Hierarchical Unsupervised Anomaly Detection for Industrial Thermocouple Sensor Data in Stainless Steel Furnaces

Master Degree Project in Informatics with a specialization in Data Science

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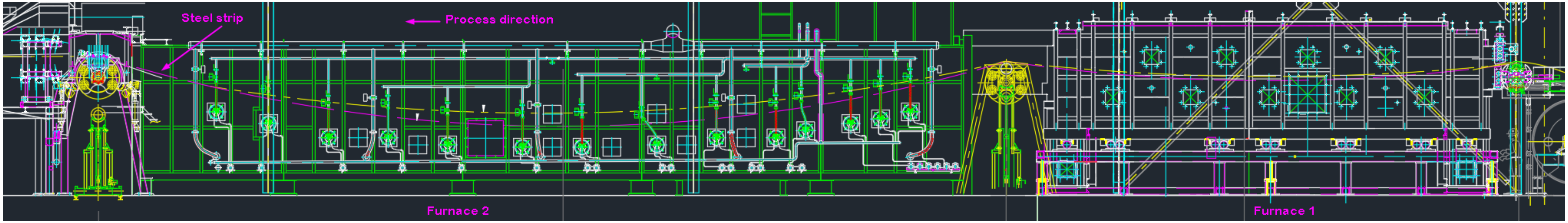
About Me

Name: Ebrahim Golriz
Background:

- B.S. in Computer Engineering	2020-2024
- M.S. in Data Science	2024-2025

Problem Statement



Problem Statement

• Importance of **temperature monitoring** in stainless steel manufacturing

• Limitations of current methods: **static thresholds**, **lack of labeled data**

Problem Statement

- **Lack of labeled anomalies** makes supervised learning impractical

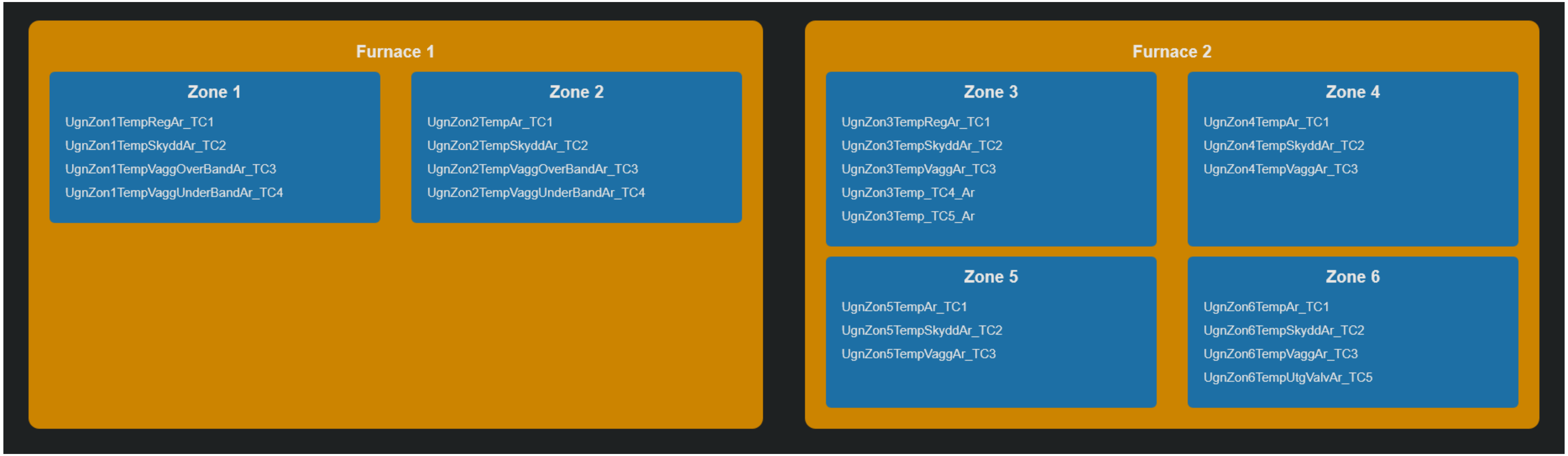
- High-dimensional, multivariate **time-series data**

- Need for **proactive** anomaly detection at **furnace, zone, and sensor levels**

Objectives

- Build **furnace** and **zone-level** **autoencoders** for unsupervised detection
- Use **regression** for **thermocouple-level** diagnostics
- Design a **hierarchical detection** framework as prototype
- **Visualize** outputs for interpretability

System Architecture and Hierarchy



Dataset Overview

- Multivariate time-series sensor data from Outokumpu's industrial furnaces.
    - Scope: 5 months of data (Dec 2024 - Apr 2025).
    - 1-minute intervals.

- 207,305 total data points (rows).

    Training Set (80%): The first 165,836 rows. (Used to learn "normal" behavior).

    Test Set (20%): The last 41,459 rows. (Used for evaluation).

Adding lag for temporal anomaly detection

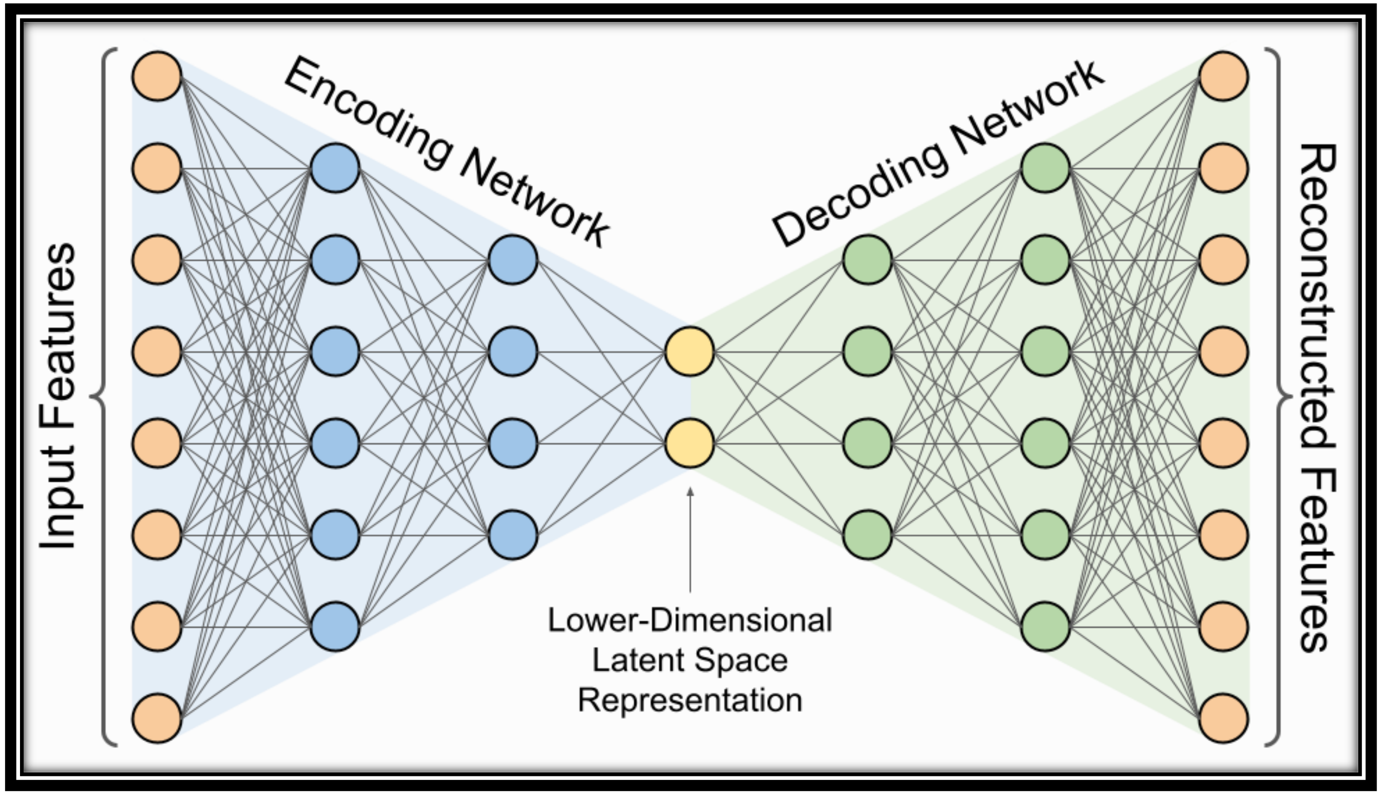
- For every sensor reading at the current time (t), we added its value from the previous timestamp (t-1) as a new input feature.

- Industrial processes have **memory**. The current state is highly dependent on the immediate past.

- This gives the models "**context**" and allows them to learn from the process dynamics, not just a static snapshot.

Autoencoders

- Autoencoders learn to reconstruct **normal** input data.
- Train on historical (mostly normal) data.
- High reconstruction error = data is "unfamiliar" / anomalous.
- **Anomaly Score**: Mean Squared Error (MSE) between Input and Reconstructed Output.
- **Threshold**: Defined (95th percentile of reconstruction errors on validation data).



Autoencoders – Feature Analysis

- *A single "**anomaly score**" is not enough. It tells you that something is wrong, but not **what** is wrong*
- When an anomaly is **flagged**, we deconstruct the autoencoder's reconstruction error.
- We calculate the **individual error** for each **input feature.**
- This provides a **ranked list of variables** contributing most to the anomaly.
- This turns an alert into a targeted diagnostic tool for operators.

Regression Models for Diagnosis

- **Purpose**: Pinpoint problematic individual thermocouples within an anomalous zone.
- **Method**:
- Train a Ridge Regression model for each thermocouple.
- Predicts a TC's reading based on other sensors in its zone (other TCs, fuel flow, strip speed, etc.).
- **Diagnosis**:
- **Significant difference** between predicted value and actual value suggests the thermocouple itself might be faulty or behaving unusually.
- The regression models showed good predictive performance, with most achieving high R-squared values on the test data, indicating they learned the relationships between sensors well.

Regression Evaluation – Furnace 1

Furnace 1

Zone 1

UgnZon1TempRegAr_TC1
RMSE: 2.93 °C
Avg: 917.58 °C
Train: 165,836 | Test: 41,459

UgnZon1TempSkyddAr_TC2
RMSE: 2.72 °C
Avg: 915.97 °C
Train: 165,836 | Test: 41,459

UgnZon1TempVaggOverBandAr_TC3
RMSE: 5.85 °C
Avg: 898.18 °C
Train: 165,836 | Test: 41,459

UgnZon1TempVaggUnderBandAr_TC4
RMSE: 3.67 °C
Avg: 915.84 °C
Train: 165,836 | Test: 41,459

Zone Average: 911.89 °C

Zone 2

UgnZon2TempAr_TC1
RMSE: 2.79 °C
Avg: 931.76 °C
Train: 165,836 | Test: 41,459

UgnZon2TempSkyddAr_TC2
RMSE: 2.86 °C
Avg: 925.79 °C
Train: 165,836 | Test: 41,459

UgnZon2TempVaggOverBandAr_TC3
RMSE: 4.16 °C
Avg: 943.57 °C
Train: 165,836 | Test: 41,459

UgnZon2TempVaggUnderBandAr_TC4
RMSE: 5.11 °C
Avg: 950.26 °C
Train: 165,836 | Test: 41,459

Zone Average: 937.84 °C

Regression Evaluation – Furnace 2

Furnace 2

Zone 3

UgnZon3TempRegAr_TC1
RMSE: 2.78 °C
Avg: 1019.72 °C
Train: 165,836 | Test: 41,459

UgnZon3TempSkyddAr_TC2
RMSE: 3.39 °C
Avg: 1026.95 °C
Train: 165,836 | Test: 41,459

UgnZon3TempVaggAr_TC3
RMSE: 4.38 °C
Avg: 1053.01 °C
Train: 165,836 | Test: 41,459

UgnZon3Temp_TC4_Ar
RMSE: 4.84 °C
Avg: 1063.44 °C
Train: 165,836 | Test: 41,459

UgnZon3Temp_TC5_Ar
RMSE: 4.31 °C
Avg: 1057.30 °C
Train: 165,836 | Test: 41,459

Zone Average: 1044.08 °C

Zone 4

UgnZon4TempAr_TC1
RMSE: 3.13 °C
Avg: 1016.91 °C
Train: 157,037 | Test: 39,260

UgnZon4TempSkyddAr_TC2
RMSE: 3.01 °C
Avg: 1000.07 °C
Train: 157,037 | Test: 39,260

UgnZon4TempVaggAr_TC3
RMSE: 5.05 °C
Avg: 1058.25 °C
Train: 157,037 | Test: 39,260

Zone Average: 1025.08 °C

Zone 5

UgnZon5TempAr_TC1
RMSE: 1.74 °C
Avg: 1019.75 °C
Train: 165,836 | Test: 41,459

UgnZon5TempSkyddAr_TC2
RMSE: 1.67 °C
Avg: 1023.95 °C
Train: 165,836 | Test: 41,459

UgnZon5TempVaggAr_TC3
RMSE: 6.09 °C
Avg: 1067.14 °C
Train: 165,836 | Test: 41,459

Zone Average: 1036.95 °C

Zone 6

UgnZon6TempAr_TC1
RMSE: 1.43 °C
Avg: 1035.83 °C
Train: 165,836 | Test: 41,459

UgnZon6TempSkyddAr_TC2
RMSE: 1.22 °C
Avg: 1031.99 °C
Train: 165,836 | Test: 41,459

UgnZon6TempVaggAr_TC3
RMSE: 4.22 °C
Avg: 1032.94 °C
Train: 165,836 | Test: 41,459

UgnZon6TempUtgValvAr_TC5
RMSE: 3.90 °C
Avg: 1013.89 °C
Train: 165,836 | Test: 41,459

Zone Average: 1028.66 °C

Implementation

- **Broad Detection:** Identify if *something* is wrong at the overall furnace level.

- **Localized Diagnosis:** Pinpoint *where* the issue is (specific zone, then specific thermocouple).

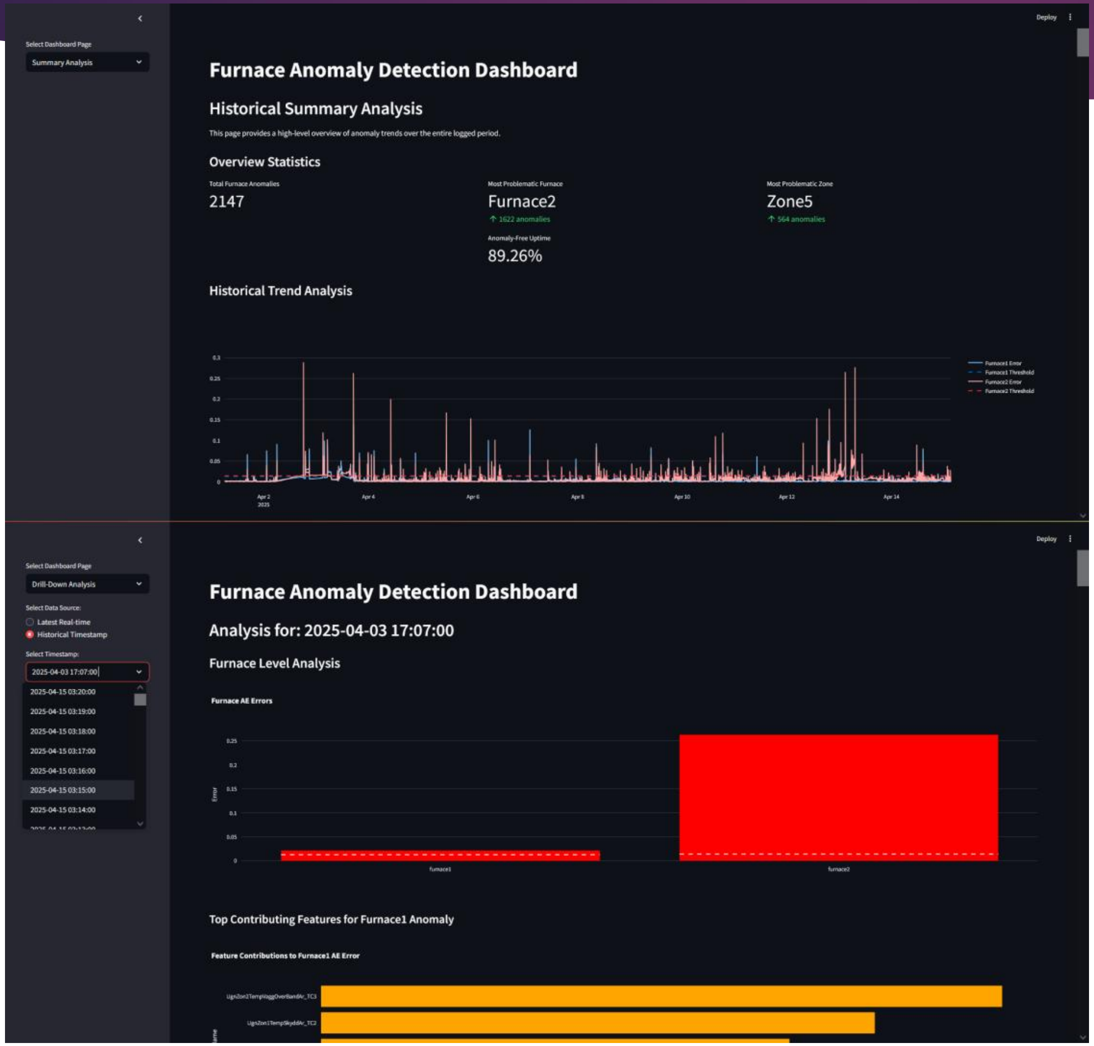
- **Efficient**: Avoids running all models all the time.

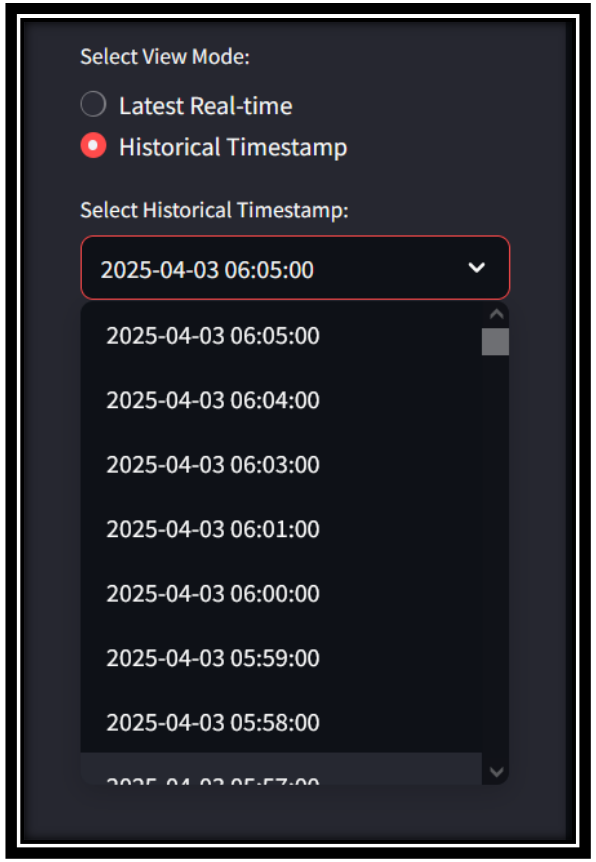
Implementation

- **Pipeline:**
  - Streamlit-based application.
  - Processes data row-by-row (simulating real-time).
  - Applies hierarchical logic.

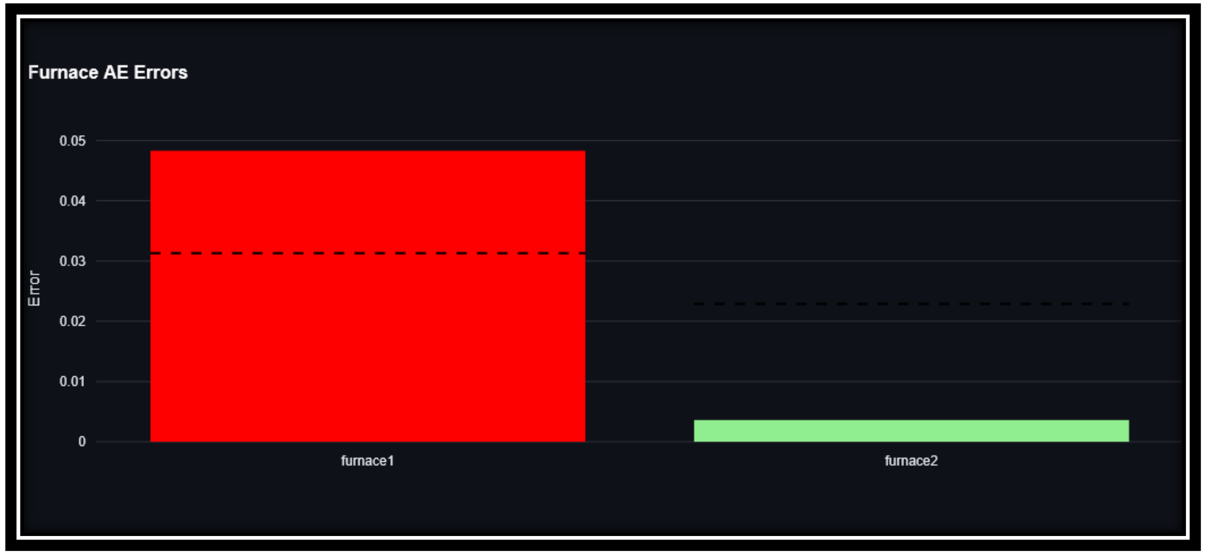
- **Dashboard**
  - Visualize anomaly status: Furnace -> Zone -> Thermocouple.
  - Show reconstruction errors, predicted vs. actual values.
  - Shows feature contribution in anomalies
  - Shows regression prediction for thermocouples

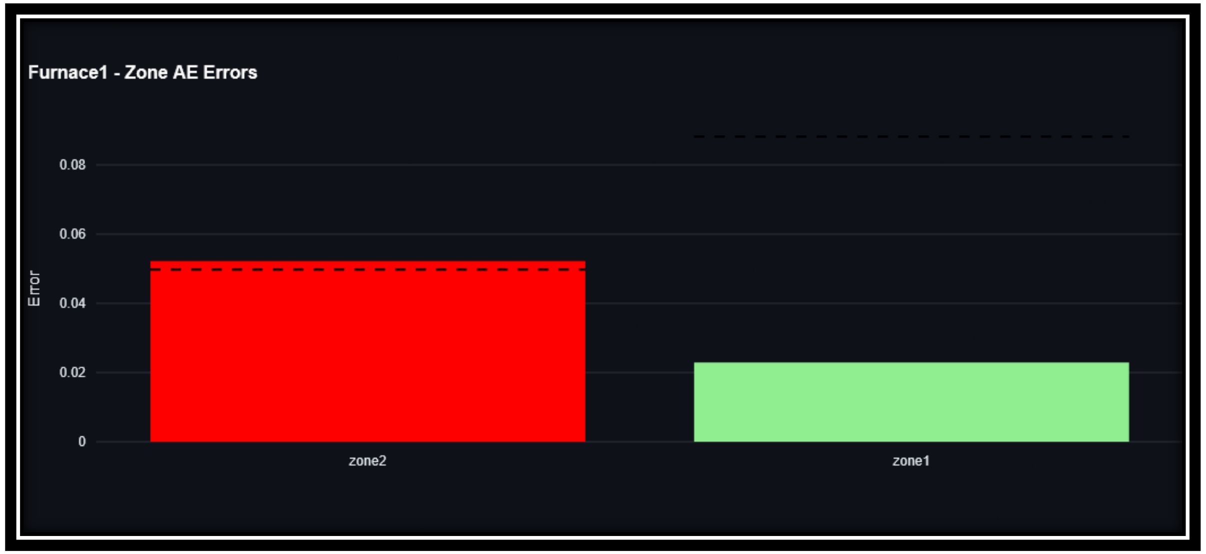
Implementation-Dashboard



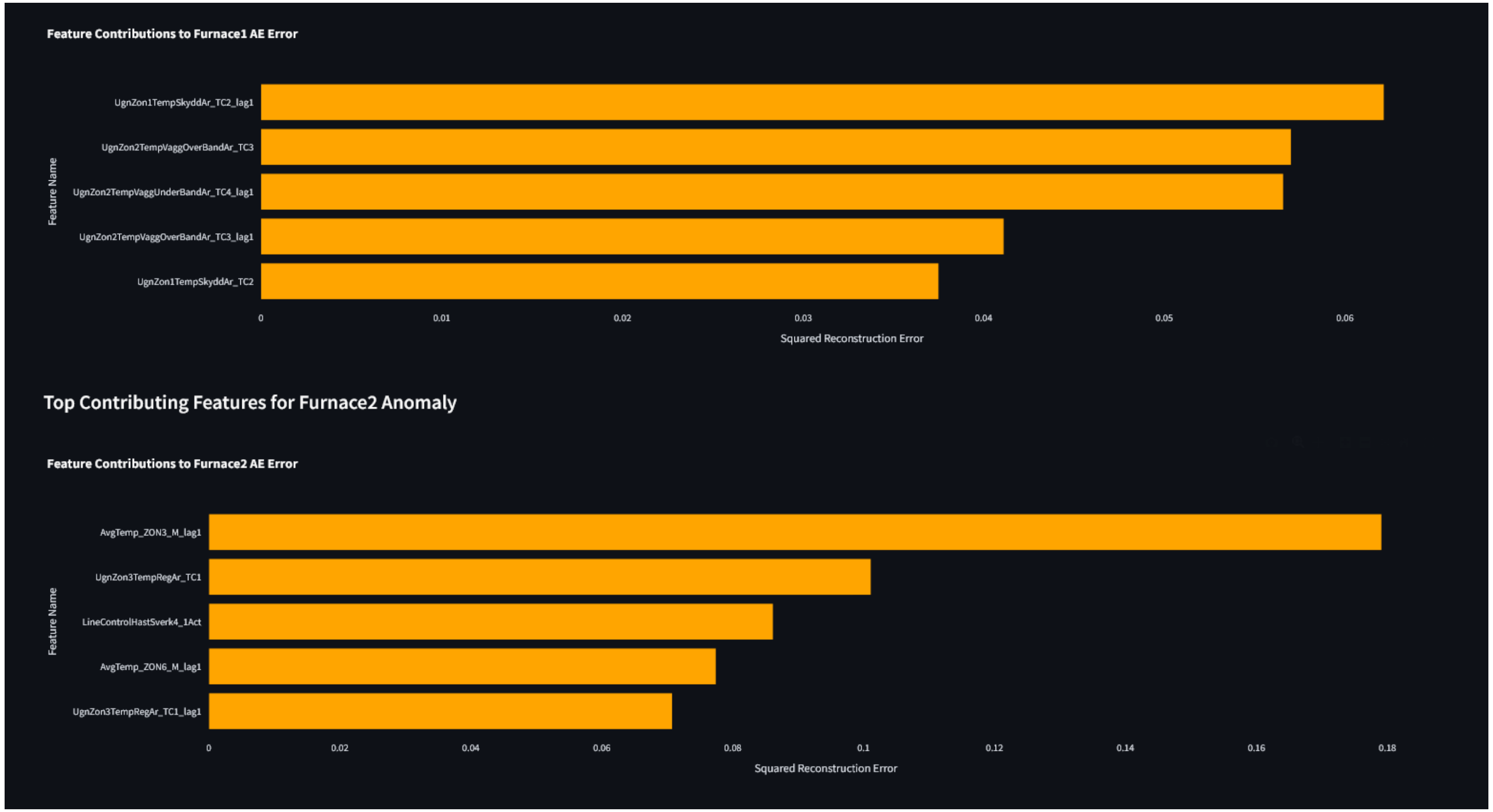


Implementation-Example Furnace & Zone Level Anomalies

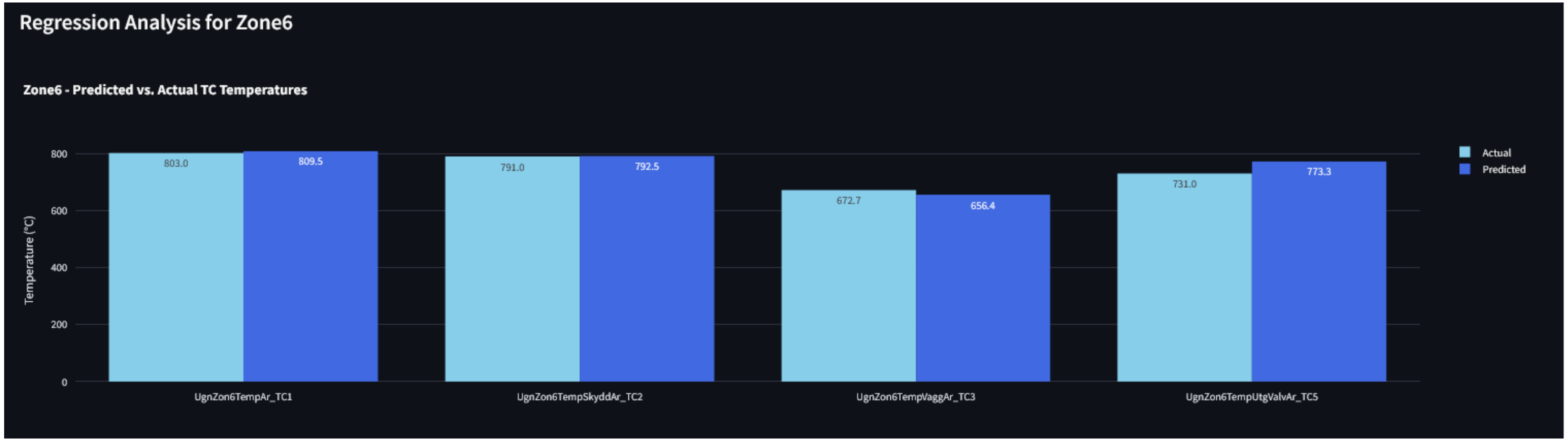




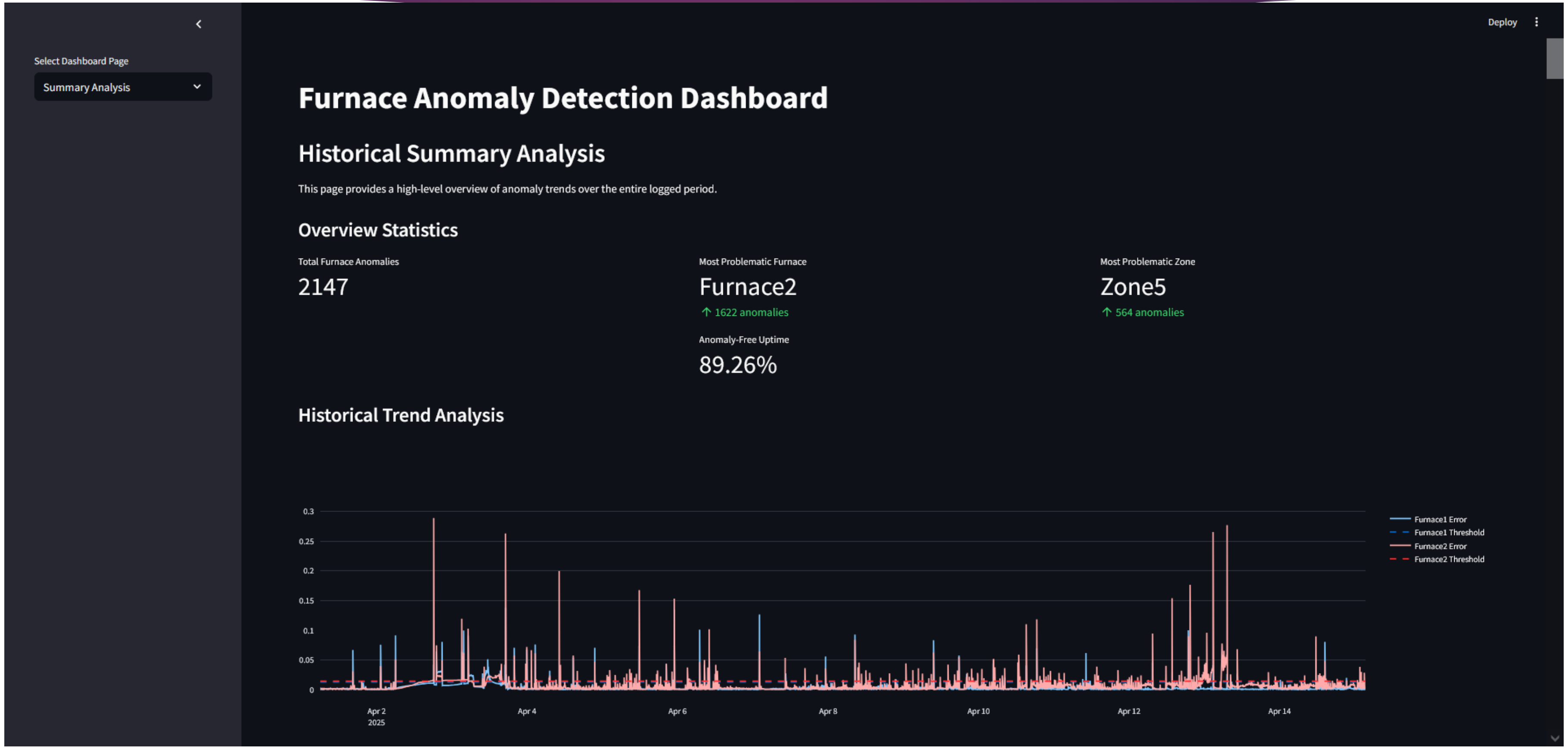
Implementation-Feature Contribution



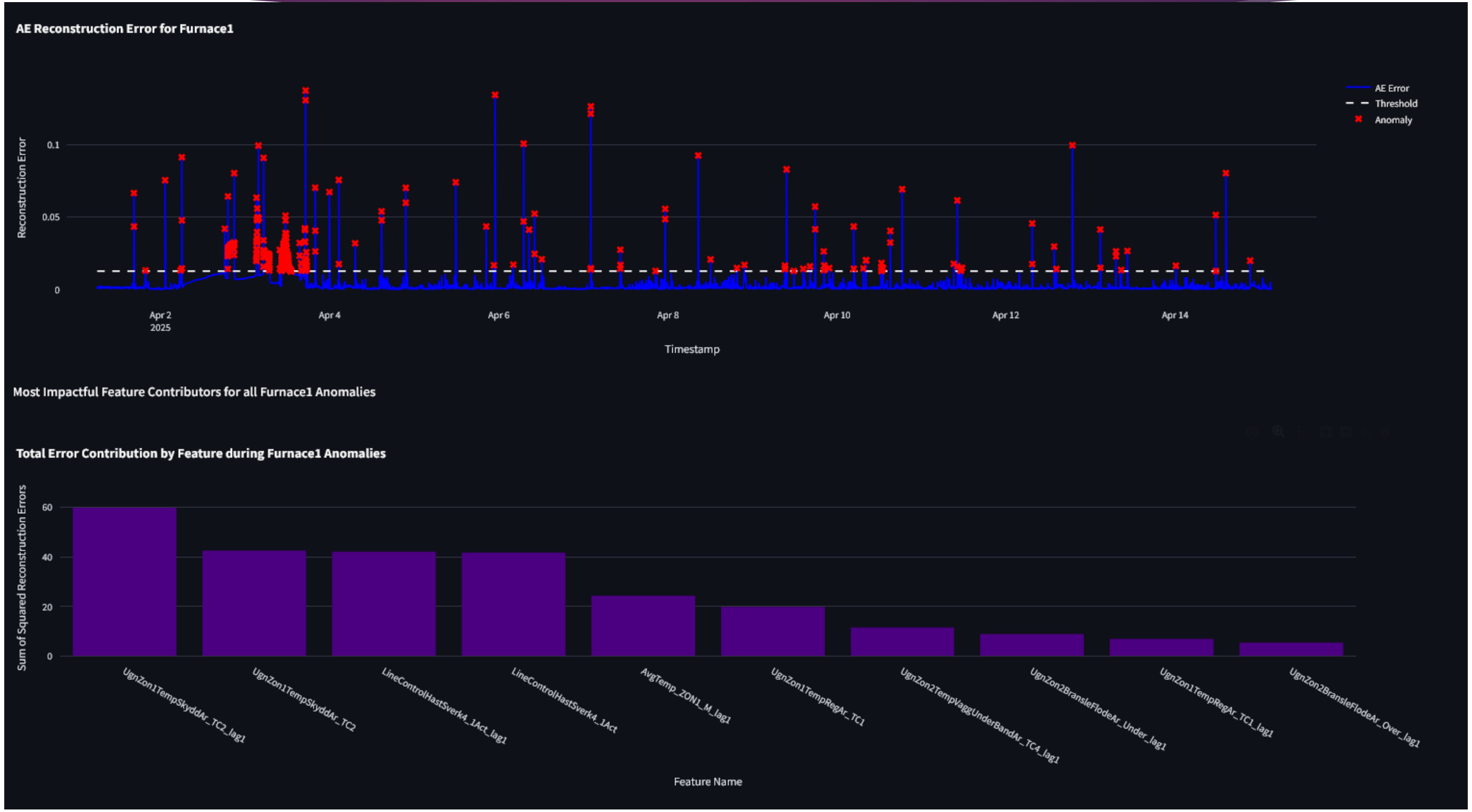
Implementation-Example Thermocouple Level Diagnostics



Implementation-Overview Page



Implementation-Overview Page, Time series Analysis for Furnaces and Zones



Implementation-Overview Page, Event Highlights

Most Severe Anomalous Events by Furnace

	timestamp	max_error	furnace_furnace1_is_anomalous	furnace_furnace2_is_anomalous
2171	2025-04-02 18:12:00	0.289	☑	☑
17352	2025-04-13 07:13:00	0.2769	☑	☑
17084	2025-04-13 02:45:00	0.2654	☑	☑
3546	2025-04-03 17:07:00	0.2629	☑	☑
4573	2025-04-04 10:14:00	0.1998	☐	☑
16644	2025-04-12 19:25:00	0.1766	☐	☑
6104	2025-04-05 11:45:00	0.1677	☑	☑
16299	2025-04-12 13:40:00	0.1541	☑	☑
6774	2025-04-05 22:55:00	0.1531	☑	☑
3548	2025-04-03 17:09:00	0.1377	☑	☐

Limitations and Future work

- **No Expert Validation Yet:** Outputs *look* reasonable but not yet confirmed by domain experts.
  - The next step is to work with Outokumpu engineers to validate the system's alerts.

- **Threshold Setting:** 95th percentile is a heuristic; may need tuning after consulting with the experts.

- **Enhanced Temporal Modeling:**
  - Use a wider window of lagged features (e.g., t-5, t-10, t-60).
  - Implement dedicated sequential models like LSTMs

Conclusion

- Successfully designed and implemented a **hierarchical unsupervised anomaly detection system**.

- Demonstrated **potential for early detection** and **diagnosis** in an industrial furnace setting.

- **Visualization dashboard** aids interpretability.

Thank You!
Questions?