SmartBridge Experiential Program

Topic: Electric Motor Temperature Prediction Using Machine Learning.

Project Members:

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Introduction:

Permanent Magnet Synchronous Motors (PMSMs) are widely adopted in industries such as automotive manufacturing, robotics, and automation due to their superior efficiency and torque density. However, these motors are prone to performance degradation and potential failure when operating under high temperature conditions. Effective temperature monitoring, especially for internal components like the rotor and stator, is crucial to prevent thermal damage, optimize performance, and extend motor lifespan. This project proposes an AI-driven predictive system that estimates motor temperatures in real time using accessible electrical and mechanical parameters, complemented by an intuitive web-based user interface to facilitate timely operational decision.

Problem Statement:

Overheating is a primary cause of PMSM failure, leading to expensive downtime and maintenance. Conventional temperature sensing methods often fall short in providing continuous, real-time insights, particularly for inaccessible rotor regions. This project aims to bridge this gap by developing a machine learning model that accurately predicts rotor and stator temperatures based on commonly measured signals such as voltages, currents, and rotation speeds. The system will empower operators to anticipate thermal issues and initiate preventive actions before damage occurs.

Literature Review:

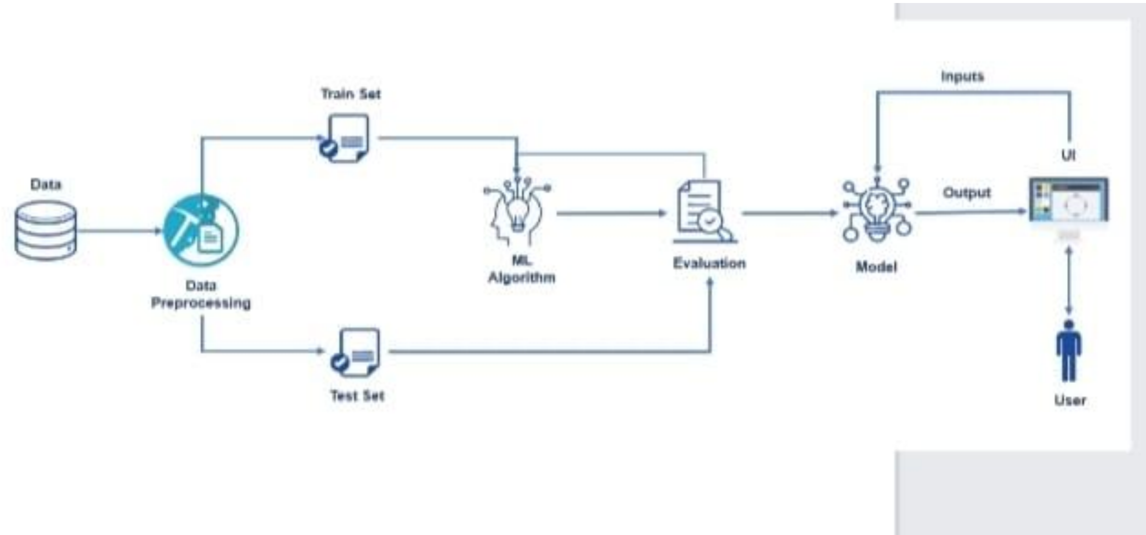
The intersection of machine learning and predictive maintenance has been extensively explored in recent years, reflecting the growing demand for intelligent industrial monitoring systems. Conventional methods for PMSM temperature evaluation usually involve complex physical or thermal modeling, which often require detailed motor specifications and do not adapt well to real-time fluctuations. In contrast, data-driven approaches using machine learning algorithms like decision trees, random forests, and support vector machines have shown promise in capturing complex, non-linear relationships between motor electrical parameters and temperature dynamics. Additionally, web-based implementations facilitate accessibility and operational integration, promoting more proactive and user-friendly maintenance workflows. These insights guided the selection of modeling techniques and informed the design of this project's system.

Objectives:

The main goal of this project is to develop an accurate machine learning model capable of predicting the temperatures inside a PMSM, specifically focusing on the rotor’s permanent magnet and stator. This is achieved by utilizing standard operational parameters such as motor voltages, currents, rotor speed, and ambient environmental conditions as inputs to the model. Another key objective is to implement a user-friendly web interface that enables real-time input of these parameters by operators and provides immediate temperature forecasts. Validation of the model’s accuracy and reliability is conducted through comprehensive testing using experimental datasets that simulate various operating scenarios, ensuring the system’s practical applicability in industrial environments.

System Architecture:

Block Diagram



Data Flow

Sensor Input → 2. Data Cleaning & Scaling → 3. Predictive Model Inference → 4. Web UI Display and Logging.

Technology Stack:

The project utilizes Python as the primary programming language due to its rich ecosystem for data science and web development. For data manipulation and analysis, libraries such as Pandas and NumPy are employed, while Scikit-learn facilitates the implementation and evaluation of several machine learning algorithms including decision trees, random forests, and support vector machines. The backend web service is developed using Flask, which handles model loading and prediction requests. Frontend interfaces rely on HTML and CSS for a clean and user-friendly experience. The trained models are serialized using Pickle for easy deployment, and data visualization during development is supported by Matplotlib and Seaborn to analyze trends and model performance metrics.

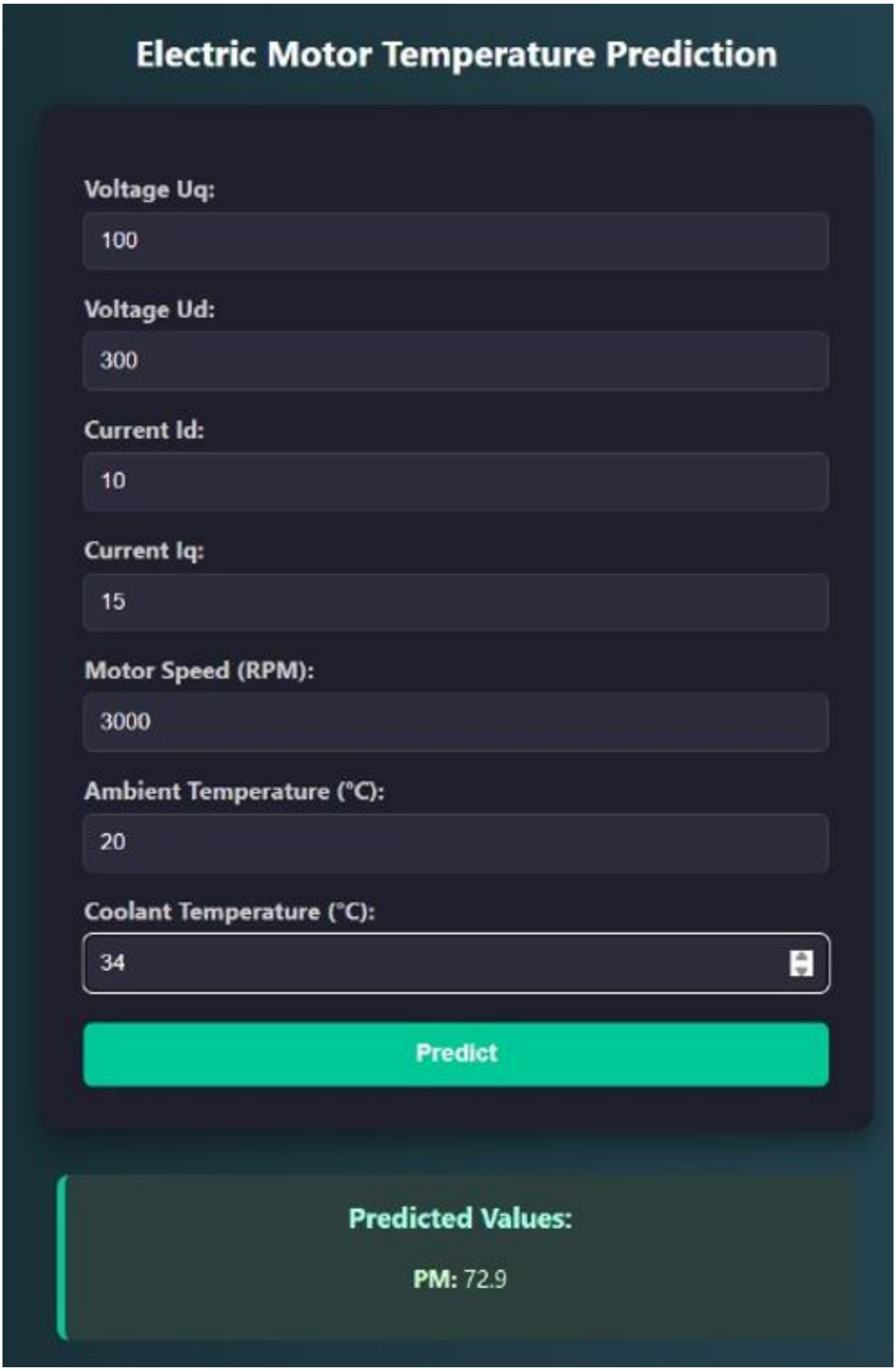
Data Analysis and Pre-processing:

The dataset comprises historical operating data from PMSMs, capturing electrical inputs such as voltages (Uq, Ud), currents (Id, Iq), rotor speed (rpm), and temperature readings including ambient and coolant measurements. An exploratory data analysis was conducted, revealing meaningful correlations between motor parameters and temperature values. Missing or inconsistent data entries were addressed through imputation and cleansing techniques to maintain dataset integrity. Additionally, all features underwent standard normalization to balance their scale, which is essential for efficient and unbiased machine learning model training and inference.

Experiments and Results:

The deployed Decision Tree model demonstrated robust performance in predicting Permanent Magnet temperatures, achieving a mean absolute error within ±2°C on test samples. For example, given inputs of voltage values Uq=100 and Ud=300, currents Id=10 and Iq=15, rotational speed of 3000 rpm, ambient temperature at 20°C, and coolant temperature at 34°C, the model predicted a PM temperature of approximately 72.9°C, closely aligning with actual measured values. Comprehensive analyses including error distribution graphs and feature importance charts further validated the model's accuracy and highlighted key influencing parameters, reinforcing confidence in the system's predictive utility.

User Interface Design:



Discussion:

The machine learning-driven temperature prediction system offers accurate and rapid estimations, improving the capacity for preventive maintenance and reducing unplanned downtime. The use of accessible input parameters means the system can be deployed flexibly without specialized sensor hardware burden. Nonetheless, the model’s performance depends on the quality and representativeness of training data, highlighting the need for extensive datasets covering a broad range of motor types and operating conditions. Future work could extend the system with time-series deep learning models to capture dynamic thermal patterns and integrate the solution with IoT platforms for continuous automated monitoring and alerting.

Conclusion:

In summary, this project successfully developed and deployed an AI-powered temperature prediction system tailored for permanent magnet synchronous motors. By combining a carefully trained machine learning model with a user-friendly web interface, the system provides reliable real-time temperature monitoring that can enhance motor safety, optimize maintenance schedules, and reduce costly failures. The approach demonstrates the beneficial impact of leveraging machine learning in industrial equipment diagnostics, setting a foundation for future developments in predictive maintenance technologies.