Case Study Title: Proactive Anomaly Detection for Smart Radiator Efficiency

Organization: Betterspace GmbH
Role: Working Student – BI/DA
Author: Muhammad Anwar

Overview

Betterspace GmbH specializes in energy-efficient software solutions for heating management in institutional buildings. This case study presents a data-driven prototype for anomaly detection aimed at improving operational efficiency, energy usage, and maintenance scheduling for smart radiator systems.

Problem Statement

While Betterspace's current system efficiently manages heating through occupancy-based radiator control and scheduling, there is no explicit mechanism to flag anomalous heating behavior—such as excessive temperature deviation, heating when unoccupied, or ineffective performance.

> The goal is to detect early signs of inefficiency or system malfunction using historical heating data, thus minimizing energy waste and improving thermal comfort.

Dataset

A simulated dataset was created using Python to represent 200 hourly records across 4 rooms over 8 days. Key columns include:

- `timestamp`: Date and time of reading
- `room_id`: Unique room identifier
- `outside_temp_c`, `set_temp_c`, `actual_temp_c`
- `heating_status`: 0 = OFF, 1 = ON
- `occupancy`: 0 = unoccupied, 1 = occupied
- `energy_kwh`: Hourly energy usage
- `temp_diff`: Set temperature minus actual temperature

Methodology

1. Anomaly Detection Rules

Three simple rule-based anomalies were defined:

- **Temperature Deviation > 2°C**
  Indicates possible sensor drift, poor insulation, or overshooting
- **Heating ON + Room Empty**
  Wasted energy when no one is present
- **Heating ON + Temperature Still Low**
  System might be underpowered or failing

A final column `anomaly_flag` was generated by OR-ing the above conditions.

2. Visualization & Trend Analysis

- Anomaly types and frequency by room
- Temporal patterns across hours and days
- Energy usage vs. occupancy

Key Findings

- **40%** of anomalies were due to poor temperature control.
- Heating occurred during **unoccupied periods in 34 cases**, wasting energy.
- **Ineffective heating** occurred in **20+ intervals**, pointing to slow warm-up or faulty systems.
- Anomalies peaked during early morning hours (6–8 AM) and in Room_104, Room_103.

Impact & Recommendations

- ✅ **Add Anomaly Detection Module** in Betterspace's dashboard
- ✅ Enable facility managers to set alerts for persistent inefficiencies
- ✅ Prioritize rooms with recurring inefficiencies for inspection
- ✅ Use this as a foundation for **predictive maintenance models** in future

Next Steps

- Extend the prototype to integrate real Betterspace sensor feeds
- Enhance the model using machine learning (e.g., Isolation Forest, LSTM)
- Build a real-time dashboard in Power BI or Tableau

Conclusion

This case study proves that a simple, data-driven layer of anomaly detection can significantly enhance Betterspace's ability to maintain smart heating systems efficiently, saving energy and improving building comfort in the long run.

Attachments:

- Sample graphs and dashboards
- Python Jupyter Notebook (prototype logic)
- Synthetic dataset CSV
- GitHub link (optional)