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Automated Machine Learning Framework towards Predictive Maintenance for Manufacturing SMEs

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***Abstract*— Realization of efficient predictive maintenance techniques through the use of Machine Learning and Artificial Intelligence is promoted as one of the next big breakthroughs in manufacturing industries of different domains. However, although this vision has been endorsed by high interest from both the academia and industry alike due to the impressive potential gains, critical challenges remain especially related to the high demands and requirements in terms of investment, complexity, training and time required to actual achieve it. Driven by such observations this work puts forward a new paradigm proposing a cloud-based service framework allowing the application of ML/AI to develop tailor fitted model for specific scenarios posing the minimum requirements to the interested SME or industry. By analyzing the architecture and services offered we aim to demonstrate that the framework equally empowers professional and non-professional data scientists indicating specific scenarios. Finally, by adopting adequate services' model and collaborating with a very active Digital Innovation Hub (DIH) the high impact and viability of the proposed solution is also underpinned.**

Keywords*— *Predictive Maintenance, Automated Framework, Machine Learning, Manufacturing SMEs

I. Introduction

Maintenance is representing one of the most challenging as well as time-effort-budget consuming part of manufacturing industries' activities. Still, the lion's share of all respective investments is wasted in reacting to respective events rather than timely preventing them with, many times, catastrophic effects on all aspects of involved industrial process [1]. However, leveraging critical advancements in areas such as Machine Leaning (ML) and Artificially Intelligence (AI), it is becoming commonly accepted that the aforementioned "waste" can be drastically decreased, and thus respective efforts can increasingly focus on foresing and avoiding adverse events considering an end-to-end manufacturing line or process. Furthermore, respective applications indicative impressive advancements in areas like level of products' quality [2], utilization of equipment/machinery, decrease of off-time, use of raw materials [3] and others.

Nevertheless, the in-depth understanding and even more the successful application of technologies such as ML/AI in various manufacturing fields is extremely complex, challenging and require great investment in time, experts, training, and funding. This poses a clear obstacle in the widespread and acceptance of such solutions beyond the experimentation level and towards actual commercial exploitation. The proposed framework, namely AUTOMAINT (Automated Predictive Maintenance for Manufacturing SMEs) envisages a cloud-based system that empowers professional and non-professional data scientists with the ability to build high-quality predictive models for timely and optimized maintenance of the industrial machinery. AUTOMAINT is expanding OPTIPLANT [4], which is an existing technological solution for predictive maintenance already been demonstrated in an industrial environment and in particular the Tengu and Virtual Wall testbeds of FED4FIRE+ platform [5]. The scope of this paper is to present technological advances as well as the acquisition of L-BEST services [6] in order to reach a higher level of maturity by demonstrating the system prototype in an operational environment of a beta client.

Section II presents the motivation of AUTOMAINT which is to allow manufacturing industries and SMEs having access to limited human and financial resources, to set-up and deploy accurate and scalable predictive models that will help them optimize the maintenance activities and increase the quality of delivered products. Competition for existing technological systems is summarized in Section III, while Section IV presents AUTOMAINT architecture which allows industrial users to decide on the type of the model they want to build, import datasets for training on the candidate models, visualize performance metrics and finally select the best model, either manually or by automatic system evaluation based on user's

predefined preferences (i.e. the model with the highest accuracy values). An industrial Use Case is presented in Section V as a validation pathway of the presented solution, while Section VI concludes this work by presenting the market potential.

II. MOTIVATION

AUTOMAINT is inspired by the massive collection of data on the use of machinery in industrial environments and the need of industries to use this data to prevent faults of industrial machinery and, thus, increase the overall plant availability. Based on research, 80% of the maintenance time spent by manufacturing industries is wasted for reacting to issues instead of preventing them [1]. This inefficiency can be translated into a 37% of lost production time due to the downtime of the machinery. This has a direct negative effect leading to defective products of low quality, increased material waste and suboptimal use of the machinery (reduced lifetime of both equipment and materials due to suboptimal quality of the production). For an average manufacturing industry, the latter can lead to an estimated loss of two hundred and fifty thousand Euros per hour [7].

ML is the tool to transform costly, unexpected stops of machinery into shorter and less frequent ones leading to early and automatic error-detection and better run time decision-making. However, ML is complex, it requires expert skills and it takes people a lot of time to understand how to use it. At the same time, predictive maintenance involves a combination of activities that require data science, engineering and domain-specific skills and knowledge. In particular, small industries and mid-caps do not have the financial and human resources to build their own tools to cope with optimised maintenance of their machinery. Even for big manufacturers that are willing to invest in the predictive maintenance domain it is not easy to create a group of Data Scientists with Machine Learning skills that can customise generic purpose predictive models according to the needs of their production line.

Considering the above, a clear need for low-cost solutions and tools that can be utilised by people with limited or zero programming skills becomes evident. The vision of the proposed framework is to help manufacturing industries build their own workflows that best fit their needs by removing unnecessary complexity.

III. STATE-OF-THE-ART

Industrial maintenance has received significant attention in academic literature for many decades. Specifically, a lot of studies have been devoted in the area of condition-based predictive maintenance [8] for the prediction of faults and errors in complex technical systems including sensor networks. Most of industrial approaches are based on existing statistical methods to identify alerting situations due to abrupt changes of the probability distributions of the observed parameters [9]. In [10], the authors discuss the problem of rare events prediction in multidimensional data and they propose two approaches that address the problem. The first approach focuses on degradation detection (i.e., abnormal system behavior) that is based on one-class Support Vector Machines model [11]. The proposed method formulates a quadratic program that detects anomalies by minimizing the distance of each new multidimensional data vector with regard to a training dataset. Then, a moving average model is used for modeling multidimensional degradation behavior in time. The second approach exploits a regularized logistic regression classification method where the predictor function consists of a transformed linear combination of explanatory variables. Both approaches are evaluated over datasets resulted by real-world cases from aircraft operational performance area. In [12], the authors propose one model-based and one data driven method for predicting faults in multi-sensor systems. The former approach is based on an autoregressive moving average model where the estimated model parameters are further used for implementing the change detector that is realized as a Neyman-Pearson hypothesis test [13]. The second approach takes advantage of an HMM and Viterbi algorithm [14] to estimate the most likely sequence of hidden states. Both approaches are validated through simulations with synthetic data.

Considering the existing commercial solutions for predictive maintenance, two kinds of predictive maintenance solutions have been identified. The first family of tools involves existing cloud vendors that offer access to cloud-based ML services. These services are usually based on generic purpose algorithms that cannot be easily customised to the needs of an industry. Many of them do not even support the use of Tabular Data which is normally the case for data coming from machineries (e.g., vibration, noise, current, voltage, faults). Most of the times, these solutions do not offer any explanation of the derived results since the models are usually pre-trained (e.g., Deep Learning models are trained over existing visual datasets). The second type of tools comes from individual companies that provide ML expertise and build customised predictive maintenance solutions. Such external experts usually do not acquire expertise of the industrial domain and the available data. However, without covering the gap between domain experts and Data Scientists, it is impossible to build customised solutions that efficiently tackle the problem of the optimised machinery maintenance. The approach we propose in this paper targets directly the problem of predictive maintenance for manufacturing industries taking advantage of established tools and libraries across the whole data chain (i.e., collection, cleaning, preservation, processing, visualisation, service management). It simplifies and, whenever possible, automates the process of building customised predictive maintenance solutions by bridging the gap between data scientists and domain experts and by helping industries easily develop and customize their ML models that best fit their needs. The algorithms are carefully selected and optimised to work over Tabular Data stemming from the industrial plants. AUTOMAINT project takes advantage of the Automated Machine Learning (AutoML) paradigm and facilitates the selection of the appropriate algorithms by simplifying their configuration and making data understandable even by people with limited ML skills. Contrary to the existing black box solutions, AUTOMAINT provides transparency in terms of providing clear explanations of the retrieved results.

IV. CONCEPTUAL ARCHITECTURE

In this paper, we propose the adoption of a microservices-based architecture for the realisation of the AutoML paradigm for predictive maintenance in manufacturing. AutoML

empowers professional and non-professional data scientists to easily build ML models. The time it takes to get production-ready ML models is minimized without requiring the involvement of the human factor such as ML experts. It allows data analysts and developers to build ML models with high scale, efficiency, and productivity while sustaining the quality of the generated models. First, the user may decide on the type of ML model she or he wants to build by selecting between the available ML task including Classification, Regression and Time-series Forecasting. In AUTOMAINT, the user can import the datasets that will be used for training the candidate models and visualise a wide range of performance metrics including accuracy, prediction/recall, Receiver Operating Characteristic (ROC) curve, Area Under Curve (AUC), and time duration. The user can then select which model would like to use or let the system automatically decide which one performs best according to her/his preferences (e.g., the model with the highest accuracy values). As a final step, the ML model is deployed and ready for use. Contrary to the current state-of-the-art, AUTOMAINT is customised for the industrial domain. The high-level architecture of the proposed AutoML system is given in Fig. 1.

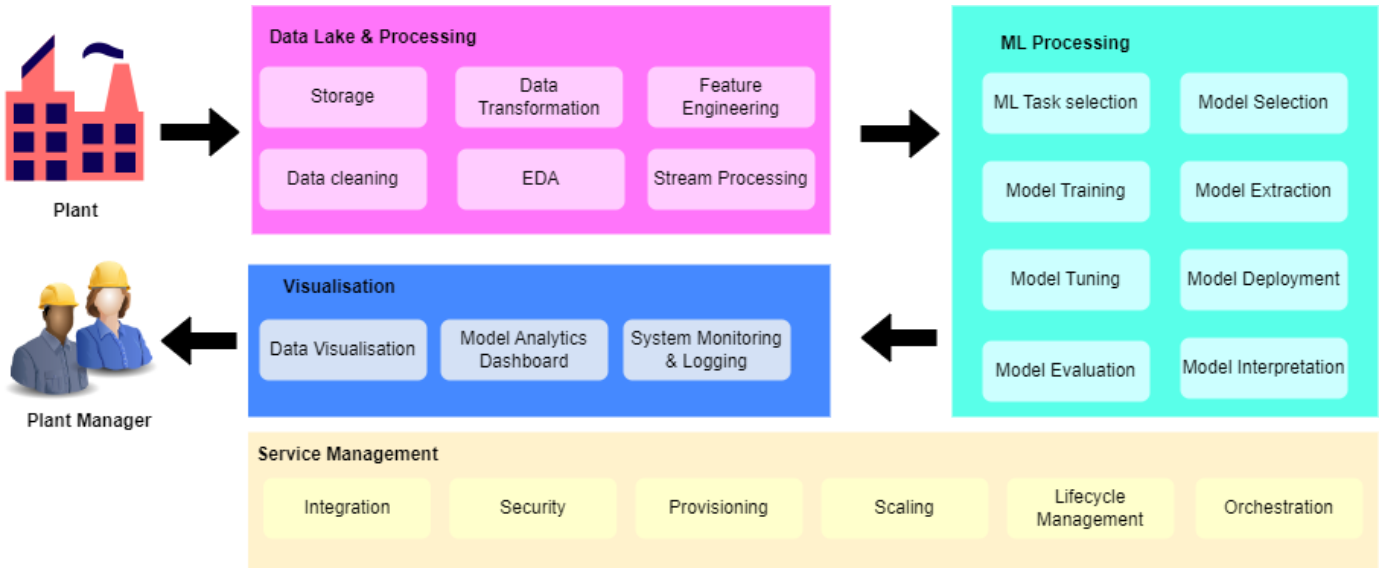

Figure 1. AUTOMAINT architecture

The system collects data from the plant in real-time using IoT connectors that are responsible for bridging the gap between the data provider (industry) and the cloud-based data lake. At this step, a set of data pre-processing algorithms are taking place to prepare the data before its storage. These steps include the data cleaning (e.g., harmonisation and missing value substitution), the data transformation (e.g., aggregation), the feature engineering (e.g., dimensionality reduction), data stream processing mechanisms (e.g., message broker), exploratory data analysis (e.g., correlation matrix) and storage. The system is able to deal with different types of filesystems and data stores. Data sharing and real-time management of data streams are based on distributed and scalable platforms that support both synchronous and asynchronous communication. Data is then fed into the ML processing layer of the architecture which supports both the use of Visual/Audio data (e.g., videos, images, audio files) and Tabular/categorical data (e.g., Tables). In addition, system provides enough flexibility in order to support popular ML algorithms that are included in open ML libraries, already publicly available (e.g., Decision Trees, Neural Networks, time-series forecasting), but also proprietary algorithms customised for the manufacturing domain (e.g., change detection algorithms for statistical control and detection of anomalies). The support of specialized visual recognition algorithms is required to involve also the visual input (e.g., cameras attached in the plant). Once the basic ML steps are completed (model training, selection, extraction, tuning and evaluation), the models which performed best considering the metrics specified by the user are automatically selected by the system. As a final step, the results are visualized to the Plant Manager through a set of dashboards for the real-time data visualisation, the model health and analytics dashboard and a user interface for system monitoring and logging offered to the system administrator. Considering the above conceptual architecture, the service management constitutes a horizontal process for all the separate system modules. This horizontal activity involves the service integration, provisioning, security, scaling, orchestration and management of the service lifecycle.

V. Industrial Use-Case

For the validation of the proposed framework, we consider a real-life business scenario with data coming from the production line of a manufacturing industry. The considered dataset corresponds to the production line of automated car parking solutions. The production line is equipped with a SCADA system and ERP to manage real-time data and notifications. Among other things, such data include measurements coming from the PLCs of the machinery, detected faults, vibration levels, and noise measurements.

This data is fed into the considered platform using IoT agents and, as a next step, will be used to validate the trained ML models. The goal of the use case is to prevent machinery faults by timely identifying issues in the production line. In particular, the objective is to predict faults of industrial machinery to optimise the overall plant availability. The target is to reduce

unplanned stops of the machinery due to predictive maintenance.

Starting from the collection of data on the use of machinery, AUTOMAINT will develop an AutoML platform that allows the implementation of corrective maintenance actions capable of transforming unexpected stops into shorter and less frequent maintenance stops. The collection and analysis of data allows the definition of predictive models that allow to warn of plant problems and to plan maintenance activities.

Table 1 shows the schema of a real-world dataset originating from the domain of automated car parking manufacturing.

TABLE I. DATASET EXAMPLE

Variable		Type	Description
UID		Integer	Unique identifier of the record
System Alarm		Enumeration	0 → no alarm 1 → subsets of faults 2 → subsets of faults 3 → subsets of faults 4 → NOT ACTIVE
Noise		Float	db
Vibration		Float	Hz
Humidity		Float	%
Motor 1..N	status	Enumeration	Normal Fault Warning Not active
	runtime since last replacement	Integer	sec
	runtime since last maintenance	Integer	sec
	output voltage	Float	Volt
	output current	Float	Ampere
Timestamp		Sec	Time step of the trace

In this scenario, we also investigate the means by which the scalability of the proposed technological solution could be enhanced through the involvement of a DIH. In particular, considering the current solutions in the market, there are two basic families of solutions that can be adopted for predictive maintenance: (a) apply single ML algorithms most of the times developed by external technology providers for offering predictive maintenance services tailored to the needs of the industry (AS IS-1 scenario, Fig. 2); (b) utilise an AutoML solution supporting multiple ML algorithms offered by a technology provider (AS IS-2 scenario, Fig. 3).

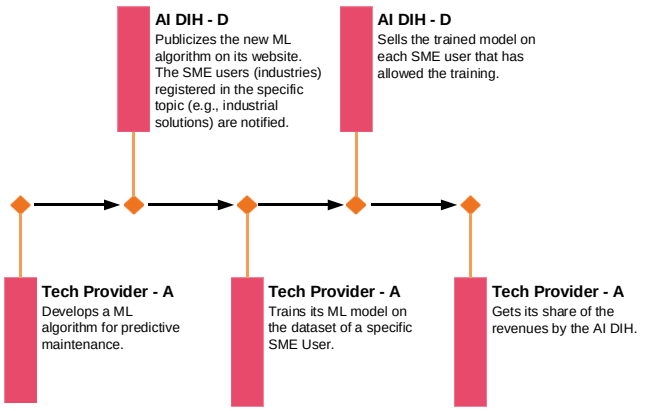

Figure 2. AS IS Business Process/Scenario 1 (without AutoML)

In AS IS-1 scenario, which was the most usual case met between industries until very recently, we consider only single ML algorithms developed by technology providers for offering predictive maintenance services. Each of these algorithms is published through the DIH website and the interested SME users are notified about it. The technology provider then trains the algorithm based on the dataset offered by the user. The DIH sells the algorithm, and the provider gets its merits, as illustrated in Fig. 2.

In the AS IS-2 scenario, which recently has gained popularity between industries, we assume the existence of an AutoML solution supporting multiple ML algorithms offered by a technology provider. The AutoML solution is published through the DIH website and the interested SME users are notified about it. The DIH sells the service, and the technology provider has to deploy the solution locally in the premises of the SME user. This includes both the software and the specialised hardware required to support the all the steps (training of models, execution of trained models, real-time validation), as illustrated in Fig. 3.

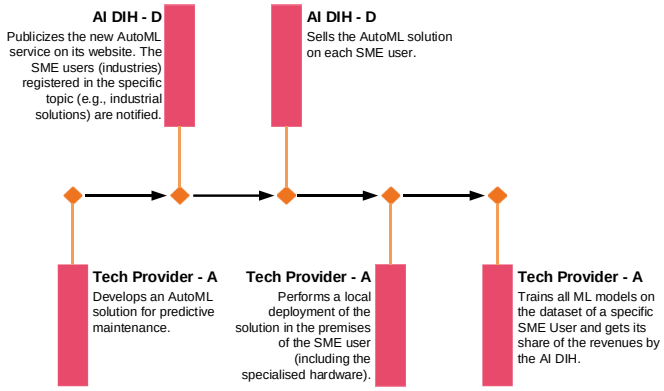

Figure 3. AS IS Business Process/Scenario 2 (without Cloud)

In AUTOMAINT, we assume that a technology provider has developed the AutoML solution that is deployed on the AI DIH cloud infrastructure equipped with the necessary software and hardware to support the demanding ML tasks, as illustrated in Fig. 4.

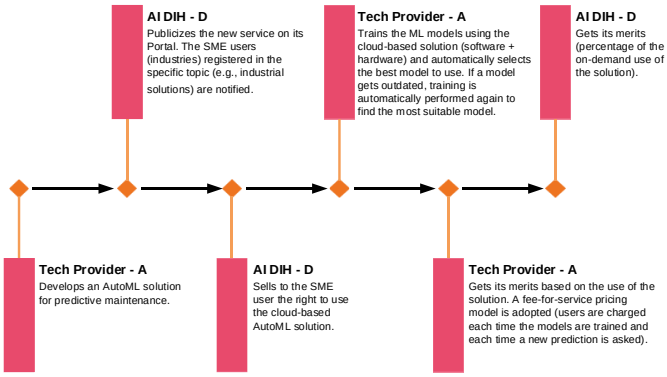

Figure 4. TO BE Business Process/Scenario

The DIH publicises the solution on its website and interested SME users are notified. The DIH sells to the interested users the

right to use the cloud-based solution. The solution is used to automatically train, validate and deploy the most accurate model. The technology provider is paid based on the use of the solution (more use results in higher fees). A fee-for-service pricing model is adopted. Users are charged (a) each time the models are trained, and (b) each time a new prediction is asked. The DIH also gets its merits according to the use of the solution which is hosted in its infrastructure. Rates and fees should be agreed between the technology provider and the DIH in advance. Such model constitutes a novel business case scenario that could improve the scalability of the offered technical solutions and at the same time decrease the necessary costs leaving more space and resources to the solution providers for technological improvements and quality enhancements.

VI. MARKET POTENTIAL

According to [7], the global market of manufacturing industries is huge exceeding the 800 billion Euros and still growing with predictive maintenance having a market share of 8.2 Billion Euros in 2020. At the same time, the current technological status in predictive maintenance assumes that experienced ML experts usually undertake the responsibility of building customized solutions for the industries. However, small industries such as the manufacturing SMEs and mid-caps do not have the human and financial resources to build their own predictive maintenance tools. Also, they cannot outsource this task since external IT experts and Data scientists lack the required domain knowledge. What they need is a way to easily build, validate and deploy their own predictive maintenance solutions. This is what AUTOMAINT intends to bring on the table; an easy way for non-experts to build their own predictive maintenance solutions through automated machine learning [15].

Hence, there is a clear need in the market for predictive maintenance solutions that manufacturing SMEs can easily uptake and apply in their production lines. The target group of AUTOMAINT consists of any type of manufacturing industry suffering from unexpected and unscheduled downtimes of the machinery. Starting from the near-term target market of local manufacturing SMEs, AUTOMAINT aims to acquire a significant share within this market sub-group.

With the support of a regional DIH with long-standing experience and a big network of industries operating in the manufacturing domain (ESDALAB DIH [16]), AUTOMAINT will reach a higher level of maturity getting closer to the market. ESDA LAB DIH's established collaboration with DIHs, EU initiatives and H2020 projects that focus on the manufacturing sector, along with Marketplace services [17] provided by ESDA LAB DIH that enable data sharing (e.g. datasets, containers) among registered SMEs and beyond, will be utilized for the benefit of AUTOMAINT target groups, enhancing a go-to-market strategy that is based on building strong partnerships and on providing tutorials, training and relevant events for promoting AUTOMAINT tool. Potential partnerships among members of the ESDALAB DIH are facilitated by the AI-based Matchmaking tool [18] which enables search for partners according to selected criteria and keywords matching to a wide range of scientific fields and services. Additionally, ESDA LAB's infrastructure and specifically a high-performance computing center (HPC) [19] which offers a bouquet of services with 24/7 availability, can be used by Marketplace members upon request and evaluation by a committee of experts.

Therefore, targeting the manufacturing SMEs as our near-term market group and evaluating the competitive advantages that AUTOMAINT brings both at technical and business level thanks to the bouquet of services offered by ESDALAB DIH it is estimated that AUTOMAINT will reach a share of 1.6M Euros within the first 5 years, as illustrated in Fig. 5.

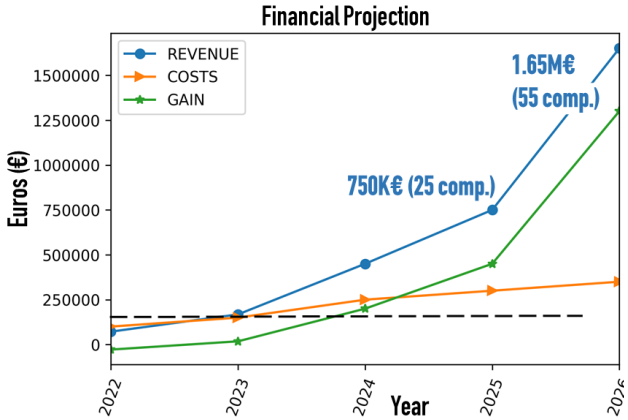

Figure 5. AUTOMAINT financial projection

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