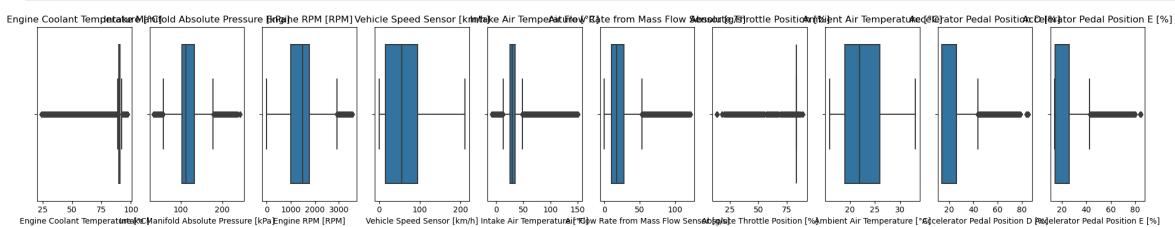
	Accelerator Pedal Position D [%]	Accelerator Pedal Position E [%]
count	368245.000000	368233.000000
mean	21.330466	21.649893
std	12.670384	12.681027
min	14.100000	14.100000
25%	14.100000	14.500000
50%	14.100000	14.500000
75%	25.900000	25.900000
max	85.100000	84.300000

Missing values in each column:

Time	0
Engine Coolant Temperature [°C]	0
Intake Manifold Absolute Pressure [kPa]	12
Engine RPM [RPM]	24
Vehicle Speed Sensor [km/h]	36
Intake Air Temperature [°C]	48
Air Flow Rate from Mass Flow Sensor [g/s]	60
Absolute Throttle Position [%]	72
Ambient Air Temperature [°C]	84
Accelerator Pedal Position D [%]	96
Accelerator Pedal Position E [%]	108

dtype: int64

```
In [6]: # Visualize distributions and outliers of numeric columns (limit to first 10 to
num_cols = df.select_dtypes(include=np.number).columns.tolist()
plt.figure(figsize=(20, 4))
for i, col in enumerate(num_cols[:10]):
    plt.subplot(1, 10, i + 1)
    sns.boxplot(x=df[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



```
In [7]: # Step 3: Outlier treatment based on domain knowledge (clip coolant temp)
coolant_col = 'Engine Coolant Temperature [°C]'
if coolant_col in df.columns:
    df[coolant_col] = df[coolant_col].clip(60, 130)
```

```
In [8]: # Step 4: Feature engineering
df['overheating'] = (df[coolant_col] > 100).astype(int)
rpm_col = 'Engine RPM [RPM]'
df['rpm_rolling_mean'] = df[rpm_col].rolling(window=5, min_periods=1).mean()
df['rpm_rolling_std'] = df[rpm_col].rolling(window=5, min_periods=1).std().fillna(0)
```

```
In [9]: # Select features for modeling (ensure they exist)
features = [
    rpm_col,
    'Vehicle Speed Sensor [km/h]',
    coolant_col,
    'Absolute Throttle Position [%]',
    'Air Flow Rate from Mass Flow Sensor [g/s]',
    'rpm_rolling_mean',
    'rpm_rolling_std'
]
features = [f for f in features if f in df.columns]
X = df[features]
y_class = df['overheating']
```

```
In [10]: # Step 5: Scale features (no PCA to avoid NaN issues)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
In [13]: # Step 7: Regression modeling with RandomForestRegressor (fast, handles NaNs if
regression_target = 'Air Flow Rate from Mass Flow Sensor [g/s]'
regression_features = [
    'Vehicle Speed Sensor [km/h]',
    rpm_col,
    'Absolute Throttle Position [%]'
]
if regression_target in df.columns and all(f in df.columns for f in regression_features):
    X_reg = df[regression_features]
    y_reg = df[regression_target]

    # Minimal imputation if needed (simple mean for any remaining NaNs, to keep
    # from sklearn.impute import SimpleImputer
    imputer_reg = SimpleImputer(strategy='mean')
    X_reg = imputer_reg.fit_transform(X_reg)
```

```
In [14]: # Scale features
scaler_reg = StandardScaler()
X_reg_scaled = scaler_reg.fit_transform(X_reg)

# Split dataset
X_train_r, X_test_r, y_train_r, y_test_r = train_test_split(X_reg_scaled, y_reg)
```

```
In [19]: # Minimal imputation if needed (simple mean for any remaining NaNs, to keep
# from sklearn.impute import SimpleImputer
imputer_reg = SimpleImputer(strategy='mean')
X_reg = imputer_reg.fit_transform(X_reg)
```

```
In [24]: # Step 7: Regression modeling with RandomForestRegressor (fast, handles NaNs in
regression_target = 'Air Flow Rate from Mass Flow Sensor [g/s]'
regression_features = [
    'Vehicle Speed Sensor [km/h]',
    'Engine RPM [RPM]',
    'Absolute Throttle Position [%]'
]
if regression_target in df.columns and all(f in df.columns for f in regression_features):
    X_reg = df[regression_features]
```

```
y_reg = df[regression_target]
```

In [27]:

```
# Minimal imputation for X_reg (handles any remaining NaNs in features)
from sklearn.impute import SimpleImputer
imputer_reg = SimpleImputer(strategy='mean')
X_reg = imputer_reg.fit_transform(X_reg)

# Handle NaNs in target y_reg: Drop rows where y_reg is NaN (avoids model error)
mask = pd.notna(y_reg) # Create a mask for non-NaN targets
X_reg = X_reg[mask] # Filter X_reg to match
y_reg = y_reg[mask] # Filter y_reg
print(f"After dropping NaNs: X_reg shape: {X_reg.shape}, y_reg shape: {y_reg.shape}")
```

After dropping NaNs: X\_reg shape: (368281, 3), y\_reg shape: (368281,)

In [28]:

```
# Scale features
scaler_reg = StandardScaler()
X_reg_scaled = scaler_reg.fit_transform(X_reg)

# Split dataset
X_train_r, X_test_r, y_train_r, y_test_r = train_test_split(X_reg_scaled, y_reg)
```

In [29]:

```
# Regression with RandomForestRegressor + hyperparameter tuning
reg = RandomForestRegressor(random_state=42)
param_grid_reg = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5]
}
grid_reg = GridSearchCV(reg, param_grid_reg, cv=3, n_jobs=-1, verbose=2)
grid_reg.fit(X_train_r, y_train_r) # Should now work without NaN errors
```

Fitting 3 folds for each of 12 candidates, totalling 36 fits

Out[29]:

```
► GridSearchCV
  ► estimator: RandomForestRegressor
    ► RandomForestRegressor
```

In [ ]:

```
if regression_target in df.columns and all(f in df.columns for f in regression_target):
    y_pred_r = grid_reg.predict(X_test_r)
    rmse = mean_squared_error(y_test_r, y_pred_r, squared=False)
    print("Best regression params:", grid_reg.best_params_)
    print(f"Regression RMSE: {rmse:.4f}")

    # Residuals plot (insert the fixed code here)
    if len(y_test_r) > 0 and len(y_pred_r) > 0:
        residuals = y_test_r - y_pred_r
        if residuals.isna().sum() == 0:
            plt.figure(figsize=(8, 3))
            sns.histplot(residuals, bins=30, kde=True)
            plt.title('Regression Residuals')
            plt.xlabel('Residual')
            plt.show()
        else:
            print("Warning: Residuals contain NaNs; skipping plot.")
```

```

    else:
        print("No test data available for residuals plot.")
else:
    print(f"Regression target '{regression_target}' or features not found. Skip")

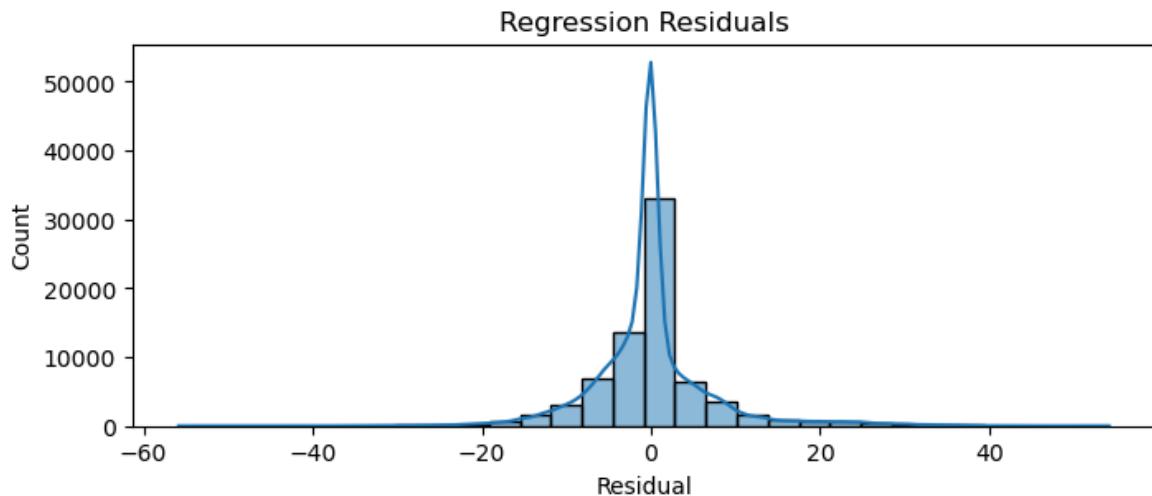
```

Best regression params: {'max\_depth': None, 'min\_samples\_split': 5, 'n\_estimators': 200}

Regression RMSE: 7.0326

c:\Users\Neha\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119: FutureWarning:  
g: use\_inf\_as\_na option is deprecated and will be removed in a future version. Co  
nvert inf values to NaN before operating instead.

```
with pd.option_context('mode.use_inf_as_na', True):
```



In [34]:

```

from sklearn.metrics import r2_score, mean_absolute_error

# Existing RMSE
rmse = mean_squared_error(y_test_r, y_pred_r, squared=False)
print(f"Regression RMSE: {rmse:.4f}")

# Additional accuracy checks
r2 = r2_score(y_test_r, y_pred_r)
mae = mean_absolute_error(y_test_r, y_pred_r)
print(f"R² Score: {r2:.4f} (closer to 1 is better)")
print(f"Mean Absolute Error (MAE): {mae:.4f}")

# Scatter plot for visual accuracy check
plt.figure(figsize=(6, 6))
plt.scatter(y_test_r, y_pred_r, alpha=0.5)
plt.plot([y_test_r.min(), y_test_r.max()], [y_test_r.min(), y_test_r.max()])
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted (Regression Accuracy)')
plt.show()

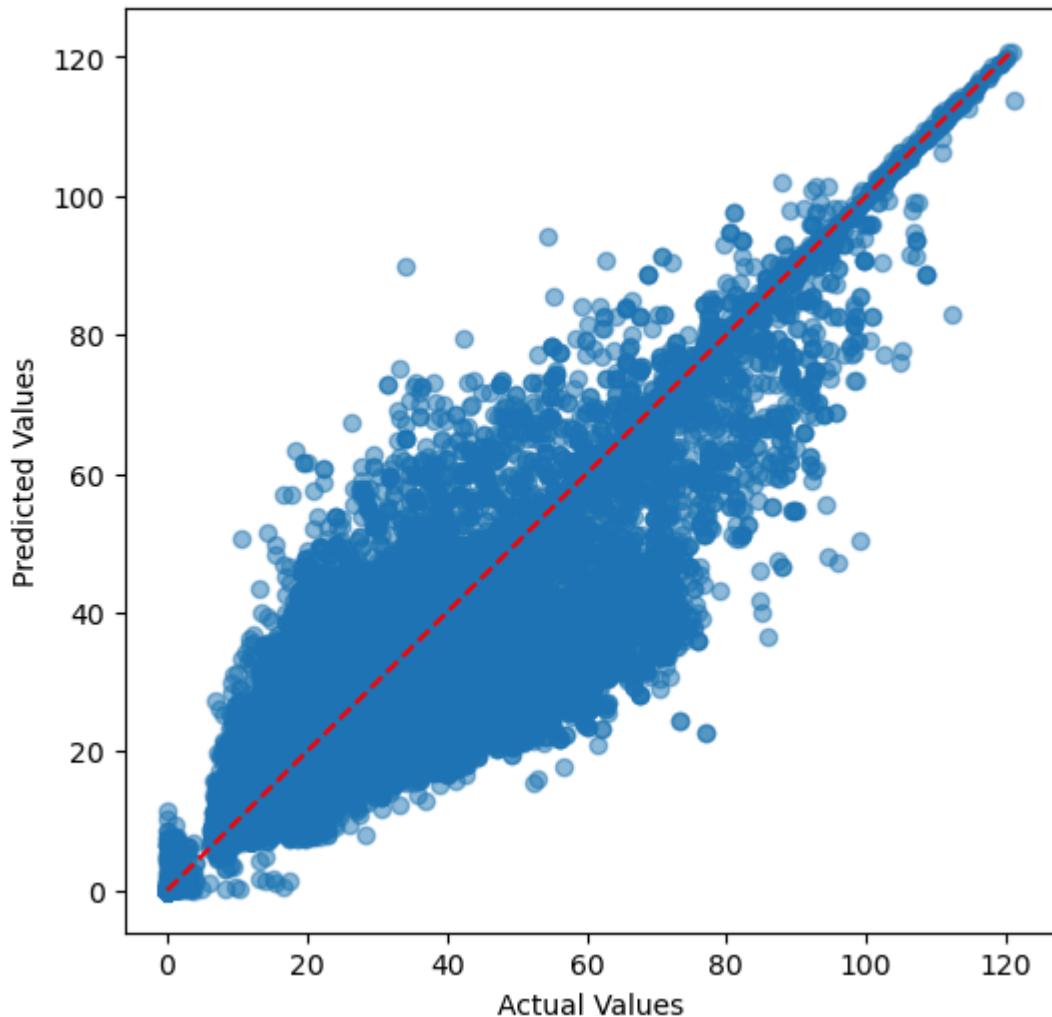
```

Regression RMSE: 7.0326

R<sup>2</sup> Score: 0.8164 (closer to 1 is better)

Mean Absolute Error (MAE): 4.1858

### Actual vs. Predicted (Regression Accuracy)



In [35]:

```
# Regression accuracy checks
rmse = mean_squared_error(y_test_r, y_pred_r, squared=False)
r2 = r2_score(y_test_r, y_pred_r)
mae = mean_absolute_error(y_test_r, y_pred_r)
print("Best regression params:", grid_reg.best_params_)
print(f"Regression RMSE: {rmse:.4f}")
print(f"R2 Score: {r2:.4f} (closer to 1 is better)")
print(f"Mean Absolute Error (MAE): {mae:.4f}")
```

```
Best regression params: {'max_depth': None, 'min_samples_split': 5, 'n_estimators': 200}
Regression RMSE: 7.0326
R2 Score: 0.8164 (closer to 1 is better)
Mean Absolute Error (MAE): 4.1858
```

In [ ]: