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A Cognitive Assistance System To Support The Implementation Of Machine Learning Applications In Manufacturing

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Abstract

Despite the increasing spread of digitalisation in manufacturing, humans will still play an important role in future production environments. Evidently, their role will change from physical to rather cognitive tasks, such as decision-making or control and monitoring of processes. A suitable medium that can support employees in interpreting the data generated are machine learning (ML) applications. Nevertheless, recent studies show that the knowledge required to implement an ML solution is not available in a large number of companies. In order to close the knowledge gap and subsequently prepare human operators for the implementation and use of ML applications, it is highly relevant to provide proper assistance. For this reason, the present publication aims to develop a cognitive assistance system that supports shop floor managers in implementing ML use cases in manufacturing (referred to as CAS-ML). The CAS-ML concretizes a previously published procedure model with additional steps as well as learning material and is realized as a software thereupon. Finally, the CAS-ML is evaluated by operative employees and tested on an open-source data set.

Keywords

Machine learning; Operator 4.0; Cognitive assistance system, Shop floor manager; Vocational education

1. Introduction and problem definition

In recent years, the number of Industry 4.0 applications in manufacturing environment has increased strongly [1], thereby offering previously unrealizable insights into production processes in real time. Yet, human operators remain a central part of manufacturing halls [2]. Noteworthy, their jobs will change from rather physical to rather cognitive tasks [3] such as decision-making, control and monitoring of processes [4]. A possible mean to support them in interpreting the data generated by Industry 4.0 technologies are machine learning applications (MLA) [5], which yield the advantage to evaluate large data in a short time. Nevertheless, a gap between potentials and actual ML dissemination – especially in small and medium enterprises (SMEs) – can be identified due to a lack of ML competences, a lack of IT infrastructure, a lack of data as well as a rather unstructured project management [6–8]. Concerning competences, a general change has been taking place in times of digitalization from information knowledge about individual processes to action knowledge and thereby acting in unknown scenarios [9]. Besides, many competences such as problem-solving competences can hardly be developed in non-formal settings such as seminars [10]. Indeed, practitioners asked by [8] declared that the transfer from knowledge gained in ML seminaries to industrial problems to be complex. This transfer obstacle in combination with the general shift of required competences in digitized manufacturing environments displays the need to realize suitable learning materials to train workforces for their changing roles [2]. In terms of vocational education, literature agrees that a promising approach to prepare employees for future challenges at work is the concept of work-integrated

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learning [11]. For the sake of enabling work-integrated learning, cognitive assistance systems are considered to be a supportive technology [3,12].

Hence, the goal of this paper is the development of a software-based cognitive assistance system to support the integration of machine learning (CAS-ML) in manufacturing environments. To mitigate the hurdle of transferring knowledge gained to industrial problems, the aim is to enable competence development with respect to MLA in a work-integrated manner. It has to be noted that the focus of this paper lies on ensuring guidance, which in return limits the competence development. Since especially SMEs lack designated ML departments [6], the focus of this paper is on shop floor managers who possess the knowledge to select data sources as well as parameters and are therefore seen as essential for successful MLA implementation [13].

The remainder of this paper is structured as follows: chapter 2 provides the theoretical background needed to understand most relevant terms used and gives an overview over similar publications. In chapter 3 the development of the CAS-ML is described. Chapter 4 displays the evaluation of the CAS-ML with potential users. Finally, chapter 5 summarizes the paper and yields an outlook to further development steps.

2. Theoretical background and related work

In the following, the most important terms introduced in chapter 1 will be described further before delivering the state of the art in cognitive assistance systems for the implementation of ML in manufacturing.

2.1 Theoretical background of the paper

The term machine learning describes the capability of a computer or a program to automatically improve itself in the execution of a certain activity through the experience gained in the past. The term experience refers in particular to the data that the computer receives as feedback from processes. For this purpose, ML methods make extensive use of statistical methods to analyze data, detect errors within the data, and make and test hypotheses regarding the data. [14]

According to Dehnbostel [11] the term "work-integrated learning" displays a scenario where learning takes place in the process of working or where learning place and workplace are identical. Most frequently, learning is ensured by active participation in real work processes. Thereby, learning incorporates cognitive, affective and psycho-motorical tasks. Learners are i.e., assisted by coaches or so-called communities of practice [15]. Another learning method in terms of work-integrated learning is the combination of informal and formal learning, e.g., by integrating learning bays or e-learning materials into real processes. In sum, learning takes place self-directed, experimental and situated. [16] As indicated above, the model within this paper follows principles which have been described in this sub-section (for more details please see below).

To meet the emerging changes in the range of tasks in manufacturing environments and thereby aid humans in processing and retrieving new information in similar situations, CAS are required to support workforces in diagnosis, situational awareness, decision-making and planning [12]. In consequence, CAS are digital systems that help its users with information processing and thereby enable learning in real time based on end devices like as smartphones and tablets or extended reality. In addition, they are capable to generate guidelines for actions, steps, and processes. [17]

2.2 Related work

Villanueva Zacarias et al. [18] describe a software consisting of four modules that supports the implementation of ML algorithms in manufacturing. The framework thereby facilitates the cooperation of different stakeholders (domain experts, IT specialists, data engineer and data scientist) that are required in the implementation process. In this context, domain experts are obliged with the specification of the task and the final evaluation. In return, a data engineer and a data scientist are responsible for data analysis and algorithm selection, respectively. Final validation is performed on a predictive quality use case. In terms of SMEs the exchange of several stakeholders is not applicable due to the frequent absence of data engineer and data scientist.

Frye et al. [19] develop a software that includes a holistic ML-pipeline based on the CRISP-DM for the integration of MLA in manufacturing and extend this with a final certification of the AI solution developed in the process. To support data pre-processing and hyperparameter tuning, the authors provide a rule-based expert system that proposes solutions based on domain knowledge and past data. A collaboration between domain experts, IT specialist and data scientists is facilitated by the framework. Just like previously described, the lack of data scientists prevents SMEs from using such software systems.

Garouani et al. [20] describe a software application that allows non-ML experts to select and design ML algorithms such that they are adapted best possible to their needs. For this, they make use of automated machine learning and explainable AI (XAI). The platform then enables the choice between algorithm and hyper-parameter combination. Additionally, the authors deliver a mechanism to increase the explainability of results. The platform was lately tested in the field of predictive maintenance. Despite the integration of XAI, little emphasis is laid on the user and his knowledge development in terms of MLA. In contrast, respective know-how is presumed.

Fischbach et al. [21] develop a software application for implementing an MLA in cyber-physical production systems. Central part of the architecture is a cognitive module that processes the goals defined by the user, selects suitable algorithms and lastly creates a configuration for the execution of a processing pipeline. An evaluation is conducted against different performance criteria. For realization, several technologies such as Docker containers are used. Validation is finally performed on a use case from a learning factory. A description of the roles of single stakeholders is not described in their paper. Likewise, it is assumed that data is already existent and can be included in the application.

As evident, several articles on research in this field were published in recent years. The approaches overcome the problem of unstructured project management by integrating a process model or transferring development steps to a software. Nevertheless, it can be noticed that the focus lies on technical aspects and technical developments, respectively or a collaboration between domain and ML expert is facilitated. A competence development among manufacturing domain experts as later users especially by means of work-integrated learning is only considered marginally. Yet, it is of high importance to familiarize them with the functionalities of MLA. Moreover, the obstacles of SMEs when implementing ML in practice described in chapter 1 are not considered in detail. As such, it is often assumed that a data scientist is employed and therefore available for working with the systems described above. Besides, little focus is put on data collection. Rather the authors suppose that data was collected previously.

3. A CAS for ML implementation

In this chapter, the concept as well as the software-based realization for the CAS-ML that guides practitioners in the development and implementation of an MLA for their manufacturing environment is pointed out. Therefore, foundations and assumptions are described first before an in-depth description of the CAS-ML is provided. The development of the CAS-ML follows the systematics described in ISO EN 9241-210 [22].

3.1 Foundations and context of use

In their research, the authors of [23] describe that employees' trust in MLA is a basic prerequisite for successful collaboration. To ensure trust and increase the likelihood that an ML project becomes successful, the involvement of employees in the design and implementation is therefore essential. In particular, they need to be trained accordingly. Additionally, the research results of [24] indicate that a step-by-step approach is a suitable level of detail for non-ML experts when providing assistance.

For this reason, the basis of the CAS-ML is the so-called Data Mining Methodology for Engineering Applications (DMME) [25]. The individual sections of the DMME are briefly introduced in the following.

- **Business Understanding** is about comprehensively defining the problem to be solved and to define a goal for the implementation of MLA. Additionally, a project plan which contains time frame, budget and potential stakeholders of the project is built up.
- **Technical Understanding** contains the formulation of technical goals based on the previously defined goals in Business Understanding and the development of a technical project plan with the target variables to be measured as well as the required technical infrastructure.
- **Technical Realization** includes the execution of the technical project plan while the main goal is to collect high-quality data.
- In **Data Understanding** companies gain an overview of the previously recorded data by analyzing it comprehensively and identifying potential data problems.
- The aim of the section **Data Preparation** is to preprocess data so that it can later be used within an MLA. It includes e.g., data filtering, feature generation, feature selection and normalization of data.
- **Modeling** contains the applications of an ML-algorithm to the preprocessed data.
- In the section **Evaluation** the performance of the ML-algorithm is evaluated with regard to the problem and general goal formulated in Business Understanding as well as the technical goal defined in Technical Understanding.
- **Technical Implementation** is about the application of the ML algorithm within the real process and ensuring the long-term stability of the technical system.
- The section **Deployment** follows the target to maintain the functionality of the MLA.

The CAS-ML focuses on shop floor managers (production managers and team leaders with decision-making competence [26]) as a suitable hierarchy level for implementation of MLA due to their broad domain knowledge and decision-making competence [13,27]. The goal of the CAS-ML is to allow an easy implementation of MLA for this target group. Since the perception of the complexity of the CAS-ML depends on the prior knowledge and competence of a user, the following assumptions are made:

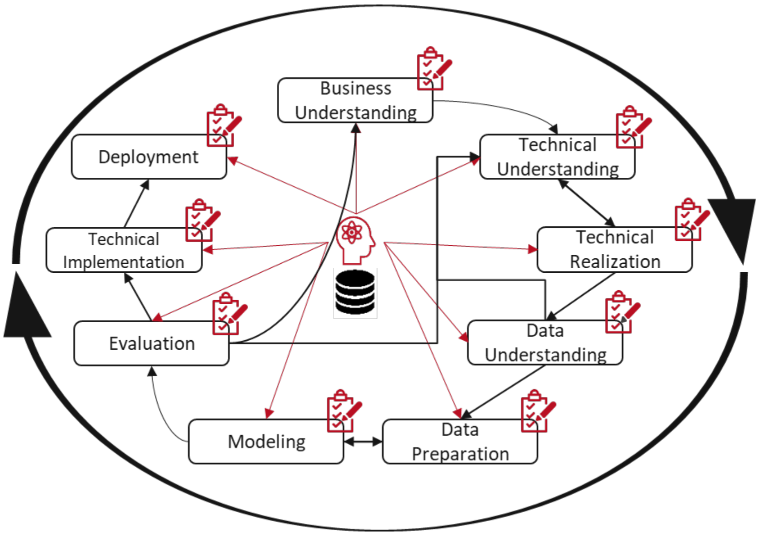
- A user has deep domain-knowledge in the subject of discrete manufacturing and can therefore assess whether a process known to him is in a normal or abnormal state.
- A user knows the basics of descriptive statistics (e.g., differ quantitative and qualitative variables, understand scale levels, interpret location measure and measure of dispersion) and programming (e.g., differ several data types (integer, float, string), understand tabular data) and is able to utilize sources of information outside the CAS-ML in case of upcoming ambiguities.
- A problem definition in manufacturing environment is available. Contrarily, its identification is not part of the CAS-ML nor are traditional solutions other than an MLA meaningful.
- Explicitly, it is assumed that a user does not have extensive knowledge in the field of ML.

The focus of the CAS-ML is on predictive maintenance (PM), as PM is among the most frequently regarded application areas in manufacturing [28]. In the first step, the CAS-ML is limited to milling machines as these are a common use case of PM [29] and have a high relevance for manufacturing environments. Extensions to further processes are planned in future development steps.

3.2 Usage requirements and Design solutions

In order to use the CAS-ML for work-integrated learning when implementing MLA, it has to fulfil a number of functionalities, which are described in the following.

Project management: Considering that ML projects often fail due to unstructured project management and with regard to the findings of [24], the CAS-ML includes a proven process model (DMME) and extends it by respective questions within each step. Thereby a user is lead systematically and generating guidelines for actions, steps, and processes. The underlying concept of the CAS-ML is shown in Figure 1. Therein, the steps displayed in black are taken from the DMME. The lists marked in red represent the single questions made in the steps and the head the learning materials attached.



Procedure within Technical Understanding (excerpt)

- Goals of Technical Understanding
- Definition of process (currently only “milling machine”)
- Definition of sensors, data type, communication standard, message-exchange protocol
- Definition of sampling rate
- Definition of data storage
- Definition of trigger signal

Figure 1: Underlying concept of the CAS-ML with specifications for Technical Understanding; own illustration based on [25]

Visual representation: As a suitable form of presentation, the CAS-ML is visualized by means of tablets. A prototypical implementation of the CAS-ML was realized in Python using the library PyQt5 for building the user-interface. The entries made by the user are saved within a non-SQL Database which makes it possible to interrupt the program and continue without losing any information. An exemplary visualisation of the CAS-ML is represented in Figure 2.

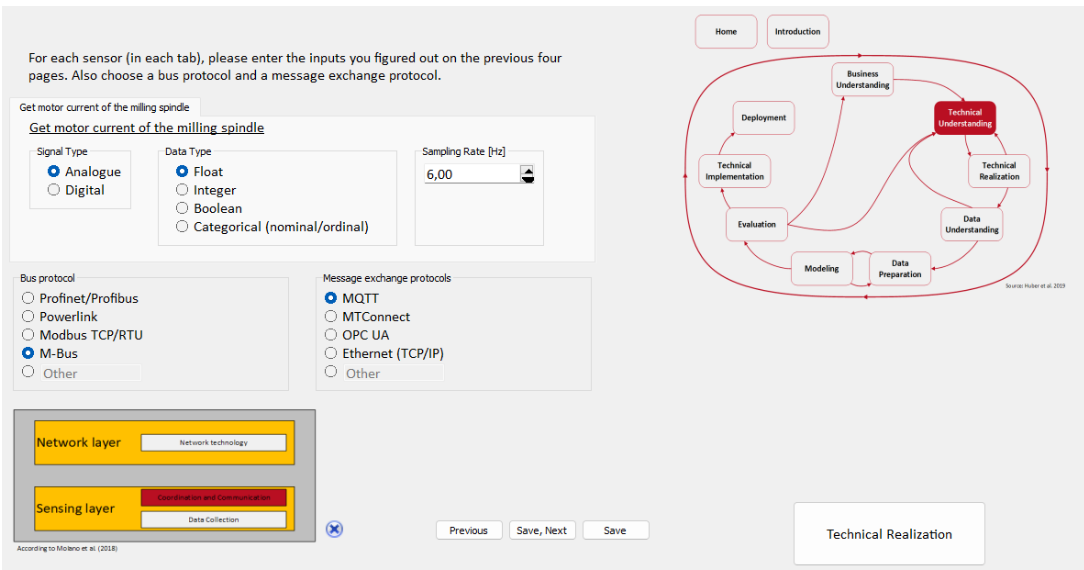


Figure 2: Exemplary visualisation of the CAS-ML (Technical Understanding)

Obstacles of SMEs: To mitigate the previously described obstacles, the CAS-ML focuses on the construction of appropriate sensors and IT infrastructure. By integrating a framework published by [30] which puts emphasis on sensors, their connection to the company's IT infrastructure and the storage of data as well as by the inclusion of best practices from research about PM on milling machines, users are guided through the process systematically. Likewise, the CAS-ML contains default settings for entries to simplify its use, which, however, can always be individualised by the user.

Use for work-integrated learning: As described, the CAS-ML is developed for work-integrated learning to train users accordingly for the integration and use of MLA. Thereby, users are involved both in the design and implementation. In this context, the CAS-ML aims to enhance users' capabilities for diagnosis and decision-making, respectively. For ensuring self-directed learning, digital learning materials [31,27] as well as background information is context-related included in the CAS-ML and can be consumed in the form of problem-pull [32]. Following the systematics of the DMME, backward steps are integrated allowing experimental learning. Since the CAS-ML can be used at specific use cases within production environment, situated learning is ensured. Thus, informal learning is made possible due to the proximity to production processes. Likewise, formal learning takes place through the provision of learning materials.

Within the first section **Business Understanding**, a user has to provide a problem definition before he can specify a goal for the MLA which is currently limited to PM. As stated before, the problem finding is not part of the CAS-ML. Based on the specified goal, suitable key performance indicators based on [33] are suggested to the user. Those can be used to later estimate and evaluate the effect of the MLA. In addition, colleagues who can support and accompany the user through the project have to be defined. Hence, it is specified according to [34] that in order to increase the probability of a successful implementation of PM colleagues from e.g., the departments of shop floor and maintenance management, IT and operative production has to be indicated. A learning by means of a community of practice is thereby made possible. At the end of the section, a summary of all inputs can be exported for forwarding purposes.

The second section **Technical Understanding** aims to create the conditions for MLA that do not exist in SMEs as described above. It starts with the selection of a machine type, which is currently limited to a milling machine. First, the technical goal to measure acoustic emission [35], vibration [36] and the motor current of the spindle [37] is automatically recommended by the CAS-ML. In order to define the technical infrastructure that is required for the implementation of the MLA, the user is guided by a framework based on [30] during the next steps. According to the technical goal, respective sensors are recommended by the CAS-ML within Data Collection. Within Coordination & Communication, the user is informed about the IT infrastructure required for data recording and can then select sensor-specific details such as signal and data type, as well as bus and communication protocols. The level Network Technology involves selecting a cloud service based on [38] that can be used for data storage and deciding to what extent edge computing should be used with regard to [39]. Insofar not yet available, it is suggested that the hardware is retrofitted. Just like in the section Business Understanding the end of the section is given in a summary of all inputs.

After the user has performed his data recording within the section **Technical Realization** and uploaded the data to the CAS-ML, he can analyse it exploratively in the section **Data Understanding**. Therefore, descriptive statistics methods are available and user-defined diagrams such as a boxplot, histogram and scatter-plot can be generated. In addition, missing values in the data can be displayed using the missingno library [40] and outliers can be removed using the method of interquartile range. In this context, the required information knowledge about processes by the users becomes significant. Based on existing domain-knowledge, the recorded data has to be interpreted and evaluated for later use in the model development. Also, it is particularly necessary for a user to have knowledge of descriptive statistics.

The first step of the section **Data Preparation** consists in editing missing values within the data. After the user has selected those columns of his data that contain meaningful sensor data within the second step, he must filter them. For this purpose, an auto-filter based on the interquartile range as well as a user-defined filter are available. The next step deals with labelling the data, which the user has to do graphically on the basis of observations made during the recording of the data. A graphical labelling provides the opportunity to include process knowledge more easily and thereby enhances data competences of the users. The labels are noted according to [41] in such a way that a worn-out state is labelled as positive and a non-worn-out state as negative. The user is then guided to select a sensor signal that he considers most promising for distinguishing normal and abnormal conditions. The features are calculated by the CAS-ML on the basis of this signal, with e.g., min., max., average, kurtosis and skewness in accordance with [42] and [43]. The calculated features are automatically evaluated using an ANOVA F-test [44]. The ten best features are recommended to the user for further use. Since normalization of the data leads to increased accuracy of the MLA [45], a min-max normalization according to [46] is applied in the last step of Data Preparation.

Within the **Modeling** section, the dataset is first divided into training and test data, with a ratio of 75-25 as the default ratio following [47]. Nevertheless, the user is given the opportunity to select a customized ratio. Next, a binary classification algorithm [41,48] is learned to distinguish normal and abnormal states. Here the user can choose between the application of e.g., random forest, k-nearest-neighbours and Gaussian Naïve Bayes, whereof the latter is selected as default due to its compromise between accuracy and computation speed [49]. After the learned algorithm has been applied to the test data, the user is presented with the result of the classification graphically. In addition, the user can display the performance indicators accuracy, recall and precision based on a confusion matrix [50]. If necessary, the user is given the opportunity to return to the algorithm selection and change his choice.

The **Evaluation** section allows the user to evaluate the results of the MLA with respect to the objectives defined in the Business Understanding and Technical Understanding sections, which are displayed again for this purpose. To the extent that the original goals were missed, users can go back to previous steps and make adjustments according to the systematics of the DMME. Within the last two sections **Technical Implementation** and **Deployment**, guidance is provided to the user to apply the MLA to the real process and maintain long-term functionality.

4. Evaluation of the CAS-ML

In order to assess users' acceptance and the usability of the first prototypical realization of the CAS-ML, it is finally evaluated by potential users from lower management (n = 9) using the Technology Acceptance Model (TAM) [51]. The evaluation serves as basis and inspiration for future development steps by revealing weaknesses in the current prototype from the user's point of view. As data for the evaluation the NASA milling data set was used [52]. Based on a given task, the users were asked to pass through the CAS-ML and provide the necessary information required therein. Finally, a digital questionnaire was provided. Following the systematics of the TAM, answers were given on a 7-point Likert-scale with anchor points "Strongly Agree", "Neutral", and "Strongly Disagree", whereby a rating of 4,0 can be regarded as an average value.

The answers indicate that the users perceived the CAS-ML as useful. Thus, they highlighted its use as usefulness at work (Ø = 5,89), working performance (Ø = 5,44) and work facilitation (Ø = 5,44). In contrast, the users expressed concerns regarding the usability. They especially marked the operation with the system (Ø = 4,78) and its customization to their needs (Ø = 4,78).

In light of the feedback by the testers included in the evaluation, the necessity of the CAS-ML is seen. Yet, an emphasis in future steps needs to be put on the usability whereby facilitating the ease-of-use and customization.

5. Summary and Outlook

In this paper, a cognitive assistance system to support the implementation of MLA, with special focus to predictive maintenance, in manufacturing environments was presented. It supports shop floor managers by providing a step-by-step instruction based on the DMME and concretizes where necessary. Additional learning content for each step was integrated that can be consumed context related. The CAS-ML offers the opportunity to learn foundations of MLA and important steps in the introduction process in a work-integrated manner, whereby allowing situated, self-directed and experimental learning and thus simplifying the transfer of knowledge gained to real industrial problems. As output, using companies exhibit higher competences in terms of machine learning, an improved IT infrastructure as well as data suitable for predictive maintenance. The CAS-ML was realized as a software application in Python and evaluated in terms of acceptance and usability by practitioners on an open-source data set.

Considering the assigned usability, the focus of future development steps is on a human-centered design such that the requirements of users are more deeply integrated and on facilitating learning. Besides, an extension to other machines such as a band saws or lathe as well as other use cases is planned. The existing prototype shall then be used in an industrial environment on real recorded data and in this context, users will be tested on competence development. Future development will also focus on the competence development through an interrogation of knowledge and action elements. Likewise, a division in tutorial and expert system is planned.

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