Electric Motor Temperature Prediction With K-Nearest Neighbors and Convolutional Neural Network

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Motivation & Objective

- The lack of accurate temperature monitoring capabilities harms the thermal robustness of electric motor [1]
- Precise temperature predictions help with the safety and effective utilization of electric motor
- Strong correlations between temperature sequence and time is observed but not exploited yet [1, 2]

Dataset

- Data were obtained from a permanent magnet synchronous motor (PMSM) in the Paderborn University Lab [1] from multiple independent sessions. Data were divided randomly into 3:7 to test set and training set.
- Four output temperatures of different components: rotor, stator yoke, stator tooth, stator winding

Feature Extraction

Numerical Features:

- Five features were selected as input according to the correlation map (Figure 1) including: (1) Ambient temperature (2) Coolant temperature (3) Direct current (4) Motor speed (5) Time
- New features were engineered according to the domain knowledge

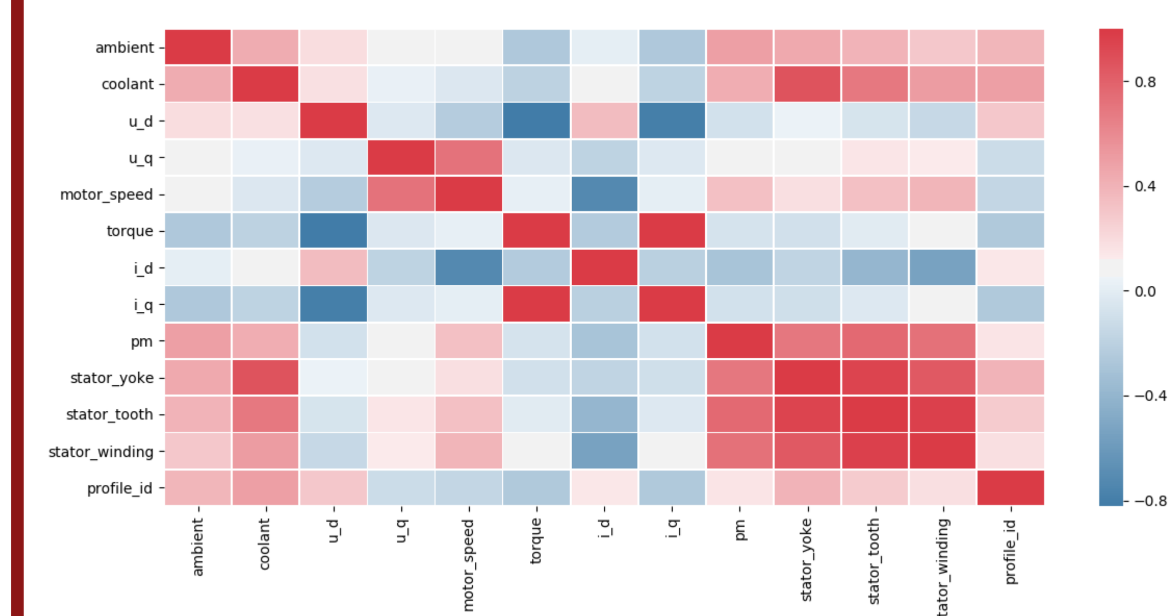

Figure 1: Correlation map

Models

Linear Regression:

- Linear Regression with selected features
- Linear Regression with kernel features: Current & Voltage magnitude, Power

$$i = \sqrt{i_d^2 + i_q^2}, \quad u = \sqrt{u_d^2 + u_q^2}, \quad P = ui$$

K-Nearest Neighbors

- K-nearest neighbors regression
  Classification with Euler distance:

$$d = \sqrt{\sum_{i=1}^{m} (x_i - c_i)^2}$$

Regression with weighted sum of neighbors:

$$o = \sum_{j=1}^{k} \frac{1}{d} y_i$$

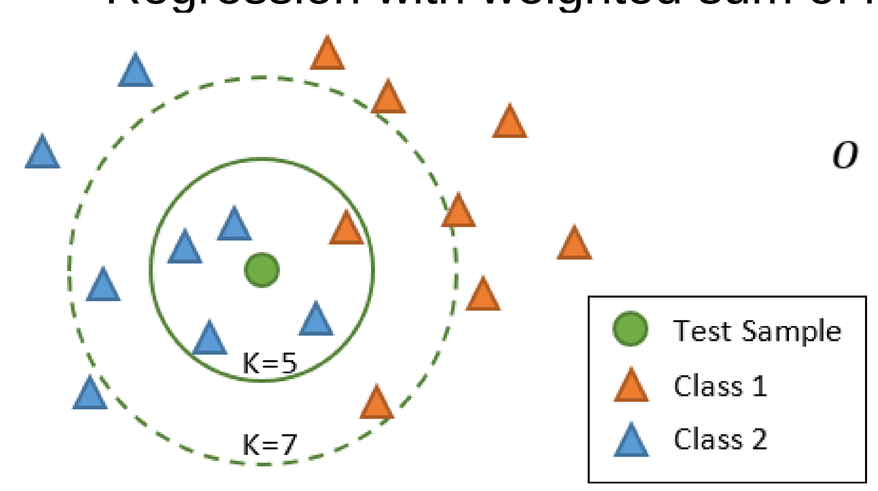

Figure 2: K-nearest neighbors regression

CNN+Regression

- 1-D convolutional neural network structure:

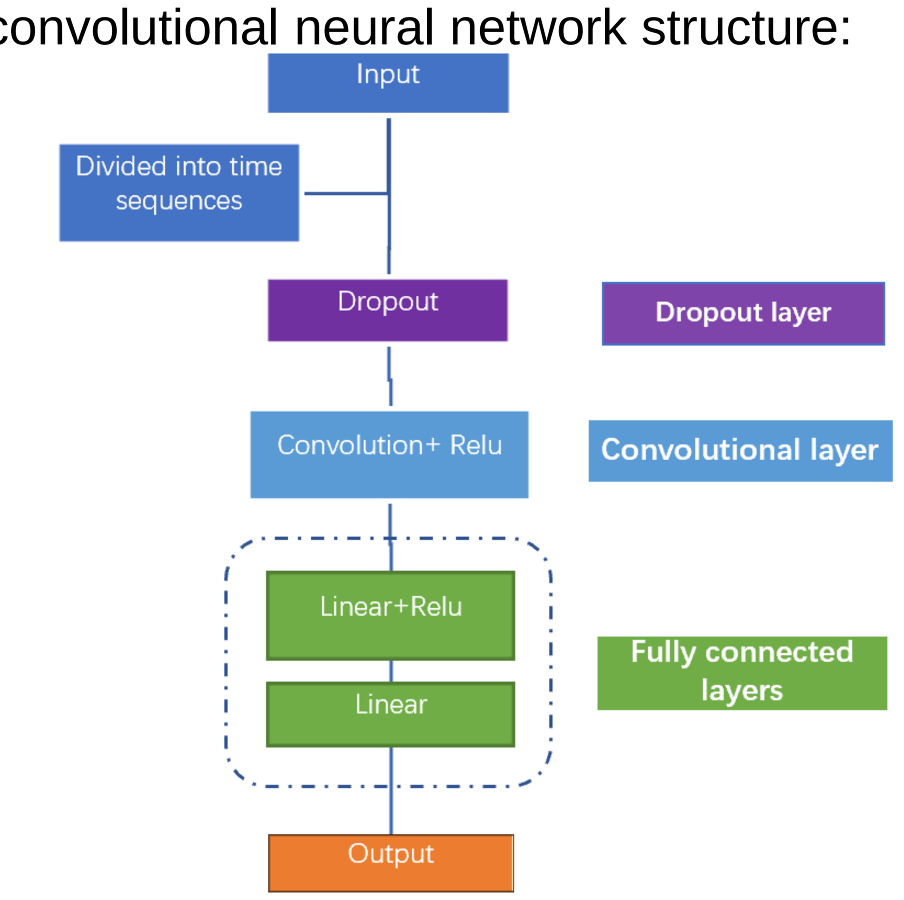

Figure 3: CNN structure

Results

- **Regression Models**

Model	*pm*	*stator_yoke*	*stator_tooth*	*stator_winding*
Linear Regression Without Kernel features	0.5286	0.2729	0.2230	0.1812
Linear Regression with Kernel features	0.3487	0.1846	0.1495	0.1229
K-nearest neighbor regression with k=7	0.0387	0.0085	0.0157	0.0186

Table 1: Test set MSE

- **Convolutional Neural Network**

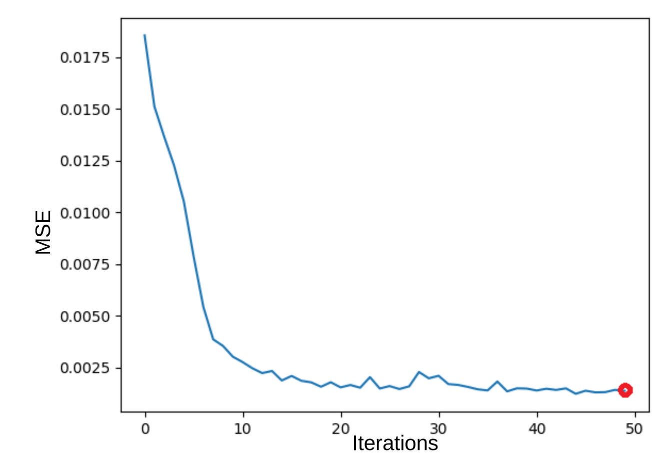

Figure 5: Training loss

Testing MSE
=**0.000667**

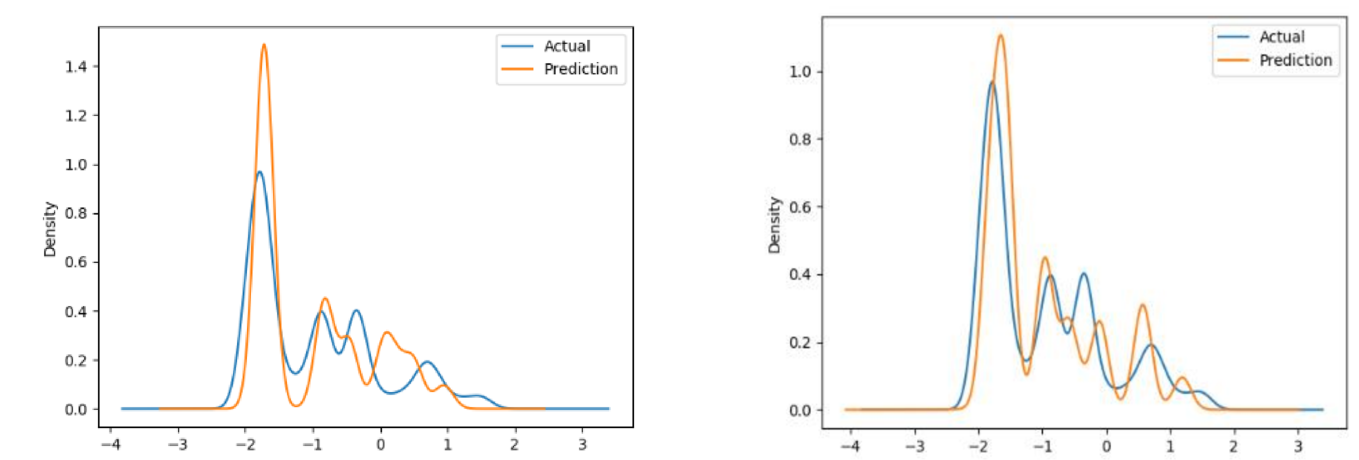

Figure 4: Density distribution without kernels (left) and with kernels (right) for Linear regression

Discussion

- Prediction results for *PMSM* temperature are better and bias were reduced when kernel method was used to reduce bias.
- Data is highly **time-dependent**. K-nearest Neighbors regression with 7 neighbors gives us a better result. The algorithm increases the accuracy by first classifying data and applying regression.
- CNN performs very well here and gives us the highest accuracy, and the MSE could be reduced further by increasing neurons in the hidden layer and increasing learning rate.

Conclusion & Future Work

It is shown that with careful feature selection and feature engineering, it is possible to precisely predict motor temperatures with different machine learning tools. Among all the tested models, CNN performs the best. The time sequence is investigated and proved to be an important component for making predictions. Future works could focus on transferring the model to other types of electric motors and validate the accuracy

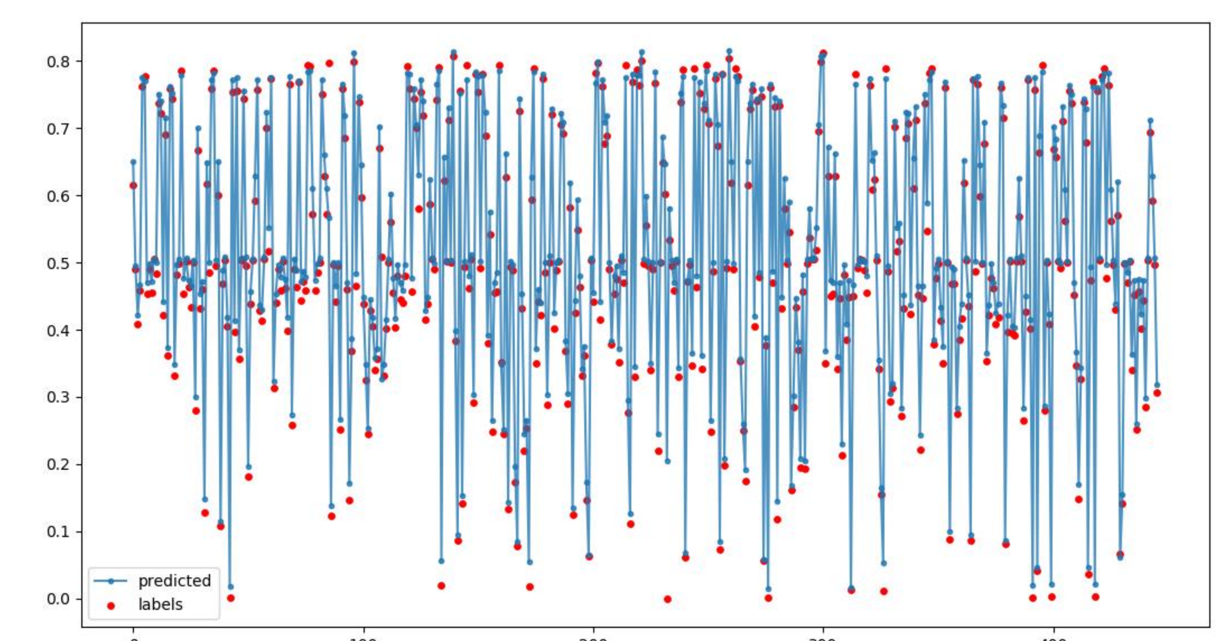

Figure 6: Comparison between predictions and test samples

References

[1] Kirchgässner, Wilhelm & Wallscheid, Oliver & Böcker, Joachim. (2019). Empirical Evaluation of Exponentially Weighted Moving Averages for Simple Linear Thermal Modeling of Permanent Magnet Synchronous Machines.
[2] Kirchgässner, Wilhelm & Wallscheid, Oliver & Böcker, Joachim. (2019). Deep Residual Convolutional and Recurrent Neural Networks for Temperature Estimation in Permanent Magnet Synchronous Motors.