Meteorologic Real-time Extreme Learning Machine for Pressure Prediction

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Rationales

➔ **Why is weather prediction on the edge important?**
- This approach provides a cost-effective, scalable solution for monitoring and predicting hazardous atmospheric conditions in real time.
- Low atmospheric pressures (<1000 millibar) can be malignant weather for humans [2].

➔ **Why ELM on the Edge?**
- Use of machine learning based applications on the edge are growing to address various use cases including weather prediction.
- We are extending prior work by using an ELM model implemented within IBIS [1] to detect weather anomalies in real-time.

➔ **Our methodology:**
- Data from InfluxDB, encompassing pressure and wind sensor readings, is pre-processed, with a model trained on 80% of 550,000 records, achieving a 92% R^2 score.
- The real-time implementation within IBIS demonstrates effective anomaly detection, with results visualized via Grafana.

Extreme Learning Machine (ELM)

➔ **Extreme Learning Machine (ELM),** introduced by Huang et al. [3] in 2006, is noted for its fast learning, easy implementation, good generalization with limited data, and suitability for real-time analysis.

➔ **Unlike feed-forward neural networks (FFN),** ELM, eliminates multiple iterations, using a single learning step. Instead of gradient-based back-propagation, ELM uses the Moore-Penrose inverse of the hidden layer output matrix.

IBIS

IBIS [1] is an adaptable platform capable of integrating edge and multi-sensor technologies, including environmental sensors and cameras, for comprehensive data acquisition and analysis.

EML Training

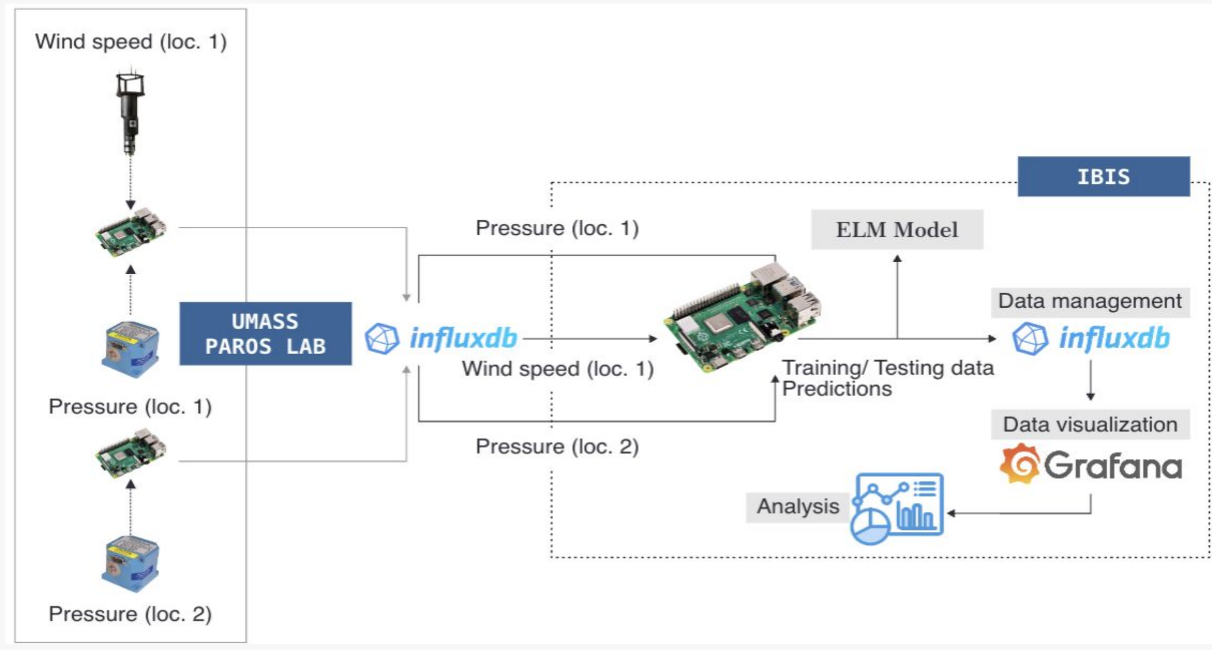

Figure 1. Comprehensive End-to-End Pipeline for ELM Model Training deployed on IBIS up to Visualization

Data Ingestion: Historical pressure data from 2 sensors & wind speed data from 1 sensor via InfluxDB is correlated on standard timestamp using Pandas. This results in training and testing data.
Model Creation ELM regression model is trained using pressure (loc. 2), wind speed and 96 hidden units with sigmoid activation.

ELM Inference on IBIS

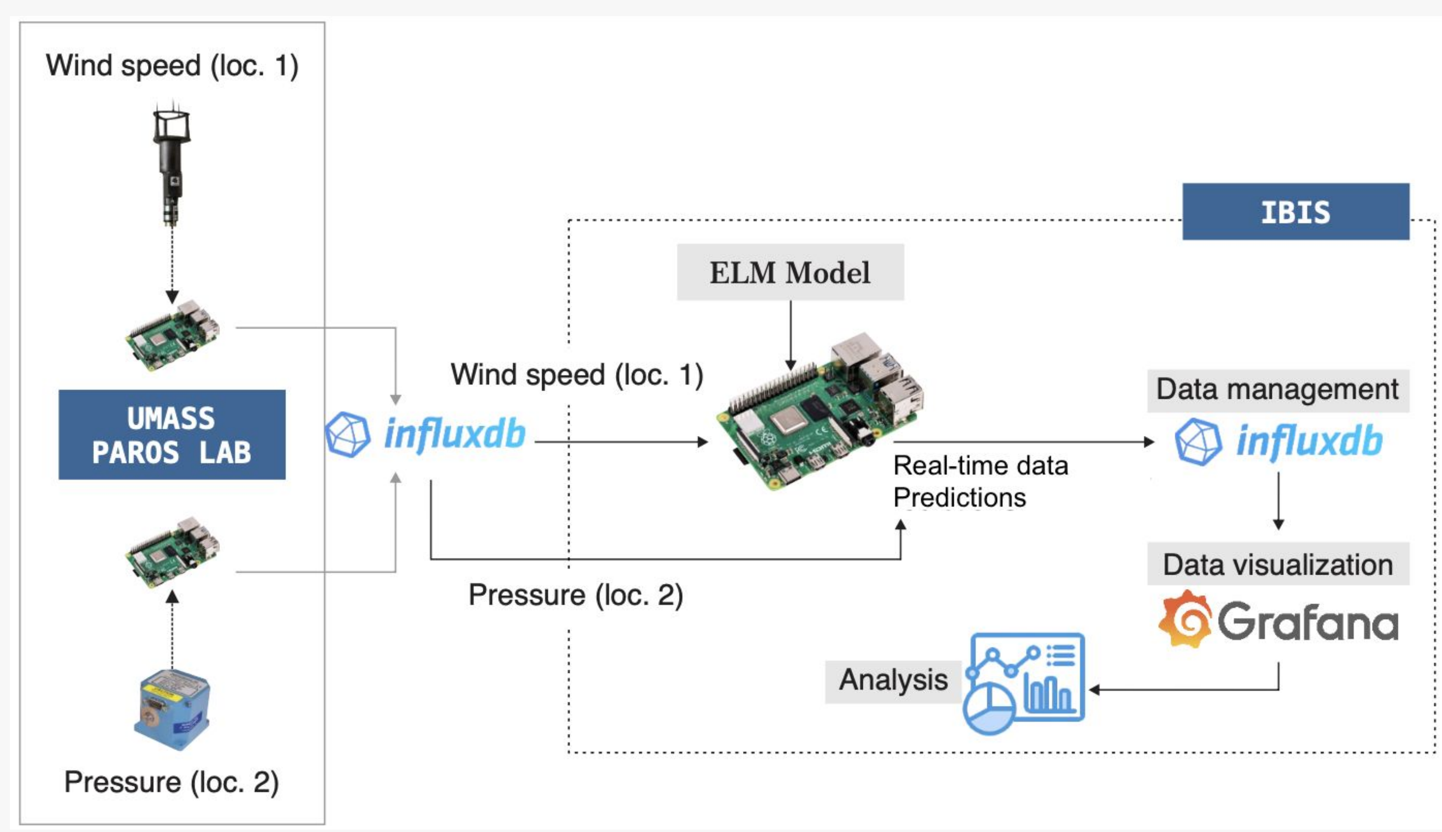

Figure 2. Comprehensive End-to-End Pipeline for ELM Model Real-time Runtime

Data Ingestion & Preparation Real-time data from pressure (loc.2) and wind speed data via InfluxDB is correlated on standard timestamp using Pandas.
Model Prediction & Anomaly Detection on IBIS Pressure 1 is predicted using the data from the prior step and the model.

Evaluation

- **With the 80% of 550,000 records** input of training data and 96 hidden units with a Sigmoid activation function, the ELM model accuracy obtained was 92%. This was measured using R^2 score.
- **Fig. 3 and Fig. 4 show the comparison** between testing measured *pressure 1* data and model predictions for *pressure 1* for the testing data.

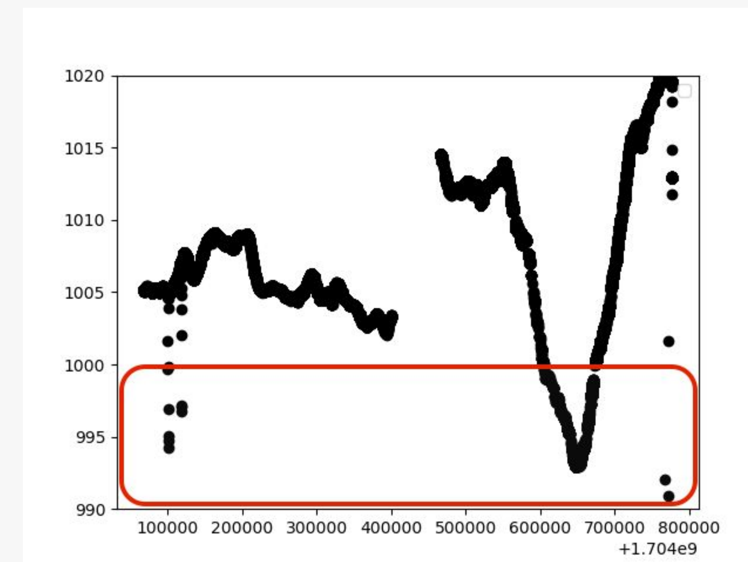

Figure 3. Time Series Plot for the Predicted Pressure at Location 1 over Time (y: millibar / x: Unix timestamp)

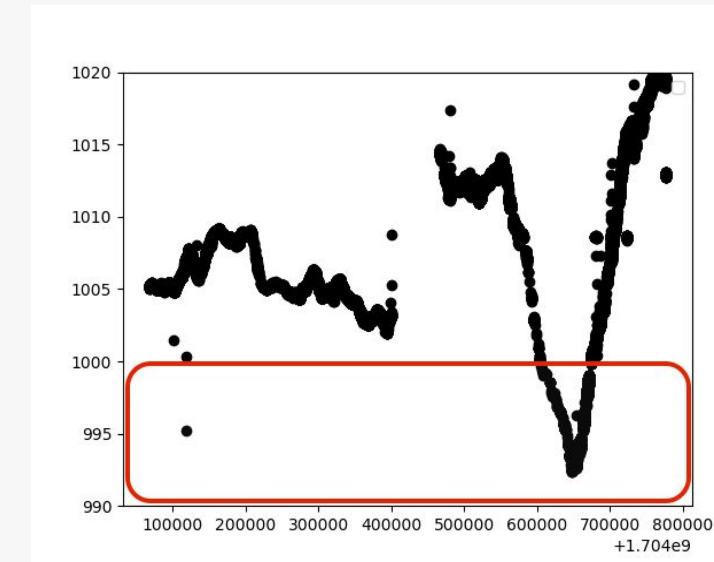

Figure 4. Time Series Plot for the Measured Pressure (loc. 1) over Time (y: millibar / x: Unix timestamp)

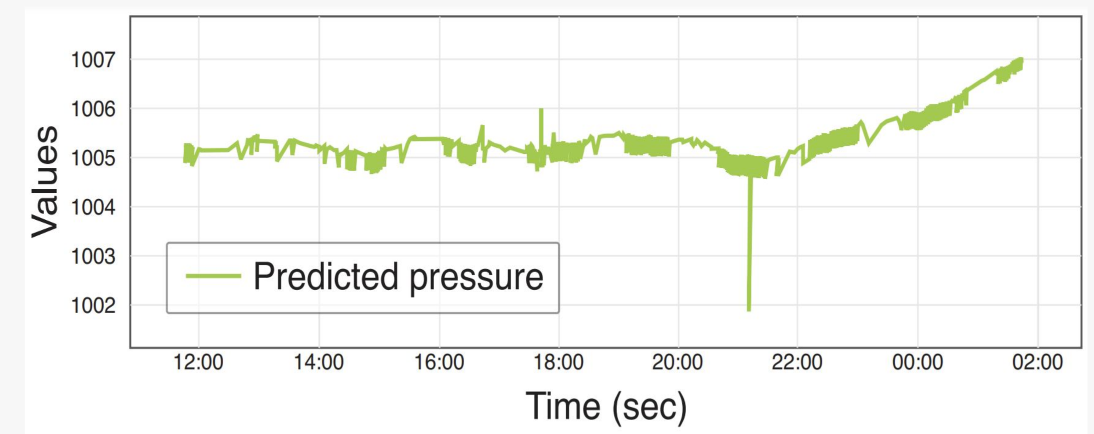

Figure 5. Time Series Plot for the Predicted Pressure at Location 1 over Time (y: millibar / x: Unix time stamp)

- **The next step** is to replace InfluxDB with a data pipeline from the 2 Raspberry Pis, which are connected to the 3 sensors, directly to our ELM pressure prediction program which already exists on the edge.

References:

[1] K. Keahey Z. Murry T. Sitzmann J. Zhou A. Esquivel Morel, M. Powers and P. Calyam. 2024. IBIS — An Infrastructure Management Framework for Adaptable, Multi-Sensor Data Collection in Scientific Research. ISC High Performance 2024 International Workshops (2024). https://doi.org/10.13140/RG.2.2.11758.22082 Preprint available on ResearchGate.
[2] S. Sarna, M. Romo, and P. Siltanen. 1977. Myocardial infarction and weather. *Annals of Clinical Research* 9, 4 (Aug. 1977), 222–232. [PubMed: 616207].
[3] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew. 2006. Extreme learning machine: Theory and applications. *Neurocomputing* 70, 1-3 (2006), 489–501.