AI Service for Module 1
in the Service Life Cycle:
Service message

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SERVICE MEISTER

AUTOMATED DETECTION OF ERROR CLASSES IN MEASURING

Automated and real-time detection of defects and errors in measuring instruments can minimise outages in critical infrastructure areas and in industrial manufacturing. Service work can be planned in a targeted manner, thus saving costs.

Non-automated monitoring or monitoring of the operation of measuring instruments on the basis of threshold values is costly and inaccurate. The automated acquisition and analysis of sensor measurement data with machine learning algorithms in real time enables the accurate and timely identification of errors during operation.

FOR THE FOLLOWING CHALLENGES

- Automated detection of malfunctions
- Precise classification of malfunctions
- Forward planning of maintenance intervals
- Shortening of maintenance intervals
- Safeguarding industrial production processes
- Safeguarding infrastructural processes
- Reduction of service costs

THE USE CASE

Flow meters are used both in the industrial sector and in critical urban infrastructures, for example to measure the consumption of drinking water, the load on supply lines within a utility network, or to control fluids within industrial manufacturing processes.

In addition to acute electronic defects within the measuring system, slowly increasing malfunctions can also occur, such as the calcification of connecting lines or their clogging due to contamination.

In the worst case, the failure of measuring systems or the late detection of defects in the supply lines can lead to downtime of, for example, the drinking water supply or industrial manufacturing processes for hours or days. In the industrial sector, this may only lead to high costs due to production downtimes, but in the public infrastructure, such downtimes are critical because basic services for the general public are no longer guaranteed.

Up to now, errors have mostly been found manually, which means that they can only be corrected slowly and with a great deal of time. A real-time automated solution now addresses this problem.

THE SOLUTION IN DETAIL

Based on previously collected sensor data, various machine learning models are trained for supervised classification. These can detect and distinguish between different malfunctions of the flow meters based on sensor data in real time (such as short circuit of the installed coil, air bubbles in the water, blockage of the supply line).

Depending on the requirements for precision and time to availability of analysis results, predictions can be considered aggregated to individual time windows.

Models can be retrained and re-trained for different use cases and new fault classes to cover a wide range of possible anomalies.

Both the acquired sensor data and the labels of the detected malfunctions are clearly displayed in a dashboard. This allows service technicians to quickly identify errors, carry out targeted maintenance work, reduce costs and ensure uninterrupted operation.

PROJECT STATUS

A prototype for the detection, classification and visualisation of malfunctions in real time has been developed and is now in the evaluation and improvement phase.

REQUIREMENTS

- A cloud infrastructure exists that can provide a database optimised for time series (InfluxDB), a frontend connected to it (Grafana dashboard), and resources to run the trained classification model.
- Defined error classes must exist.
- Specific, previously unrecognised error classes can/must be re-trained.

AVAILABILITY

Trained models and information on the developed infrastructure are available upon request and can be customised for the given use case.

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SPECIFICATION

	Input data	Preprocessing	Data storage	Algorithms	Interfaces
High-level description	Multivariate numerical time series and an associated categorical variable	Time aggregation of the data	Storage of sensor data in a time series database and, prospectively, off-loading into raw data archive	Automated defect class recognition using machine learning algorithms	Web dashboard with marking of the anomalies found and display of the sensor readings
Configurability	Selection of devices and relevant channels	Type of aggregation	Retention time, data format, storage location	Possibly model parameters	Type of visualisation
Technical Implementation	Streaming sensor data from edge devices	Python script executed via GitLab CI in Kubernetes cluster	InfluxDB and Google Buckets	Python script executed via GitLab CI in Kubernetes cluster	Grafana dashboard connected to InfluxDB
Specific example from the speedboat project	KROHNE Edge connection via MQTT or directly to an Influx: numerical measured values (~ 10) in different resolutions	Aggregation of the measured values on second level	Raw data streamed entirely in InfluxDB; regular off-loading to Google Buckets planned	Detected error class for the KROHNE measuring instruments	Interactive display of multivariate time series and classification results

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