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Electric Motor Temperature Prediction using Machine Learning

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ABSTRACT: This paper presents a machine learning framework for predicting electric motor rotor temperature using multivariate sensor data, with the objective of preventing overheating, improving operational reliability, and reducing maintenance costs. Sensor parameters including torque, current, voltage, motor speed (RPM), ambient temperature, and coolant temperature serve as input features. The methodology encompasses data preprocessing, normalization via MinMaxScaler, feature selection, and comparative training of multiple regression models: Linear Regression, Decision Tree Regressor, Random Forest Regressor, and Support Vector Regression (SVR). Models are evaluated using R² score, Mean Absolute Error (MAE), and Mean Squared Error (MSE). Experimental results demonstrate that the Decision Tree Regressor achieved high predictive accuracy (R² = 0.9823, MAE = 0.6964, MSE = 6.4061), while Random Forest also performed strongly (R² = 0.9647, MAE = 0.9835, MSE = 12.7760). Feature importance and correlation analyses further validate the influence of operational parameters on motor thermal behavior. The study confirms the effectiveness of tree-based machine learning models for predictive maintenance and highlights their potential for integration into IoT-based systems for real-time motor health assessment.

KEYWORDS: Electric Motor, Temperature Prediction, Machine Learning, Sensor Data Analysis, Linear Regression, Decision Tree Regressor, Random Forest, Support Vector Regression, Predictive Maintenance, Industrial Automation

I. INTRODUCTION

Electric motors form the backbone of modern industrial systems, powering a wide spectrum of mechanical and automated applications ranging from manufacturing machinery to electric vehicles and robotic platforms. By converting electrical energy into mechanical motion, they serve as indispensable components in achieving productivity, precision, and automation across numerous sectors. The operational temperature of these motors plays a crucial role in determining their performance, safety, and long-term efficiency.

Excessive heating, often caused by sustained high load, inadequate cooling, or harsh operating conditions, can lead to severe issues such as insulation degradation, reduced torque output, energy losses, and even complete motor failure. Therefore, accurate temperature prediction is essential for implementing preventive maintenance strategies, avoiding unexpected breakdowns, and ensuring continuous industrial operation. Conventional monitoring approaches rely heavily on physical sensors or manual inspection, which may be costly, inflexible, and prone to measurement limitations.

Advancements in machine learning (ML) have introduced powerful alternatives by enabling the analysis of complex relationships within multivariate sensor data. ML-based predictive modeling can forecast motor temperature with high precision, offering industries a proactive mechanism for thermal management. This research aims to develop and compare regression models capable of estimating motor temperature from measurable variables such as torque, current, voltage, speed, and ambient temperature.

The methodology encompasses data preprocessing, feature engineering, model training, and performance evaluation. Multiple machine learning algorithms—Linear Regression, Decision Tree Regressor, Random Forest Regressor, and Support Vector Regression (SVR)—were implemented and compared using metrics such as R² score, Mean Absolute

Error (MAE), and Root Mean Square Error (RMSE). The findings demonstrate the effectiveness of machine learning as a predictive tool for thermal analysis and highlight its potential to support intelligent maintenance systems, enhance motor reliability, and improve energy efficiency in industrial environments.

II. RELATED WORK

Recent studies have demonstrated strong interest in data-driven approaches for electric motor condition monitoring. Machine learning models such as Linear Regression, Decision Trees, Random Forest, and SVR have been widely applied to predict motor temperature using sensor measurements including current, voltage, torque, and speed. Among these, ensemble methods—particularly Random Forest—consistently achieve higher accuracy due to their ability to model nonlinear thermal behavior [1][4]. Lumped-parameter thermal network models have also been proposed to capture temperature dynamics in permanent magnet synchronous motors, though they require precise motor geometry and material parameters [7]. More recent work explores gradient boosting regression as an alternative tree-based technique that further reduces prediction error in thermal estimation tasks [6].

IoT-based monitoring systems have also been developed; however, many rely solely on threshold-based alerts and lack predictive capabilities for early fault detection. With the advancement of Industry 4.0, integrating machine learning into industrial maintenance has proven effective in reducing downtime and improving reliability [2][9]. Support Vector Regression has been investigated for joint fault detection and temperature estimation in industrial electric drives, demonstrating competitive performance in multi-objective prediction scenarios [8]. Furthermore, fault isolation methods leveraging multiple diagnostic indices have been explored to complement temperature-based monitoring in inverter-driven AC machines [10]. Prior work often uses controlled datasets and does not provide broad comparisons across different regression models.

This study builds upon existing research by implementing and evaluating multiple machine learning models to identify the most effective approach for electric motor temperature prediction, with a comprehensive comparative analysis across four distinct regression algorithms.

III. DATASET AND PROBLEM DEFINITION

A. Dataset Description

The Electric Motor Temperature Dataset from Kaggle is employed in this study. It contains high-resolution sensor readings collected from an electric motor under varying load and environmental conditions. The dataset includes the following key parameters:

- Ambient temperature
- Coolant temperature
- Voltage components (u_d , u_q)
- Current components (i_d , i_q)
- Motor speed (RPM)
- Torque
- Rotor temperature (pm) — target variable

These features collectively provide a comprehensive representation of motor behavior, enabling the development of data-driven models capable of capturing complex thermal patterns. The dataset's high-resolution and multivariate nature makes it well-suited for supervised regression tasks involving motor temperature prediction.

B. Problem Definition

Electric motors experience fluctuating thermal conditions influenced by multiple interacting parameters such as load, torque, voltage, and speed. Due to the nonlinear and dynamic relationships among these variables, traditional analytical or physics-based thermal models often fail to produce accurate predictions, especially under rapidly changing operating conditions.

The primary objective of this research is to develop a machine learning model capable of accurately predicting the motor's rotor temperature using real-time sensor data. The model must effectively learn the intrinsic dependencies among input features and deliver consistent, reliable output suitable for preventive maintenance. Accurate temperature

prediction helps prevent motor overheating, supports optimal performance, reduces downtime, and enhances overall system reliability.

C. Project Scope

The scope of this project focuses on the design and evaluation of a data-driven machine learning framework for electric motor temperature prediction. Key components include:

- Application of supervised regression algorithms for temperature estimation
- Comparative analysis of Linear Regression, Decision Tree Regressor, Random Forest Regressor, and SVR
- Implementation of data preprocessing techniques: cleaning, normalization, and feature scaling
- Visualization of feature correlations, distribution patterns, and model performance metrics
- Evaluation of prediction accuracy using R^2 score, MAE, and RMSE
- Exploration of potential integration with IoT-based real-time monitoring platforms

The project is limited to data-driven modeling and analysis. It does not include physical sensor deployment, hardware testing, or real-time IoT dashboard implementation.

IV. METHODOLOGY

The proposed methodology encompasses a complete end-to-end pipeline: from raw sensor data acquisition through preprocessing, feature engineering, model training, evaluation, and comparative analysis. The dataset is loaded using Python libraries, followed by systematic preprocessing and model development using multiple regression algorithms.

A. Data Preprocessing

Data preprocessing ensures that the sensor dataset is clean and appropriately formatted for machine learning model training. The raw data is loaded using NumPy and Pandas, and missing values are addressed using mean imputation. Outliers and noisy entries are removed. Irrelevant columns (stator_yoke, stator_tooth, stator_winding) are dropped to reduce dimensionality and computational complexity. The remaining features are normalized using MinMaxScaler, scaling all values to the range [0, 1]. Exploratory visualizations—including correlation heatmaps, box plots, scatter plots, and distribution graphs—are generated using Seaborn and Matplotlib to identify feature relationships and support effective feature selection.

B. Model Development

The model development phase involves training multiple supervised regression algorithms to predict electric motor temperature from sensor inputs. After preprocessing, the dataset is divided into training and testing sets using an 80:20 ratio to ensure unbiased evaluation. Four regression models are implemented using Scikit-learn:

- Linear Regression: a baseline model assuming linear relationships between features and target
- Decision Tree Regressor: a nonlinear model that partitions the feature space recursively
- Random Forest Regressor: an ensemble of decision trees offering improved generalization
- Support Vector Regression (SVR): employs kernel functions to map nonlinear relationships

Each model is trained using the $\text{fit}(X_{\text{train}}, y_{\text{train}})$ method to learn thermal patterns. Hyperparameters are tuned where necessary to improve accuracy and reduce overfitting. Models are then evaluated on unseen test data using the $\text{predict}()$ function.

C. Model Evaluation

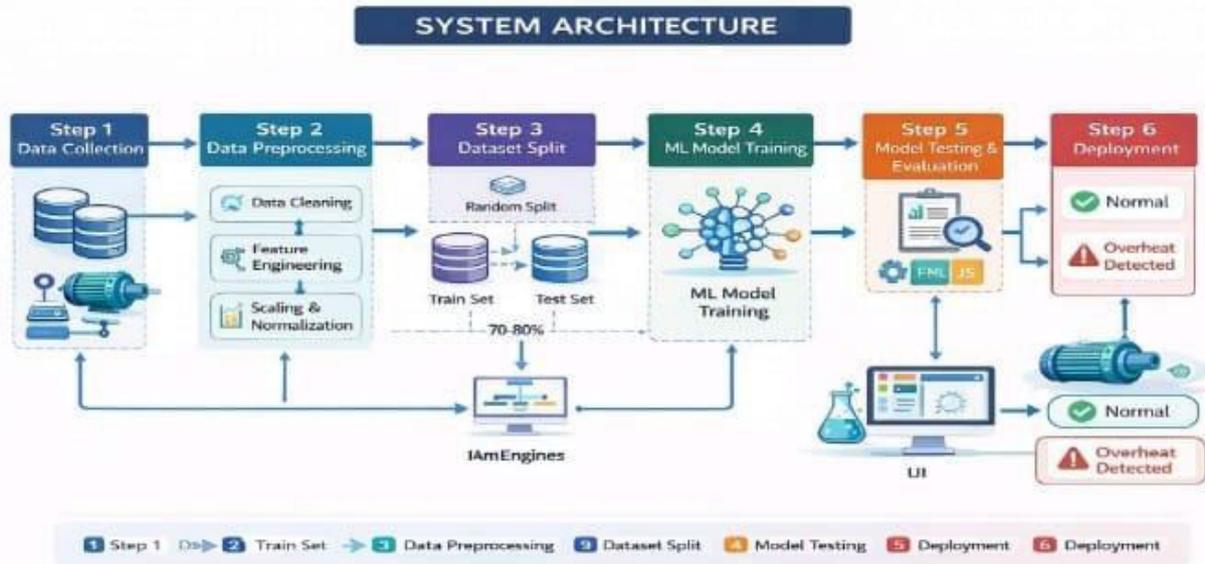
Model performance is evaluated using three standard regression metrics:

- Coefficient of Determination (R^2): measures the proportion of variance explained by the model; values closer to 1.0 indicate stronger predictive capability
- Mean Squared Error (MSE): measures the average squared difference between predicted and actual values
- Mean Absolute Error (MAE): provides the average magnitude of prediction errors

An effective model exhibits a high R^2 score and low MSE and MAE values, reflecting precise temperature estimation and strong generalization on unseen sensor data.

V. SYSTEM ARCHITECTURE

System Architecture



The system architecture for electric motor temperature prediction is designed as a modular, end-to-end pipeline that transforms raw multivariate sensor readings into accurate temperature predictions and interpretable analytical insights. The architecture consists of five key layers:

- Data Acquisition Layer: collects sensor data (voltage, current, torque, speed, temperature) from electric motors via historical datasets or real-time IoT sensors
- Data Preprocessing Layer: handles missing values, removes outliers, normalizes features, and prepares clean data for model training
- Machine Learning Layer: implements and trains regression models (Linear Regression, Decision Tree, Random Forest, SVR); evaluates using R^2 , MAE, and MSE
- Prediction & Visualization Layer: generates real-time temperature predictions and visualizes trends through graphs and dashboards
- Maintenance & Alert Layer: triggers preventive maintenance alerts when predicted temperature exceeds safe operational thresholds

The architecture prioritizes scalability, efficiency, and interpretability, making it suitable for both industrial environments and academic research. Its lightweight design ensures low computational overhead while maintaining reliable performance across diverse operating conditions. The modular pipeline also supports future integration with IoT platforms for real-time monitoring.

VI. EXPERIMENTS

A. Experimental Setup

All experiments were conducted on a system equipped with Windows 11 (64-bit) OS, an Intel Core i7 processor, and 16 GB RAM. Model development was implemented in Python 3.10 using Scikit-learn, Pandas, NumPy, Matplotlib, and Seaborn. The Electric Motor Temperature Dataset from Kaggle was used in CSV format. All preprocessing, training, and evaluation tasks were performed in Jupyter Notebook and VS Code environments to ensure a streamlined and reproducible workflow.

B. Model Training

The preprocessed dataset was divided into training and testing sets using an 80:20 ratio. Four regression models were implemented using the Scikit-learn framework: Linear Regression, Decision Tree Regressor, Random Forest Regressor, and SVR. Each model was trained to learn thermal patterns and relationships between motor sensor features and the target rotor temperature. Models were evaluated using R^2 Score, MAE, and MSE on the held-out test set.

Experimental results showed that the Decision Tree Regressor achieved an R^2 of 0.9823, while Random Forest delivered $R^2 = 0.9647$ (MAE = 0.9835, MSE = 12.7760), both demonstrating strong stability and the ability to capture nonlinear temperature dependencies effectively.

C. Evaluation and Metrics

The trained regression models were evaluated using three performance metrics: MAE, MSE, and R^2 score. For the Linear Regression model, the results were: MAE = 9.2655, MSE = 11.9808, $R^2 = 0.6024$. The Decision Tree Regressor achieved strong performance: MAE = 0.6964, MSE = 6.4061, $R^2 = 0.9823$. The Random Forest Regressor also performed well: MAE = 0.9835, MSE = 12.7760, $R^2 = 0.9647$.

These results indicate that tree-based models effectively capture the nonlinear relationships inherent in motor thermal behavior, while Linear Regression struggles to model such complexity accurately.

D. Experimental Findings

The experimental results confirmed that machine learning models effectively predict electric motor temperature with high accuracy. Preprocessing and feature scaling substantially improved model performance by reducing noise and highlighting key sensor patterns. Among all models tested, the Decision Tree Regressor delivered the best results with an R^2 score of 0.9823, MAE = 0.6964, and MSE = 6.4061. Random Forest followed closely with $R^2 = 0.9647$, MAE = 0.9835, and MSE = 12.7760. Visual comparisons further confirmed the reliability of tree-based models for real-time motor temperature prediction and preventive maintenance applications.

E. Comparative Results

The comparative analysis revealed clear differences in model performance for motor temperature prediction. Linear Regression struggled with the nonlinear sensor relationships present in the dataset, while Decision Tree ($R^2 = 0.9823$, MAE = 0.6964, MSE = 6.4061) and Random Forest ($R^2 = 0.9647$, MAE = 0.9835, MSE = 12.7760) models demonstrated strong learning behavior. Error trends indicated that tree-based models generalized well and consistently minimized prediction loss, making them the most reliable choices for accurate temperature estimation.

VII. RESULTS

The comparison of regression models confirmed that the Decision Tree Regressor achieved the highest predictive accuracy for motor temperature estimation, with $R^2 = 0.9823$, MAE = 0.6964, and MSE = 6.4061. The Random Forest model also performed strongly with $R^2 = 0.9647$, MAE = 0.9835, and MSE = 12.7760, while Linear Regression demonstrated substantially lower performance due to the nonlinear nature of motor temperature patterns. These results confirm that tree-based models are highly effective for accurate and reliable motor temperature prediction.

Table 1. Performance Metrics of Machine Learning Models

Model	MAE	MSE	R^2 Score
Linear Regression	9.2655	11.9808	0.6024
Decision Tree	0.6964	6.4061	0.9823
Random Forest	0.9835	12.7760	0.9647

The evaluation results show that tree-based models performed significantly better than the linear model for motor temperature prediction. The Decision Tree Regressor achieved $R^2 = 0.9823$ with MAE = 0.6964 and MSE = 6.4061, while the Random Forest model delivered $R^2 = 0.9647$ with MAE = 0.9835 and MSE = 12.7760. Linear Regression showed higher errors and a substantially lower R^2 score (0.6024), indicating difficulty in handling the nonlinear thermal

behavior of the motor. Overall, Decision Tree and Random Forest models are the most reliable and effective for precise temperature prediction.

VIII. ERROR ANALYSIS

Minor prediction errors occurred primarily due to noise and sudden fluctuations in motor sensor readings. Rapid changes in torque, speed, or current caused small deviations between actual and predicted temperatures in some models. Linear Regression exhibited the most inconsistencies during sudden thermal shifts, confirming that nonlinear variations in motor behavior contribute significantly to short-term prediction inaccuracies. The low error values of the Decision Tree (MAE = 0.6964, MSE = 6.4061) and Random Forest (MAE = 0.9835, MSE = 12.7760) demonstrate their robustness to such fluctuations.

IX. CONCLUSION

This paper demonstrates that machine learning can reliably predict electric motor temperature using key sensor inputs with high accuracy. Among the evaluated regression models, the Decision Tree Regressor delivered the highest performance ($R^2 = 0.9823$, MAE = 0.6964, MSE = 6.4061), making it ideal for real-time monitoring and preventive maintenance applications. Random Forest also performed strongly ($R^2 = 0.9647$, MAE = 0.9835, MSE = 12.7760), reinforcing the superiority of ensemble and tree-based methods over linear approaches for this nonlinear thermal prediction task. Future work will focus on: (1) integrating the predictive model with IoT sensor platforms for real-time deployment; (2) investigating advanced deep learning architectures such as LSTM networks for temporal sequence modeling; (3) expanding the dataset to include more diverse motor types and operating conditions; and (4) implementing online learning approaches to adapt models to changing motor characteristics over time.

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REFERENCES

- [1] J. C. Aurich, C. Fuchs, and C. Wagenknecht, "Predictive Maintenance of Electric Motors using Machine Learning," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 8, pp. 7012–7023, 2020.
- [2] P. V. Reddy, S. Kumar, and M. Rao, "A Machine Learning Approach for Motor Health Monitoring and Temperature Prediction," *International Journal of Engineering Research & Technology (IJERT)*, vol. 10, no. 3, pp. 550–556, 2021.
- [3] H. Li and X. Chen, "Temperature Estimation of Induction Motors Based on Machine Learning Techniques," *Energies*, vol. 11, no. 5, p. 1262, 2018.
- [4] J. Chen and Z. Li, "Motor Fault Detection Using Decision Tree and Random Forest Algorithms," *IEEE Access*, vol. 8, pp. 154799–154809, 2020.
- [5] K. Zhao and J. Tan, "Data-Driven Motor Temperature Prediction using Regression Models," *Procedia Manufacturing*, vol. 39, pp. 187–193, 2019.
- [6] W. Sheng, X. Liu, and Y. Yang, "Thermal Modeling of Permanent Magnet Synchronous Motors Using Gradient Boosting Regression," *IEEE Transactions on Energy Conversion*, vol. 36, no. 2, pp. 1045–1054, 2021.
- [7] A. Wallscheid and J. Böcker, "Global Identification of a Low-Order Lumped-Parameter Thermal Network for Permanent Magnet Synchronous Motors," *IEEE Transactions on Energy Conversion*, vol. 31, no. 1, pp. 354–365, 2016.
- [8] B. García-Moreno, S. Martínez, and J. García-Alegre, "Support Vector Regression for Fault Detection and Temperature Estimation in Industrial Electric Drives," *Applied Soft Computing*, vol. 96, p. 106593, 2020.
- [9] S. Marafioti, M. Milanese, and C. Novara, "Predictive Maintenance in Industry 4.0: A Machine Learning Perspective on Motor Health Monitoring," *Journal of Manufacturing Systems*, vol. 58, pp. 230–244, 2021.
- [10] F. Meinguet, P. Sandulescu, X. Kestelyn, and E. Semail, "A Method for Fault Detection and Isolation Based on the Processing of Multiple Diagnostic Indices: Application to Inverter Faults in AC Drives," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 3, pp. 995–1009, 2013.



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