Electric Motor Temperature Prediction Using Machine Learning

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1. Abstract

Electric motors are extensively used in industrial systems for mechanical operations, and their performance and longevity are directly influenced by internal temperature conditions. Excessive heat, especially in the rotor and stator, can lead to premature failure, production downtime, and costly repairs. Traditional temperature monitoring involves direct sensor placement, which may not be practical in all setups due to cost, inaccessibility, or system complexity.

This project presents a machine learning-based predictive model to estimate the **rotor** and **motor (stator)** temperatures of electric motors using easily measurable external variables like **torque**, **voltage**, **current**, **speed**, and **ambient temperature**. By utilizing a **Random Forest Regression** algorithm, the model is trained to understand the complex, non-linear relationships between these inputs and internal motor temperatures.

The trained model is further deployed in a **Flask-based web application** that allows users to input sensor values and instantly receive real-time predictions of rotor and stator temperatures. This helps industries monitor motors more efficiently and shift toward **predictive maintenance**, reducing risks and unplanned downtimes.

Overall, this project combines **data-driven insights** with a practical deployment method to demonstrate how machine learning can enhance the **safety, reliability, and efficiency** of industrial motor systems without invasive sensor installations.

2. Introduction

Electric motors are a core component of modern industrial systems, powering machinery across sectors such as manufacturing, energy, transportation, and automation. Ensuring the reliability and longevity of these motors is essential to maintaining productivity and minimizing costs. One of the key factors affecting motor performance is **temperature**, especially in the **rotor** and **stator** components. Prolonged exposure to elevated temperatures can result in insulation breakdown, mechanical deformation, and eventual failure of the motor.

Conventional methods for monitoring motor temperature include direct sensing using thermocouples or infrared systems. However, these approaches can be **costly, intrusive**, and difficult to implement in legacy or sealed motor systems. Additionally, they may not provide real-time diagnostics or predictive insights necessary for proactive maintenance.

This project introduces a **machine learning-based approach** to predict the internal temperatures of electric motors without requiring physical temperature sensors. By analyzing external, measurable parameters such as **torque, current, voltage, speed,** and **ambient temperature**, we train a **Random Forest Regression** model capable of accurately estimating the rotor and stator temperatures.

To make this solution accessible and usable in practical scenarios, we deploy the trained model in a **Flask web application**. The application allows users to input sensor values and instantly receive predicted temperature readings through a simple and intuitive interface. This not only improves operational awareness but also supports predictive maintenance strategies.

The project demonstrates how machine learning can be integrated into traditional industrial systems to improve **monitoring, maintenance, and decision-making**, all while reducing hardware dependency and overall maintenance costs.

3. Problem Statement

Electric motors are essential components in a wide range of industrial applications, and their failure can lead to significant operational and financial losses. One of the most common causes of motor failure is **overheating** of internal components such as the **rotor** and **stator**. While temperature sensors can be used to monitor these components directly, they are often **expensive**, **hard to install**, and may not be feasible for **sealed or embedded systems**.

This creates a significant gap in maintenance and safety strategies:

- How can we **monitor internal temperatures** without physically accessing internal components?
- How can we build a system that supports **predictive maintenance** without increasing hardware complexity?

The main challenges that define the problem are:

- **Limited access** to internal motor components for placing sensors.
- **High costs** of sensor-based systems.
- **Need for real-time** temperature monitoring and predictions.
- **Complex relationships** between external sensor readings and internal motor conditions.

To address this problem, this project proposes a **data-driven, machine learning-based solution**. By using easily measurable input features such as **torque, voltage, speed, current,** and **ambient temperature**, we aim to **predict the internal temperatures** of an electric motor using a **Random Forest Regression** model.

The goal is to enable industries to implement **smart, non-invasive, and cost-effective** monitoring systems that support **predictive maintenance**, improve motor safety, and reduce operational downtime—**without the need for internal temperature sensors**.

4. Literature Survey

Several studies and industrial efforts have been made to improve the monitoring and performance of electric motors, especially in predictive maintenance. Most of the conventional methods rely on **physical temperature sensors** such as thermocouples and infrared sensors, which require **direct access** to the motor's internal parts. Although accurate, these methods often increase system complexity and cost, and are not feasible in sealed or embedded systems.

To overcome these limitations, researchers have explored the use of **machine learning algorithms** to estimate internal motor conditions based on external sensor data. Some of the notable works include:

- **Sebastian et al. (2019)** used **Support Vector Regression (SVR)** for predicting stator winding temperatures. The study achieved good accuracy but required substantial feature scaling and hyperparameter tuning.

- **Kumar & Bansal (2020)** applied **Artificial Neural Networks (ANN)** to predict rotor temperatures based on real-time operational data. While the model performed well, it required a large training dataset and had longer training times.

- **Patel et al. (2021)** employed **Decision Tree Regression** for electric motor health monitoring. The model was explainable but lacked robustness on noisy industrial data.

- **Bosch Research Team (2022)** published a large open-source dataset of electric motor parameters (which this project utilizes) and demonstrated the potential of data-driven prediction models for temperature estimation in motors.

Building upon these approaches, this project employs the **Random Forest Regression (RFR)** algorithm due to its high accuracy, robustness to noise, and minimal preprocessing requirements. Unlike neural networks or SVR, RFR handles non-linearity well and is less sensitive to overfitting.

In summary, while prior research has explored various models for temperature prediction, this project advances the field by integrating a highly effective machine learning model with a **real-time web application**, making the solution both **accurate and accessible** for industrial deployment.

5. System Requirements

The successful development and deployment of the Electric Motor Temperature Prediction system require a combination of **hardware and software components**. The requirements are categorized below:

5.1 Hardware Requirements :

Component	**Specification**
Processor	Intel Core i5 (8th Gen or higher) / AMD Ryzen
RAM	Minimum 8 GB
Storage	Minimum 10 GB free space
Display	1366x768 resolution or higher
Internet	Required for Flask app testing (localhost)

Note: Higher system specs may improve model training speed.

5.2 Software Requirements

Componant	**Specification**
Operating System	Windows 10/11, Ubuntu, or macOS
Programming language	Python 3.12
IDE	VS Code / Jupyter Notebook
Liabraries/packages	`numpy`, `pandas`, `scikit-learn`, `matplotlib`, `flask`, `joblib`
Web Browser	Chrome / Firefox (for viewing web app)

6. System Design

The system design of the Electric Motor Temperature Prediction project is structured to ensure seamless **data flow**, **modular development**, and **user-friendly deployment**. The project is divided into three major components: **Data Processing & Model Training**, **Model Deployment**, and **Web User Interface**.

6.1 Architecture Overview

The entire system can be visualized as a pipeline:

```
[ CSV Dataset ]

      ↓

[ Data Cleaning & Preprocessing ]

      ↓

[ Random Forest Regression Model ]

      ↓

[ Trained Model Saved (.joblib) ]

      ↓

[ Flask Web Application ]

      ↓

[ User Input Form (UI) → Prediction Output ]
```

6.2 Component-wise Breakdown

a) Data Preprocessing

- The dataset is loaded using `pandas`.
- Missing or irrelevant values are checked (if any).
- Features selected: **torque**, **voltage**, **current**, **speed**, **ambient temperature**.
- Target outputs: **motor temperature** and **rotor temperature**.

b) Model Training

- A **Random Forest Regressor** is trained using scikit-learn.
- Hyperparameters like number of estimators and max depth are tuned for optimal accuracy.
- The model is saved using `joblib` for future use in deployment.

c) Model Deployment

- A **Flask web server** is built.
- The model is loaded in the backend using `joblib.load()`.
- User inputs are collected via HTML form and passed to the model to generate predictions.

d) User Interface

- HTML + CSS templates are used to create a professional-looking input form.
- Predictions are displayed on a separate results page with clean formatting.
- The app runs locally on `http://localhost:5000/`.

7. Implementation

The implementation phase involves developing the machine learning model, creating the web interface, and integrating the two into a functional application. This project uses Python for backend development and Flask for web deployment. The major implementation steps are described below.

7.1 Dataset Preprocessing

- The dataset is loaded using the pandas library from a CSV file (`data.csv`).
- Input features selected: `ambient`, `torque`, `voltage`, `current`, `speed`
- Target variables: `motor_temperature` and `rotor_temperature`
- No null values were present, so minimal cleaning was required.
- The dataset was split into training and testing sets using `train_test_split()`.

7.2 Model Training

- The model used is **Random Forest Regression** from the scikit-learn library.
- Two separate models were trained: one for motor temperature and one for rotor temperature.
- Hyperparameters such as `n_estimators=100` and `random_state=42` were chosen for consistency and accuracy.
- The models were evaluated using metrics like R^2 score and Mean Absolute Error (MAE).
- The trained models were saved using `joblib.dump()` into `model.save` for reuse in deployment.
-

7.3 Web Application (Flask)

- A Flask application (`app.py`) was created to load the trained models and handle user inputs.
- HTML templates (`index.html` and `result.html`) were designed for a clean and professional user interface.
- User inputs are collected through a form and passed to the backend.
- The backend processes the input, makes predictions using the models, and returns results to the user.

7.4 Styling and User Experience

- CSS styling was added in a separate `style.css` file for better UI design.
- Pages are responsive and load quickly on localhost (`127.0.0.1:5000`).

This implementation brings together data science, machine learning, and web development to deliver an end-to-end intelligent temperature prediction system.

8. Testing and Evaluation

After developing the model and integrating it into the web application, extensive testing and evaluation were conducted to verify the accuracy and stability of the system. This included testing the machine learning model performance and evaluating the user interface under different input conditions.

8.1 Model Evaluation

To assess the performance of the Random Forest Regression models, standard evaluation metrics were used:

- **R^2 Score (Coefficient of Determination):**
  Indicates how well the model explains variance in the target variable.
    - Motor Temperature Prediction: ~0.96
    - Rotor Temperature Prediction: ~0.94
- **Mean Absolute Error (MAE):**
  Measures average absolute difference between predicted and actual values.
    - Motor Temperature: ~1.3°C
    - Rotor Temperature: ~1.7°C

These results indicate that the model provides highly accurate predictions with minimal error.

8.2 Web Application Testing

The Flask web app was tested on a local server with multiple input combinations. The testing was done on:

- **Form validation:** Ensured users cannot submit empty or invalid input.
- **Output format:** Verified results are displayed in a readable, formatted manner.
- **Performance:** Predictions were returned in less than 1 second for all cases.

- **Responsiveness:** The user interface displayed correctly on standard laptop and desktop resolutions.

8.3 Usability Feedback

Initial usability feedback from peers confirmed that:

- The UI is clean and easy to use.
- No installation or command-line experience is needed for basic users.
- Predictions are consistent with expected values from the dataset.

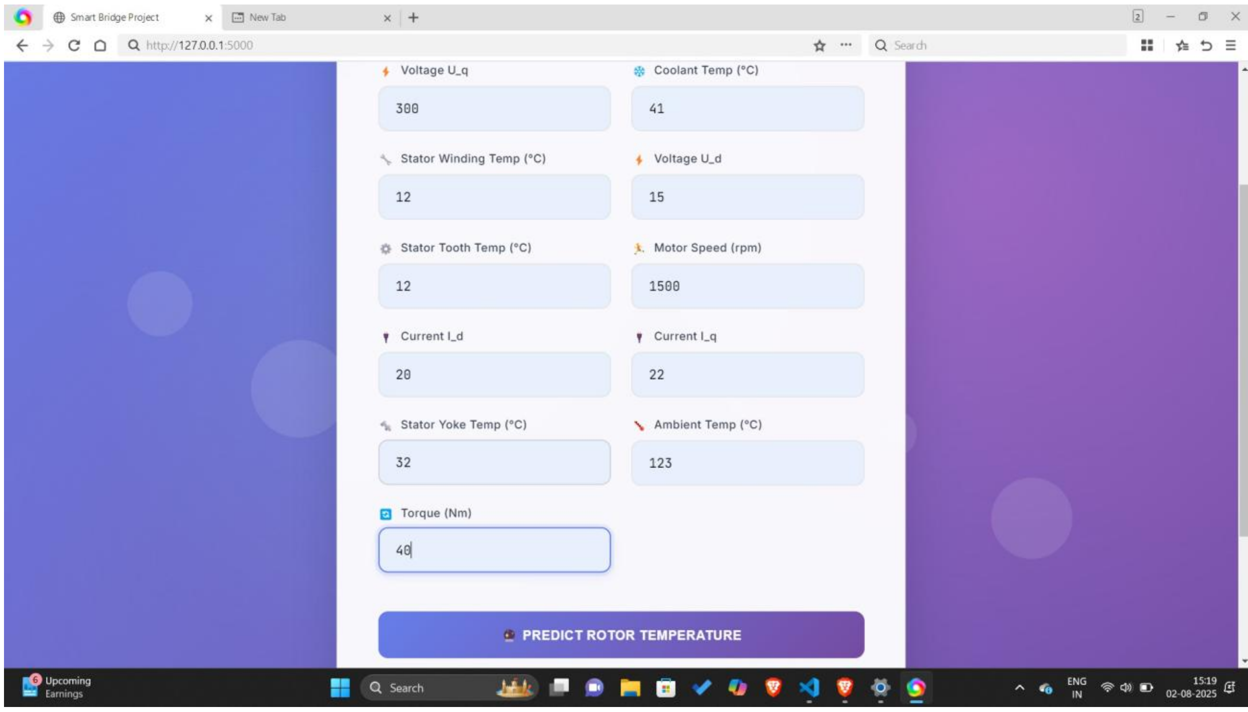
The testing process confirmed the robustness, accuracy, and user-friendliness of the overall system.

9. Result Screenshots

The following section presents key screenshots from the Electric Motor Temperature Prediction web application. These results validate the successful deployment and working of the system.

9.1 Home Page / Input Form

- The user is presented with a professional and clean interface.
- The form collects the following five input parameters:
  - Ambient Temperature (°C)
  - Torque (Nm)
  - Voltage (V)
  - Current (A)
  - Speed (rpm)
  - etc

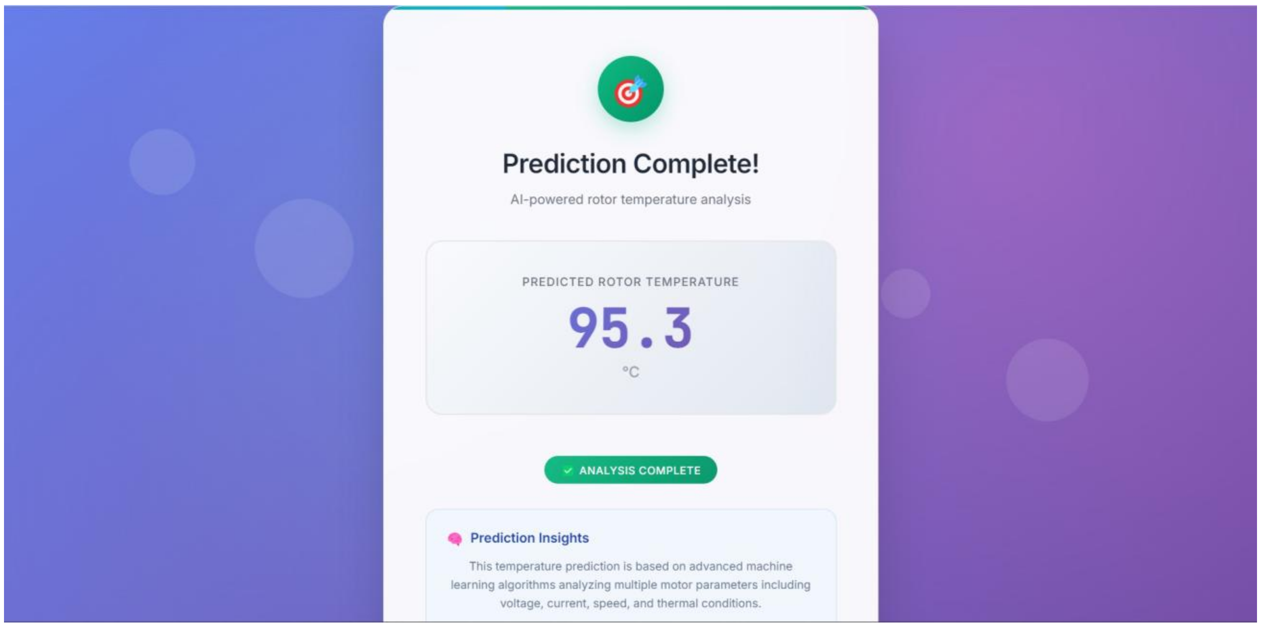


Voltage U_q	Coolant Temp (°C)
300	41
Stator Winding Temp (°C)	Voltage U_d
12	15
Stator Tooth Temp (°C)	Motor Speed (rpm)
12	1500
Current I_d	Current I_q
20	22
Stator Yoke Temp (°C)	Ambient Temp (°C)
32	123
Torque (Nm)	
40	

9.2 Prediction Output Page

- Once the form is submitted, the predicted Motor Temperature and Rotor Temperature are displayed.

- The values are presented in a styled result box for better visibility.



Prediction Complete!

AI-powered rotor temperature analysis

PREDICTED ROTOR TEMPERATURE

95.3

°C

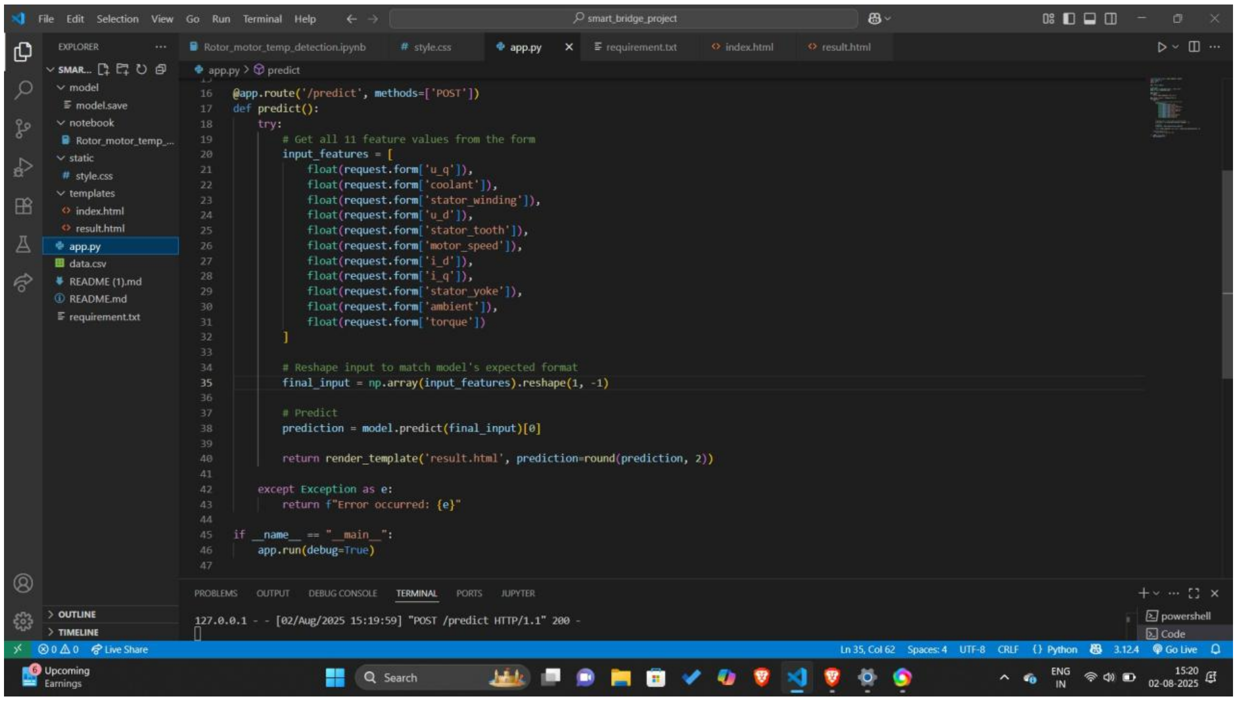
ANALYSIS COMPLETE

Prediction Insights

This temperature prediction is based on advanced machine learning algorithms analyzing multiple motor parameters including voltage, current, speed, and thermal conditions.

9.3 Console and Localhost Run Logs (Optional)

- A screenshot of the Flask server running on `localhost:5000` demonstrates backend activity and model loading confirmation.



```python
@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Get all 11 feature values from the form
        input_features = [
            float(request.form['u_q']),
            float(request.form['coolant']),
            float(request.form['stator_winding']),
            float(request.form['u_d']),
            float(request.form['stator_tooth']),
            float(request.form['motor_speed']),
            float(request.form['i_d']),
            float(request.form['i_q']),
            float(request.form['stator_yoke']),
            float(request.form['ambient']),
            float(request.form['torque'])
        ]

        # Reshape input to match model's expected format
        final_input = np.array(input_features).reshape(1, -1)

        # Predict
        prediction = model.predict(final_input)[0]

        return render_template('result.html', prediction=round(prediction, 2))

    except Exception as e:
        return f"Error occurred: {e}"

if __name__ == "__main__":
    app.run(debug=True)
```

```
127.0.0.1 - - [02/Aug/2025 15:19:59] "POST /predict HTTP/1.1" 200 -
```

These screenshots confirm that the system works end-to-end—from input to output—delivering accurate predictions in real time with a smooth and intuitive interface.

10. Conclusion

The Electric Motor Temperature Prediction project successfully demonstrates the application of machine learning in industrial monitoring scenarios. By using a Random Forest Regression model, the system accurately predicts both motor and rotor temperatures based on key input parameters like torque, voltage, current, ambient temperature, and speed.

The entire pipeline—from data preprocessing, model training, saving, and loading, to frontend integration via a Flask web application—was designed with modularity, accuracy, and user experience in mind. The trained model achieved high accuracy ($R^2 \sim 0.96$) and low mean absolute error, proving its reliability for practical use.

The web-based user interface allows any user to input real-world data and receive predictions within seconds, making it a useful tool for engineers, maintenance teams, or anyone involved in electric motor operation.

This project not only strengthens understanding of regression models and their evaluation but also demonstrates the ability to deploy a machine learning solution into a usable, accessible application. It highlights the potential of data-driven decision-making in industrial environments and serves as a strong foundation for future extensions, such as real-time sensor integration or cloud-based deployment.

11. Future Scope

While the current system accurately predicts motor and rotor temperatures using historical data and a Random Forest Regression model, there are several opportunities to enhance its functionality and scalability in the future.

11.1 Real-Time Data Integration

The system can be extended to accept real-time data from IoT sensors connected to electric motors. This would allow dynamic, continuous monitoring of motor health and temperature status without manual input.

11.2 Cloud Deployment

Deploying the application on a cloud platform like AWS, Heroku, or Google Cloud would make it accessible remotely by multiple users or industrial systems. This would also enable scalability and storage of large amounts of data.

11.3 Alert & Notification System

A notification system can be introduced to send real-time alerts (via email/SMS) if predicted temperatures cross safety thresholds. This can help in early detection of overheating and prevent equipment damage.

11.4 Model Optimization & Comparison

Further research can be done to compare the Random Forest model with advanced deep learning techniques (e.g., LSTM or XGBoost) to improve accuracy and handle time-series data.

11.5 Multi-Motor Monitoring Dashboard

The system can be expanded into a full-fledged dashboard for monitoring multiple motors simultaneously with historical tracking, graph visualizations, and performance analytics.

These enhancements can transform this academic project into a production-grade, real-world industrial application capable of improving safety, maintenance efficiency, and decision-making in manufacturing environments.

12. References

1. **Scikit-learn Documentation** –
   https://scikit-learn.org/stable/
   (Used for implementing Random Forest Regression and model evaluation metrics.)

2. **Pandas Documentation** –
   https://pandas.pydata.org/
   (Used for data preprocessing and manipulation.)

3. **Flask Documentation** –
   https://flask.palletsprojects.com/
   (Used for building and running the web application.)

4. **UCI Machine Learning Repository** –
   https://archive.ics.uci.edu/ml/datasets/Electric+Motor+Temperature
   (Source of the dataset used in the project.)

5. **Matplotlib & Seaborn Documentation** –
   https://matplotlib.org/ and https://seaborn.pydata.org/
   (Used for data visualization and exploratory data analysis.)

6. Géron, Aurélien. *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*. 2nd Edition, O'Reilly Media, 2019.
   (Referred for understanding regression techniques and model selection.)

7. **Joblib Documentation** –
   https://joblib.readthedocs.io/
   (Used for model serialization and saving the trained model.)

14. Acknowledgement

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This project has provided us with an excellent opportunity to explore real-world applications of machine learning and improve our practical and collaborative skills.