2024

Electric Motor Temperature Prediction

Capstone Project - Regression

DIBOSH BARUAH

1. Introduction

Electric motor temperature prediction is a critical task in ensuring the optimal performance and longevity of electric motors, particularly permanent magnet synchronous motors (PMSMs), which are widely used in applications such as electric vehicles, wind turbines, and industrial machinery. Overheating of motors can lead to inefficiencies, failures, and significant maintenance costs. Therefore, accurate temperature prediction can help optimize motor operation, prevent overheating, and extend the motor's service life. In this project, the goal is to predict the temperature of a PMSM's permanent magnets based on various motor parameters like voltage, current, motor speed, and ambient temperature. The dataset provided for this task contains measurements of these motor parameters across different driving cycles, with the target variable being the permanent magnet temperature ('pm'). A RandomForest Regressor model was chosen for its robust performance in regression tasks.

2. Data Collection

The dataset for this project consists of 1.33 million records from electric cars, specifically monitoring various performance parameters of the PMSM. These parameters include:

- **Motor Voltage (u_q, u_d)**: The motor voltage in two components, quadrature and direct.
- **Motor Currents (i_q, i_d)**: The motor current in two components, quadrature and direct.
- **Motor Speed (motor_speed)**: The rotational speed of the motor.
- **Ambient Temperature (ambient)**: The surrounding temperature of the environment.
- **Coolant Temperature (coolant)**: The temperature of the coolant used in the motor.
- **Permanent Magnet Temperature (pm)**: The target variable representing the temperature of the motor’s permanent magnets.

The dataset was loaded into a Pandas DataFrame, which was then preprocessed for further analysis and modeling.

3. Data Preprocessing

Before applying the machine learning model, several preprocessing steps were performed to clean and prepare the data:

3.1 Handling Missing Values

Upon checking for missing values, it was found that certain rows had null values. These were removed by dropping rows containing any missing values from the numeric columns (u_q, u_d, i_q, i_d, motor_speed, ambient, coolant, pm).

3.2 Feature Engineering

The dataset contained a categorical feature, profile_id, which was encoded using one-hot encoding. This transformation was necessary to convert the categorical values into a format suitable for machine learning algorithms. The encoded data excluded the first category (drop_first=True) to avoid multicollinearity.

3.3 Feature Scaling

To ensure all features had similar scales, especially for algorithms like Random Forest, which are sensitive to feature scaling, the continuous variables were standardized using the StandardScaler from scikit-learn. This step was important to prevent any single feature from dominating the model due to differing scales.

4. Model Building

The objective of the model was to predict the permanent magnet temperature (pm) of the motor based on the input features. The steps involved in building the predictive model are outlined below:

4.1 Splitting the Dataset

The dataset was divided into independent variables (features) and the target variable (pm). Then, it was further split into training and testing sets using an 80-20 split.

4.2 Training the RandomForest Regressor Model

A RandomForest Regressor model was initialized with 10 estimators and trained using the training data. Random forests are powerful ensemble models that perform well with complex, non-linear relationships, making them suitable for this regression task.

4.3 Making Predictions

Once the model was trained, it was used to make predictions on the test set. These predictions were then compared to the actual pm values to evaluate the model's performance.

5. Model Evaluation

The model’s performance was evaluated using several key metrics to understand its predictive accuracy:

- **Mean Squared Error (MSE)**: A measure of the average squared difference between the predicted and actual values.
- **Mean Absolute Error (MAE)**: The average of the absolute differences between the predicted and actual values.
- **Root Mean Squared Error (RMSE)**: The square root of the MSE, providing a more interpretable measure of prediction error.
- **R-Squared (R^2)**: A metric that indicates the proportion of variance in the target variable that is predictable from the features.

5.1 Performance Metrics

The model's evaluation metrics were as follows:

- **Mean Squared Error (MSE)**: 1.63
- **Mean Absolute Error (MAE)**: 0.45
- **Root Mean Squared Error (RMSE)**: 1.28
- **R-Squared (R^2)**: 0.996

These metrics indicate that the model performed exceptionally well, with a very high R^2 value, suggesting that the model was able to explain nearly 99.6% of the variance in the permanent magnet temperature.

6. Results & Discussion

6.1 Model Performance

The RandomForest Regressor model performed extremely well, with an R^2 value close to 1, indicating that it was able to predict the motor’s permanent magnet temperature with high accuracy. The RMSE of 1.28 suggests that the model’s predictions were within a reasonable range of the actual values.

Despite this high performance, some potential improvements could include:

- **Hyperparameter Tuning**: The model's performance might further improve with optimized hyperparameters, such as adjusting the number of estimators, maximum depth of the trees, or other parameters.
- **Feature Engineering**: Exploring additional features or transformations of existing features could enhance the model’s predictive power.

6.2 Feature Importance

The RandomForest model also provides insight into feature importance, indicating which variables contributed most to predicting the permanent magnet temperature. The top features, based on the model's feature importance scores, included:

- **Coolant Temperature**
- **Motor Speed**
- **Ambient Temperature**
- **Motor Currents (i_d, i_q)**

These features were found to have the highest influence on the model's predictions, and understanding their relationships with temperature could lead to more targeted optimizations for motor performance.

7. Conclusion

This project successfully demonstrated the use of machine learning, specifically RandomForest Regressor, to predict the permanent magnet temperature in permanent magnet synchronous motors. The model achieved impressive performance, with an R^2 value of 0.996, meaning that it explained nearly all of the variance in the target variable. The key features influencing temperature prediction were coolant temperature, motor speed, and ambient temperature.

8.Original Code:

```python
# Original coding process

import sqlite3
import pandas as pd

# Connecting to the database
conn = sqlite3.connect('/Users/diboshbaruah/Desktop/Database.db')
data = pd.read_sql_query('SELECT * FROM Electric_cars', conn)

# Display the first few rows to inspect the data
print("Displaying first few rows of the dataset:\n")
print(data.head())

# Closing the connection
conn.close()
```

```
Displaying first few rows of the dataset:

  profile_id          u_q      coolant          u_d  motor_speed  \
0         17  -0.450681508  18.80517197  -0.350054592  0.002865568
1         17     -0.325737  18.81857109  -0.305803001  0.000256782
2         17  -0.440864027  18.82876968  -0.372502625  0.002354971
3         17  -0.327025682  18.83556747  -0.316198707  0.006104666
4         17   -0.47115013  18.85703278  -0.332272142  0.003132823

           i_d          i_q      ambient           pm
0   0.004419137   0.000328102  19.85069084  24.55421448
1   0.000605872  -0.000785353  19.85067177  24.53807831
2   0.001289587   0.000386468  19.85065651  24.54469299
3      2.56E-05   0.002045661  19.85064697  24.55401802
4  -0.064316779   0.037183776  19.85063934  24.56539726
```

```python
# Checking data types before conversion
print("\nData types before conversion:")
print(data.dtypes)
```

```
Data types before conversion:
profile_id     object
u_q            object
coolant        object
u_d            object
motor_speed    object
i_d            object
i_q            object
ambient        object
pm             object
dtype: object
```

```python
# Converting numeric columns to float64
numeric_cols = ['u_q', 'coolant', 'u_d', 'motor_speed', 'i_d', 'i_q',
'ambient', 'pm']
data[numeric_cols] = data[numeric_cols].apply(pd.to_numeric, errors='coerce')

# Handling missing data - Impute or drop rows
data = data.dropna(subset=numeric_cols)

# Using One-Hot Encoding for categorical columns
data_encoded = pd.get_dummies(data, columns=['profile_id'], drop_first=True)

# Checking data types before conversion
print("\nData types after conversion:")
print(data.dtypes)
print()

# Checking for missing values
print("\nMissing values in dataset:")
print(data.isnull().sum())
```

```
Data types after conversion:
profile_id      object
u_q            float64
coolant        float64
u_d            float64
motor_speed    float64
i_d            float64
i_q            float64
ambient        float64
pm             float64
dtype: object


Missing values in dataset:
profile_id     0
u_q            0
coolant        0
u_d            0
motor_speed    0
i_d            0
i_q            0
ambient        0
pm             0
dtype: int64
```

```python
# Model Train - Test

import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Features (independent variables) and target variable (dependent variable)
features = data_encoded.drop('pm', axis=1)  # Dropping the target column 'pm'
target = data_encoded['pm']  # Our target variable to predict

# Train-test split with an 80-20 split
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)

# Initialize the scaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize the RandomForest Regressor model
model = RandomForestRegressor(n_estimators=10, random_state=42)
```

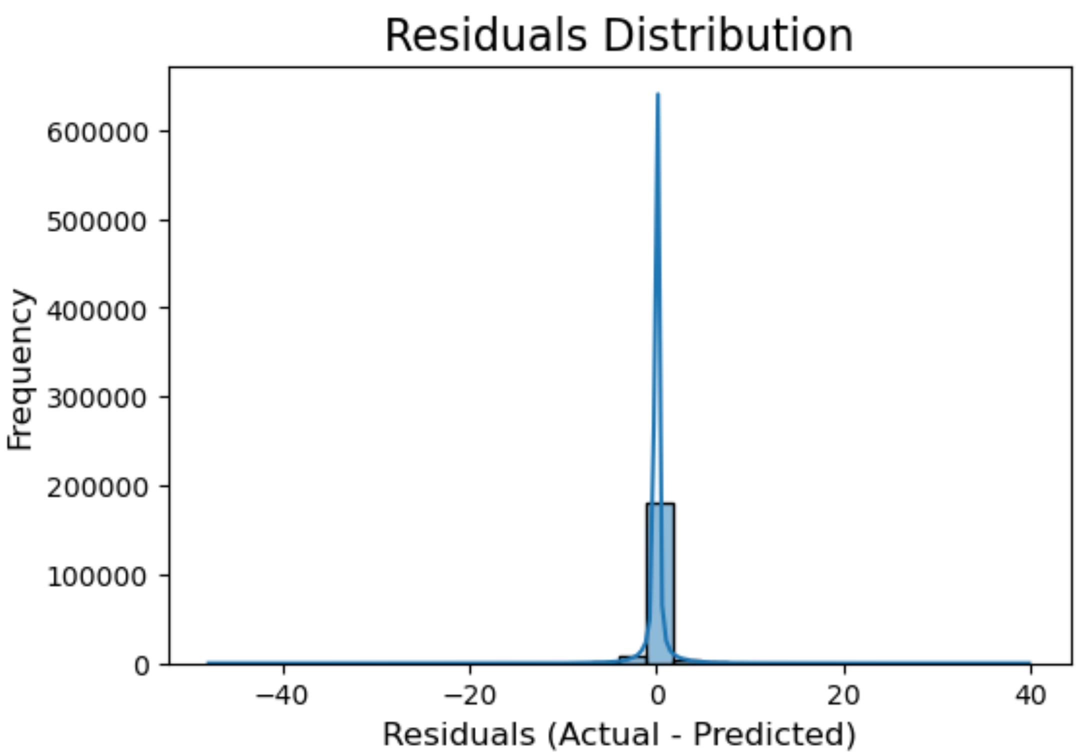
```python
# Train the model on the training data
model.fit(X_train_scaled, y_train)
```

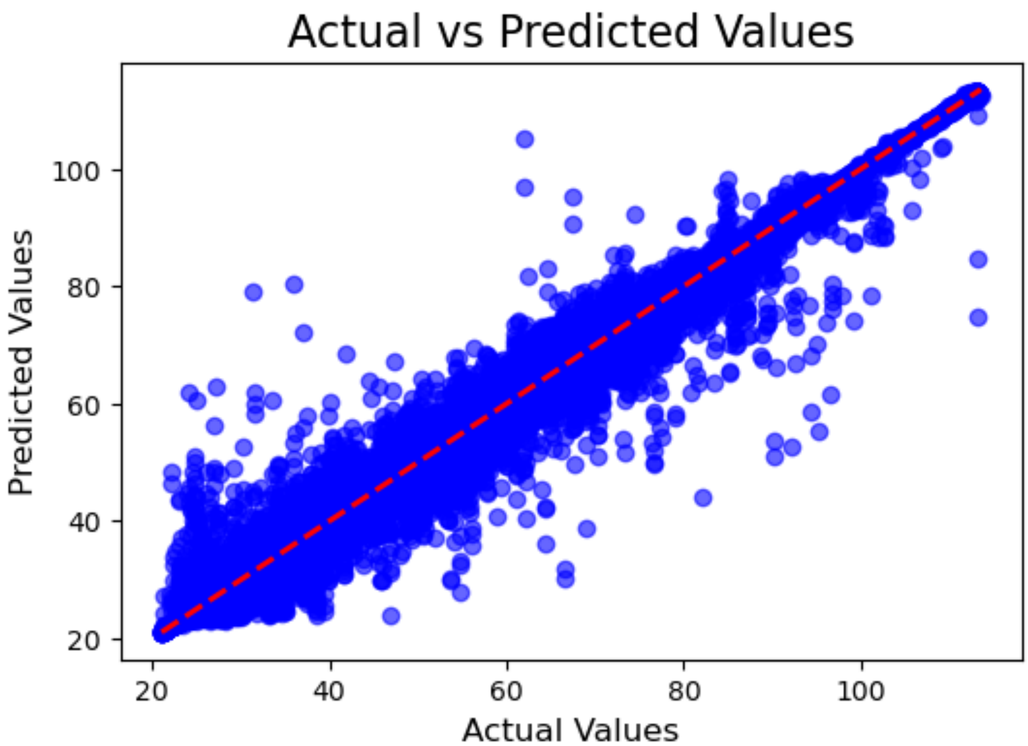
```
RandomForestRegressor(n_estimators=10, random_state=42)
```

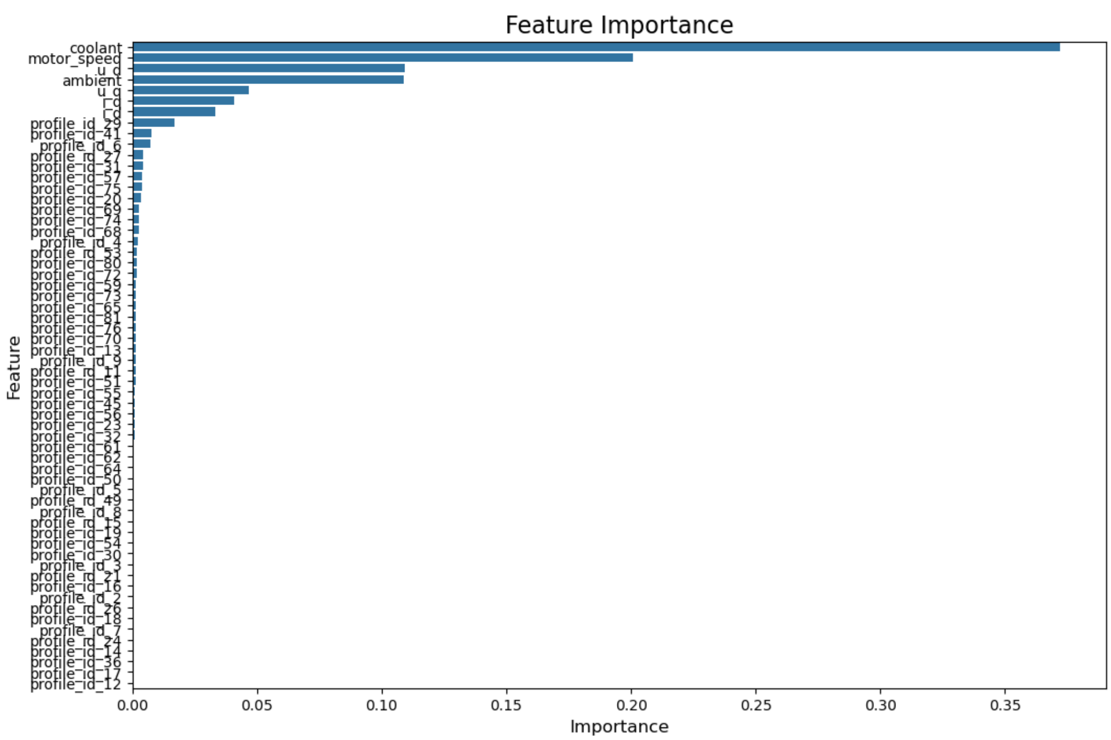
```python
# Model Evaluation and prediction

import matplotlib.pyplot as plt
import seaborn as sns

# Making predictions on the test set
y_pred = model.predict(X_test_scaled)

# Evaluating the model
mse = mean_squared_error(y_test, y_pred)  # MSE (default)
mae = mean_absolute_error(y_test, y_pred)  # MAE
rmse = np.sqrt(mse)  # Manual calculation of RMSE
r2 = r2_score(y_test, y_pred)  # R-Squared (R²)

# Printing performance metrics
print(f"\nMean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"R-Squared (R²): {r2}")

# Geting feature importance scores
feature_importances = model.feature_importances_

# Creating a DataFrame to display feature importance
importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance':
feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Plotting the residuals
residuals = y_test - y_pred

plt.figure(figsize=(6, 4))
sns.histplot(residuals, kde=True, bins=30)
plt.title('Residuals Distribution', fontsize=16)
plt.xlabel('Residuals (Actual - Predicted)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.show()
```

```python
# Plotting a scatter plot of Actual vs Predicted values
plt.figure(figsize=(6, 4))
plt.scatter(y_test, y_pred, color='blue', alpha=0.6)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',
lw=2)
plt.title('Actual vs Predicted Values', fontsize=16)
plt.xlabel('Actual Values', fontsize=12)
plt.ylabel('Predicted Values', fontsize=12)
plt.show()

# Plotting Feature Importance
plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=importance_df)
plt.title('Feature Importance', fontsize=16)
plt.xlabel('Importance', fontsize=12)
plt.ylabel('Feature', fontsize=12)
plt.show()
```

```
Mean Squared Error (MSE): 1.632221968893844
Mean Absolute Error (MAE): 0.44597788473482386
Root Mean Squared Error (RMSE): 1.2775844273056258
R-Squared (R²): 0.9959247012267057
```




Actual vs Predicted Values
Predicted Values
20
40
60
80
100
Actual Values
20
40
60
80
100


Feature Importance
Feature
coolant
motor_speed
u_d
ambient
u_q
i_d
i_q
profile_id_29
profile_id_41
profile_id_6
Importance
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35

** Now running the saved scripts on jupyter notebook - train_model.py // predict_fraud.py // app.py ***

```
# Importing the training script
!python train_model.py
```

```
Connected to database...

Data pre-processing completed

Model Training stated using RandomForestRegressor!!!

Model and Scaler have been saved as EMT_model.joblib and EMT_scaler.joblib.
```

```
# Importing the Predict script
!python predict_model.py
```

```
Predicted 'pm': 65.88811650999999
```

```
import subprocess

# Now running the Flask app using subprocess
subprocess.Popen(["python", "app.py"])
```

```
<Popen: returncode: None args: ['python', 'app.py']>
```

```
import requests
import json

# URL of the Flask API endpoint
url = 'http://127.0.0.1:5005/predict'

# Sample input data with a single 'profile_id' field instead of one-hot
encoding
input_data = {
    'u_q': 0.9,
    'coolant': 0.3,
    'u_d': 0.4,
    'motor_speed': 3500,
    'i_d': 0.9,
    'i_q': 0.5,
    'ambient': 29,
    'profile_id': 1,  # Single profile_id field instead of one-hot encoding
}

# Sending POST request to Flask API with the input data
response = requests.post(url, json=input_data)
```

```python
# Checking the response status code
if response.status_code == 200:
    # If the request is successful, print the predicted 'pm' value
    response_json = response.json()
    print("Prediction received successfully!")
    print(f"Predicted 'pm': {response_json['predicted_pm']}")
else:
    # If there is an error, print the error message
    print(f"Failed to get prediction. Status Code: {response.status_code}")
    print(f"Error: {response.json()}")
```

```
Prediction received successfully!
Predicted 'pm': 65.90054204500001
```

```
127.0.0.1 - - [20/Dec/2024 23:22:58] "POST /predict HTTP/1.1" 200 -
```