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COMETH - An Active Learning Approach Enhanced With Large Language Models

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Abstract

We present a system for supervision of technical processes, called COMETH, which involves an active learning approach. The system is able to identify anomalies with very little training data, through an efficient feedback process. COMETH has been successfully applied in the context of heating ventilation and air conditioning systems and in industrial machinery. Here, we describe the idea of combining the time series analysis COMETH with large language models to integrate further context information and thus provide the user with specific recommendations.

Keywords: anomaly detection, active learning, large language models

1. Introduction

Appropriate maintenance of machines and industrial processes has been thoroughly discussed in literature and practice [1, 2]. An ideal maintenance scheme avoids down-time of machines and ensures high throughput while keeping maintenance efforts at a low level. With the ongoing shortage of skilled labour this aspect gains increasing attention. Moreover, significant economical benefits of adequate maintenance strategies can be observed [3].

Although today more and more sensor data from machines become available, it often remains a challenge to make use of the acquired data in automized condition-based maintenance systems [4]. This is mainly due to a lack of labelled data for the training of machine learning models [2] and eventual changes in the set up of the machines or the environment, which drive models out of their prediction range. Therefore, robust methods which require few training data and quickly adapt to changes are needed in order to establish automated and flexible maintenance strategies. Promising approaches to mitigate the labelling problem are provided by active learning methods [5, 6] and human-in-the-loop strategies [7, 8].

Here, we consider an active learning method, called COMETH which at the same time provides supplementary information about detected anomalies to the user (technician). Thus, the method can be seamlessly integrated into existing maintenance procedures and support the technician by identifying anomalous behaviour, while continuously collecting labelled data to further improve the prediction accuracy.

COMETH was proposed in [9] and first applied to HVAC (heating ventilation and air-conditioning) systems. Later, its application in an industrial context was demonstrated [10]. Here, we present the idea to extend the approach further, using large language models for the generation of useful recommendations, based on the detected anomalies and additional textual machine documentation.

2. Description of the method

COMETH is based on two machine learning methods which are applied in parallel to the same data. If both methods yield the same result, the classification is likely to be correct, i.e. the user gets a notification in case of a fault or nothing happens in case of no fault. If the two methods yield distinct results a warning is generated and the user has the possibility to give a feedback telling whether the detected anomaly is a true fault or not. This information is then used to retrain the corresponding method with the labelled data. A schematic overview of this procedure is shown in Fig. 2.

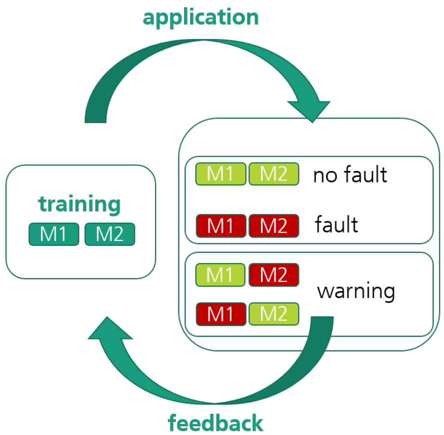

Figure 1: Schematic overview of the procedure of COMETH [10].

In order to ensure high classification accuracy and low feedback rates it is essential for M1 and M2 to be complementary, which can be realized by choosing an outlier detection method for M1 and a classification method for M2. This implies that M1 is trained only on fault-free data and tends to have a high sensitivity. M2, on the contrary, is trained on data from at least two distinct classes (fault-free and faulty data) and tends to have a high specificity.

The exact choice of M1 and M2 is arbitrary as long as the above-mentioned criteria are fulfilled. Typically, we choose a density-based clustering (DBSCAN) method for M1 and a decision tree method for M2, as this combination has proven to be successful in other applications [9, 11, 12].

To further support the feedback process and to enhance the trustworthyness of the results the user can, in case of a warning, be provided with additional information about the detected anomaly. More precisely, the most responsible variables for the detected anomaly are evaluated. For DBSCAN a fault identification mechanism was proposed in [11]. The resulting responsibility pattern can guide the user to reject the fault or take an adequate countermeasure.

3. Coupling to LLMs

As a further direction of current research we are planning to couple the results of the fault detection and identification with COMETH to large language models (LLMs), which provide specific information about the considered machine. This can be done via Retrieval Augmented Generation (RAG) [13] approaches where context in terms of handbooks, log book information or service documentation is integrated. As a result the user can interact with the system via a custom chat window and directly receives proposed countermeasures in case of a detected fault, based on the user manual of the machine. The idea is to further reduce the barriers to give feedback by providing an intuitive and conversational interface. Furthermore, the validity of the results can be double-checked by analysing time series data and additional textual documentation via the LLM.

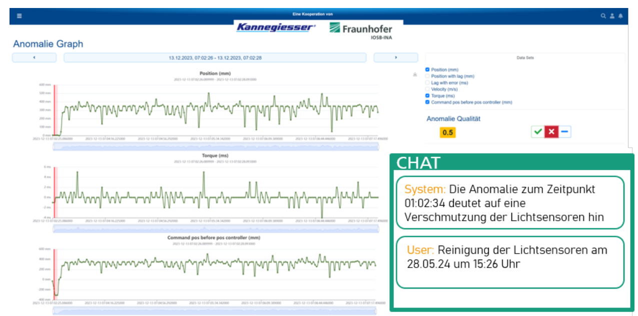

Figure 2: Illustration of the envisioned interactive GUI with chat functionality.

4. Conclusion

For the integration of an active learning approach into existing maintenance processes the user experience and user acceptance have to be carefully taken into account. Along these lines, further improvements have to be achieved concerning the user interface and enhanced decision support. The latter includes for example an automated generation of recommendations in case of faults or warnings.

To keep the required feedback from the user at a minimum level indirect feedback from maintenance log books or further external information sources, like handbooks can be used. Recent progress in natural language processing and the rapid advancements of large language models in many fields provide new opportunities to enhance the interaction of technicians with data analytics solutions and thus to foster the employment of active learning methods in machine services.

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