

11th Conference on Learning Factories, CLF2021

Human in the AI loop: Teaching shop floor workers artificial intelligence in production

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Abstract

In recent years artificial intelligence (AI) and machine learning are finding their way into production processes. The speed of introduction of these promising technologies is hampered by inadequate competencies of associates on all hierarchical levels. On the shop floor level, the challenge is to identify and teach the necessary competencies to operate and maintain complex AI-based systems. The project “Human in the AI loop” funded by the EIT Manufacturing focuses on that question and develops online learning tutorials that fit to the required competences a shop floor employee needs to understand and operate an AI-equipped production line. The approach adopted to reach this goal comprises three steps: First, interviews with experts coming from the industrial AI domain have been executed to identify the most common application areas and use cases occurring in modern production facilities, i.e., optical quality inspections and time series data analytics. Based on this input, a map of competences has been assembled, employees should have to successfully deal with AI opportunities and challenges that occur in his/her company. And finally, online tutorials have been developed to cover the needs of the different roles within the shop floor. The tutorials themselves are divided into small so-called “learning nuggets” that can be executed by the participants even “on the job” and at their own pace. Theoretical input and practical tasks alternate to not only provide theoretical knowledge as other courses already do, but to allow for experiments with industrial data, too. The paper highlights the expert interviews, presents the competence map, and - by means of an example - discusses two of the online tutorials - one with a focus on technical aspects of data and another one dealing with social aspects to build more trustworthy AI.

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Peer Review statement: Peer-review under responsibility of the scientific committee of the 11th Conference on Learning Factories 2021.

Keywords: artificial intelligence; online learning content; shop floor worker; blue collar

1. Introduction

Recent advances in robotics and artificial intelligence (AI) are pushing the boundaries of what machines can perform across all economic and business sectors [1]. All around the globe, companies are striving to leverage the potentials of AI for profit [2]. Especially in production, the use of AI offers many potentials e.g., in the field of predictive maintenance, autonomous robots, and process optimizations [3]. Once implemented shop floor workers will have to operate and maintain such complex systems. To be able to deliver the expected results, shop floor workers need to acquire new competences [4]. This paper aims at presenting the three-step approach to systematically form new learning content to develop AI-related competences of shop floor workers. Additionally, the belonging online learning content will be introduced. Based on so called learning nuggets each learner will be able to decide individually what content is relevant for him-/herself. In addition, each learner can choose him/her

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own learning speed (asynchronous learning). To encourage the use of the learning units, they will be accessible free of charge on the European Institute of Innovation & Technology (EIT) Manufacturing platform.

2. Three-step approach for AI-related learning content development

2.1. Selecting AI use cases (Step 1)

The first step to create online learning content is to select relevant use cases of AI in production. This is an important step to acquire information about the way shopfloor workers are getting in touch with AI in their everyday life. This has significant impact on the content of the learning nuggets in step 3.

According to Capgemini (2019) process analysis, product quality, and maintenance are the areas where AI offers the most promising practical applications, not only as pilot projects but already implemented in operations [5]. Similarly, an analysis of Politecnico di Milano shows that most advanced are AI application related to data processing in production, quality classification and prediction, and maintenance, followed by computer vision for quality applications and autonomous robots in production [6].

With the findings of the literature research, six expert interviews have been conducted to identify and select common industrial AI use cases. The consulted experts are working in the fields of factory automation, predictive maintenance, data analytics, learning factories and AI. Subsequently, a virtual workshop has been organized to identify, discuss, and prioritize the most relevant use cases in modern production facilities.

The results of the workshop confirmed the findings of the literature research. While a total of eight use cases were shortlisted at the workshop, two were finally selected for the project. The criteria for selection were relevance for the target group, a low level of complexity, the degree of development and data availability. The experts chose “predictive maintenance on a saw blade” and “visual quality inspection in a pizza production line” to be the most relevant use cases for training purposes for the target group of shop floor workers. Both use cases are briefly described in the following.

The use case predictive maintenance aims to identify wear on a saw blade. Therefore, sensors to measure temperature, power consumption and vibrations were retrofitted to a saw machine. The data were then labelled and via a classification a prediction of blade failure was implemented on the machine. The use case on visual quality inspection in a pizza production line aims to identify quality issues in an automated pizza production line. A camera confirms the quality of the produced pizza via computer vision. To do so the algorithm checks if for example the right number of salami slices is placed on the pizza.

2.2. Selecting general AI competences (Step 2)

Parallel to the selection of use cases, a systematic literature review was conducted to identify the needed competences. These competences are not directly connected to the use cases and give a general overview of AI-related competences for shop floor workers according to the literature. From now on referred to as “general AI competences”. After the identification of the required competences, they have been validated and complemented by interviews with the same experts that also reviewed the use cases. Two competence categories have emerged from this analysis, which are defined by Erpenbeck and Rosenstiel [7]:

- Technical-methodological competences, with which problems can be solved using experience, expertise, and appropriate methods,
- Social-communicative competences, with which communication processes can be improved and new solutions can be found.

For the technical-methodological category, a total of four skill sets have been developed and divided into the groups “Information technology” and “AI”. For the social-communicative category, the focus lies on “Personal” and “AI” competences, which also leads to four skill sets. The identified competences are displayed in Table 1:

Table 1. Competence map.

	Information technology	AI
Technical-methodological	Data related skills (statistical basics, use of databases, big data, data acquisition, data evaluation, data visualization)	Combining technical and information technology skills (data quality in a production context, data interpretation)
	Understanding and applying digital and media facts (handling computers/programs, benefits of communication systems)	Understanding of AI (basic concepts and structure of AI, neural networks, deep learning)
	Personal	AI
Social-communicative	Building trust in AI (data ethics, data sensitivity)	Being aware of AI impact (social impact, prejudices against AI)
	Cybersecurity / Data security and privacy concerns (data protection)	Understanding Risks and Benefits of AI

For example, the technical-methodological skill set combining technical and information technology skills (AI category) shows the cross-sectional knowledge the shop floor workers need to have to work effectively with AI in production. Specifically, the knowledge of data significance and data quality in the production context is of high importance. With these basics, given data can be interpreted and the concept of data labelling and augmentation is understood. Finally, these skills include the identification of critical components, from a predictive maintenance point of view, where the target group can set limit values and see when a tool needs to be changed, based on the data provided. This skill set connects the already established technical qualification of a shop floor worker with the mostly new information technology competences to form a solid collaboration base between the workers and specialists from other fields i.e., data scientists and engineers.

2.3. Combining competences with use cases to generate learning content (Step 3)

Having identified the most promising use cases and the competences relevant for shop floor workers, the combination of competences with the use cases found in production is needed to create learning content that is unique and fits with the needs of the target group (Fig. 1). By focusing only on competences needed for the use cases rather than giving a complete overview of the topic, the shop floor worker always has a comprehensible connection of the learning content to his/her everyday life in production.

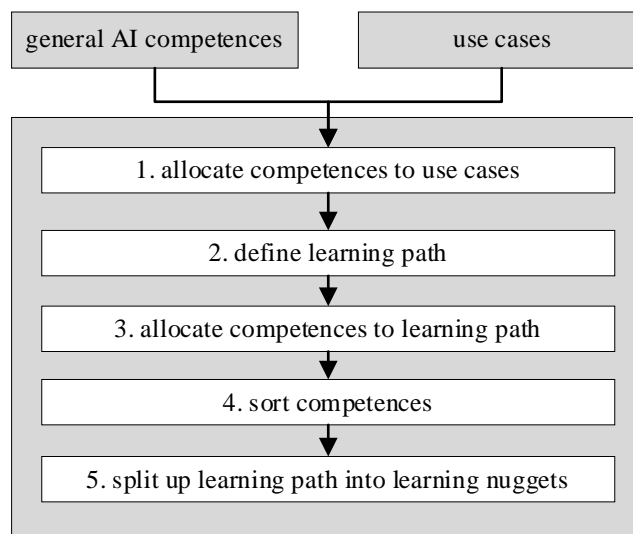


Fig. 1. Steps to combine use cases and competences into learning content.

To achieve this goal five steps to combine use cases and competences have been developed (Fig. 1). First, the general AI competences have been allocated to the use cases. This was done to find out which competences are needed for each use case. Each competence can be allocated several times to different use cases. In Table 2 the

competences for the two selected use cases are listed. The allocation is a first impression on how many of the theoretical competences are necessary for the use cases. Left-over competences that are not allocated to any use case were deleted since there is no relevance for the use cases and the everyday life of the target group.

Table 2. Allocation of general AI competences to use cases.

	Data related skills	Understanding and applying digital and media facts	Combining technical and information technology skills	Basic understanding of AI	Building trust in AI	Cybersecurity / Data security	Being aware of AI impact	Understanding Risks and Benefits of AI
Predictive maintenance	+	+	+	+			+	+
Quality inspection	+		+	+		+	+	+

Then, for online content “learning paths” were created that consist of several small “learning nuggets”. A learning nugget is an online learning unit with a specific topic to acquire competences with a maximum time expenditure of 30 minutes. A learning path consists of several learning nuggets sorted into a “path” to acquire competences. A learning path is a logically sequenced and complete set of learning content to achieve competences. To create the learning paths, the main competences that describe whole groups of competences need to be defined. The systematic literature review carried out as part of previous step already defined skill sets of competences. The learning paths are developed independently of the use cases, so that one learning path can contain examples from both use cases.

The goal is to allocate all competences to the learning path, while once again deleting duplicates. The question arises, why not use the structure given in the literature review discussed in chapter 2.2 and in the next step to create the learning paths. The sorting of competences to the use cases ensures to limit the content of the learning nuggets to the necessary minimum. This is important because the shop floor worker should only be given relevant information for him/her. Also, in the following steps, while creating the learning nuggets the link with the use cases gives practical examples for each competence and accelerates the development process.

With the competences allocated to a learning path, the next step is to sort the competences based on consecutive topics, simultaneous elaboration, and Bloom taxonomy levels. The idea is to have each learner progress through the learning path and use previously acquired competences in an advanced segment of the path.

In the last step, the learning path is split up into the learning nuggets with an approximately maximum processing time of 30 minutes each. With the competences defined for each learning nugget, the development of the learning content can begin. There exist several methods to create learning content out of a competence table e.g., Enke et al [8]. In this project, two learning paths with a total of 22 learning nuggets have been created out of the competence map for shop floor workers. One learning path focusing on technological-methodological competences while the other one focuses on social aspects that arise when realizing AI applications.

3. Learning Path Examples

Both learning paths are available at the “Guided Learning Platform” of the EIT Manufacturing. The approach of dividing the overall content into nuggets being available at an online platform allows shop floor employees (or participants in general) to complete the nuggets anywhere at any time and especially at their own pace. To make the content more interactive, so-called information nuggets, exercises/tasks, and tests – to be passed by the participants – alternate. As an example, two nuggets (one from each learning path) are highlighted in the following.

3.1. Learning Path 1, Learning Nugget “Sensor Data”

To successfully realize an AI approach, the availability of “good” data is mandatory. In the “Sensor Data” nugget the participants learn how to select and prepare data, how to distinguish between different types of data, and how to decide what data are required for a specific application.

The nugget starts with a review of component failures and its symptoms as well as possible data types. The content is based on the predictive maintenance use case selected through the expert workshop. The use case is used throughout the entire learning path and is implemented in a factory environment at TU Darmstadt, with an access to “real” data. In this scenario, the task is to determine at which point in time in the future a saw blade must be replaced by a new one due to indirect signs of wear, which can be determined based on different sensor systems like increasing power consumption, increasing vibration, or even increasing temperature to name only a few possibilities.

In the next part, the difference between samples, features, and labels is explained, before the terms data augmentation, measurement duration, and measurement repetition are introduced. While the AI approach based on process data is indirect, in visual inspection direct data of the object to be monitored is the basis. Here, the second use case – optical quality inspections in a pizza production line – comes into play. Not only because data augmentation can be explained quite easily by rotating, stretching, zooming pizza images to be classified as being “ok” or not, but also to highlight that different application areas require completely different kinds of sensor data. As an example, when checking whether a pizza is fine or not, power consumption or vibration do not matter (but they are of fundamental importance in the saw blade example). To allow for practical experiments, a web-based pizza quality checking procedure has been implemented, which will be made available to the participants via a docker container. Furthermore, the nugget also highlights the difference between cloud and edge computing and finally concludes with a short reflection on the topic.

3.2. Learning Path 2, Learning Nugget “Explainable AI”

As discussed in the previous section, the availability of “good” data is - from a technical point of view - key for a successful implementation of an AI algorithm. Good data does not only mean to have enough data points, to reduce noise, and to remove outliers, it also requires unbiased data, representing the entire “environment” the AI approach must deal with during its execution. Due to their complexity, AI systems nowadays often lead to results and decisions that cannot be understood by the user immediately, which might become critical if the system comes up with “wrong” results (for example in cases in which an AI algorithm is used to distinguish between healthy and diseased tissue). Therefore, talking about data has not only a technical aspect, but also a social aspect in increasing the users trust in such systems.

The learning nugget “Explainable AI” focuses exactly on this trade-off between opaqueness versus explainability of AI systems. In combination with the learning nugget “Sensor Data” of learning path 1, the participants get an overview of all aspects regarding data in general. First, opaqueness and typical black-box behaviour of AI systems are introduced. Based on that, examples for increasing the transparency and explainability of the next generation of AI approaches are addressed. Finally, a trade-off between performance and explainability is suggested to allow the users to calibrate their trust in the AI systems, even though the complexity of the system is high.

As shown by the two exemplary nuggets discussed before, both learning paths do interact with each other and allow participants not only to get familiar with common approaches and strategies in the field of AI but also to get to know the challenges, risks, and limitations of the corresponding algorithms. Finally, it should be emphasized that implementation details like programming language(s), libraries, tools, and most of the mathematical details have been skipped. The reason for this decision is – like already discussed – that shop floor workers typically may have to work with AI-equipped systems, but do not have to program/develop them on their own.

After the online training has been finalized and set up, a feedback workshop with the same industrial experts has been organized. The created Learning Nuggets have been presented and professional qualitative feedback regarding the content as well as the format of the learning nuggets was given by the experts. Furthermore, testing links have been sent around to the target group together with an evaluation form to gather feedback and further improve the learning content. The result of the feedback shows that concentrating on competences for shopfloor workers and combining them with relevant use cases was well received in the target group. Nevertheless, the participants still have problems to apply their new knowledge when they are only trained through online learning content. The learning nuggets help to create knowledge about the topic but cannot be seen as a replacement for practical training in e.g., learning factories. Therefore, the next step should be to create a practical learning course where the participants can further test their new competences.

4. Conclusion

In this paper, a three-step approach to develop learning content tailored for shop floor employees when faced with AI-equipped production lines has been introduced. The first step was to identify the most common application areas of AI, that occur in many production lines in today's industry (and will definitely occur in the next generation of factories). During a workshop with experts coming from different fields of production, it turned out that optical quality inspection and time series data (predictive maintenance, process optimization, sales forecasts, ...) are widely used. Secondly, the project determined which competences a shop floor worker should have to maintain and manage production lines being equipped with instances of the two use cases mentioned before. Finally, the competences were mapped into small learning nuggets to be stored on an online platform to allow participants to extend their knowledge anywhere at any time and in particular "on the job". A total of 22 learning nuggets have been developed, all of them reviewed by several shop floor workers and experts from industry and optimized accordingly.

The next steps will be to further test the nuggets on the target group. Also, the participants of the project will integrate the learning content in their learning factories. The learning nuggets will serve as a preparation for more advanced modules about Artificial Intelligence at the learning factories.

Acknowledgements

This research is funded by the European Institute of Innovation & Technology (EIT) Manufacturing.

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