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TEAMING.AI Summary M1-M18

Summary of the context and overall objectives of TEAMING.AI

Smart Manufacturing plays a critical role in maintaining the competitiveness of companies and organizations, by supporting them at different levels such as process optimization, resource efficiency, predictive maintenance and quality control. Nevertheless, current AI technologies that are rapidly penetrating industrial sectors at those levels remain essentially narrow AI systems. This is due to the lack of self-adaptation in the AI's capability to assimilate and interpret new information outside of its predefined programmed parameters. In particular, the teaming aspect of human-AI collaboration is still in its infancy in the sciences, as was recently discussed at the IJCAI 2022 workshop on Communications in Human-AI interaction[1]. The interdisciplinary research involving AI, HCI, and cognitive sciences remains mainly on the conceptual level, lacking computational models and applicable software for adapting to the needs of various industrial domains. So far, existing computational models are only applicable in a limited setting as for example for a static context with a predefined group of experts where the decision process can be modeled by an ensemble learning approach[2]. However, as a recent review analysis of human-AI collaboration[3] has shown, a key challenge and research gap is modeling dynamic process factors and temporal constraints that are implicated in managing uncertainty in task progress, interactions, and communication. This analysis is in line with our main focus in TEAMING.AI on **situation awareness of human-AI dependencies in dynamic settings**. For an overview of the main aspects of human AI teaming see Fig. 1.

[1] IJCAI Workshop 2022 on Communication in Human-AI Interaction, https://chai-workshop.github.io/

[2] Patrick Hemmer, Sebastian Schellhammer, Michael Vössing, Johannes Jakubik, Gerhard Satzger: "Forming Effective Human-AI Teams: Building Machine Learning Models that Complement the Capabilities of Multiple Experts", IJCAI 2022, https://www.ijcai.org/proceedings/2022/0344.pdf

[3] National Academies of Sciences, Engineering, and Medicine, "Human-AI Teaming: State of-the-Art and Research Needs.", 2021, https://doi.org/10.17226/26355

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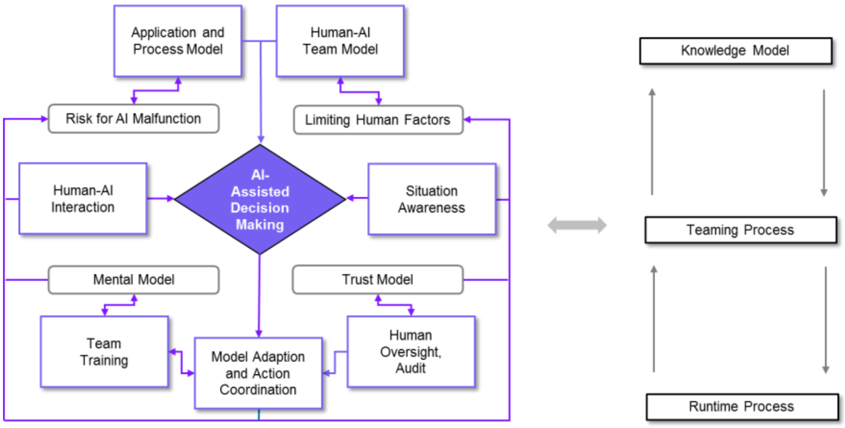

Fig. 1: Aspects of human-AI teaming and related dynamic knowledge integration. TEAMING.AI focusses on Situation Awareness as central component.

Social studies on human teamwork consider not only whether the team performed well (e.g., completed the team task) but also how the team interacted (i.e., team processes, teamwork) to achieve the team outcome. Applied to the context of human-AI collaboration, this means that to be an effective team member, the **AI needs to participate in the team's coordination activities and know what information to share or when to ask for support**. Being capable of observing one another's state, sharing information, or requesting assistance is regarded as Teaming Intelligence. Taking human autonomy into account, **team effectiveness** can be only achieved if the **interdependence relationships** used to support one another throughout the task work is fully understood by all team members. A key element for successful human-AI teamwork therefore is a careful design and implementation of the situation awareness and coordinating mechanisms involved. Mutual trust increases if the appropriate amount of information is shared through a closed-loop communication between humans and AI components.

In the TEAMING.AI project we aim to develop a **human-AI teaming framework that integrates** the strengths of both, the **flexibility of human intelligence** and the **scale-up capability of machine intelligence**. Human-AI teaming is equally motivated to meet the increased need for flexibility in the maintenance and further evolution of AI systems, driven by the increasing personalization of products and service, as well as tackling the barriers of user acceptance and ethical challenges involved in the collaborative environments where artificial intelligence will be used, in order AI can be considered as "teammate" rather than as a threat. The **envisioned TEAMING.AI platform** has the goal to orchestrate the information exchange and to organize the collected information within a layered knowledge graph, reduce the information to its key aspects and semantically enrich this knowledge with context information. Transparent storage and processing of information is the foundation for a decision support system that can be understood and further analyzed by human team members. Specifically, we tackle the following objectives in TEAMING.AI:

Situation awareness model, i.e., monitoring and tracking of states and actions based on a process model, addressing the following technical questions:

- How to represent dynamic and evolving knowledge such that it facilitates a context-dependent interpretation of manufacturing processes?
- How to cope with different granularities in time scale and event complexity?
- How can we reason about not fully observable states (human mind)?
- How to measure whether the situation awareness is correct and up-to-date?

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Situation-aware reasoning and decision making, i.e., reasoning within situation awareness model and about it (meta level), addressing the following technical questions:

- Is there a compliance violation with policies?
- When and how to update the situation awareness model?
- Who is to take over control: human or AI?
- When and how to adjust the process model, e.g. task re-allocation between humans and AI?

To tackle these problems, we investigate in TEAMING.AI to what extent a **knowledge graph** (KG) can be used as a central component in an enhanced ML system as a basis **for a situation awareness model** with update and reasoning mechanisms that allow for a **dynamic contextualization of manufacturing settings** including local situations, tasks, and organizational context. Technically, our focus in the first reporting period (M1-M18) was therefore concentrated on the development of concepts, methods, and software tools that help us to leverage a KG for the above-described vision. This includes:

- Monitoring and tracking w.r.t KG model to extract and match evidence cues, e.g., for task assignment between humans and AI („**trust model**")
- Extension to a multi-layer KG to encode also high-level policies, e.g., safety and ergonomic guidelines („**auditable ethics**")
- Utilizing KG embeddings for reasoning about the situation awareness model, e.g., uncertainty model about consistency or incompleteness („**self-diagnosis**")
- Novel techniques for the synchronization between KG and embeddings on it („**KG dynamics**")

Accordingly, the use cases of TEAMING.AI are reflected and shaped in a way to cover these main aspects mentioned above. The aspects of monitoring and process tracking, i.e., model-process synchronization, in terms of trust modeling and its meta-reasoning (self-diagnosis) are at the basis of all of them. Specific accents are as follows:

- **Dynamics** aspect in terms of adjusting the AI model for robust quality inspection of produced plastic parts (Use Case 1, Farplas, Turkey). The TEAMING.AI platform will support the setup and reconfiguration of injection machines and the adjustment and adaptation of the KG and AI model due to unforeseen new defect patterns under changing production conditions.
- **Cognitive** aspect in terms of AI-assisted machine diagnostic to improve quality and reduce waste (Use Case 2, Industrias Alegre, Spain). The TEAMING.AI platform will support the collection of side information to improve ML models for fault prediction and will guide the machine operator through the root cause analysis after defects occurred.
- **Auditability** aspect in terms of ergonomic risk prevention in large part manufacturing (Use Case 3, Goimek, Spain). The TEAMING.AI platform will assess ergonomic risk of tasks performed by workers and will ensure compliance with respect to policies due to standards, safety, ergonomic or ethical guidelines.

Work performed in TEAMING.AI

The following sections group the work done and achieved results along the main aspects we pursue in the TEAMING.AI project.

The Knowledge Graph as Model for Situation Awareness

The work in the first period of the TEAMING.AI project was concentrated on the KG design along with a supporting software framework to facilitate the creation and processing of the KG addressing the requirements from our use cases. An early insight was that the KG needs to consist of different layers

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that are either constructed (knowledge driven) or automatically populated (data-driven). This led to the development of a **layered, modular knowledge graph** [1] to support teaming scenarios and the shared decision making within. Rather than developing a single, monolithic KG, which requires a large up-front investment and bears considerable risk, our approach aims to **incrementally build a system-wide KG** as an aggregation of more granular per-use case views, while ensuring their conceptual alignment through a set of **shared core concepts**. The design of KG focused on the representation of **dynamic and evolving knowledge**, particularly in the context of processes. The development includes therefore software tools (BPMN2KG) that can **bridge the gap between process modeling approaches (BPMN) and the representation of process knowledge in a KG**.

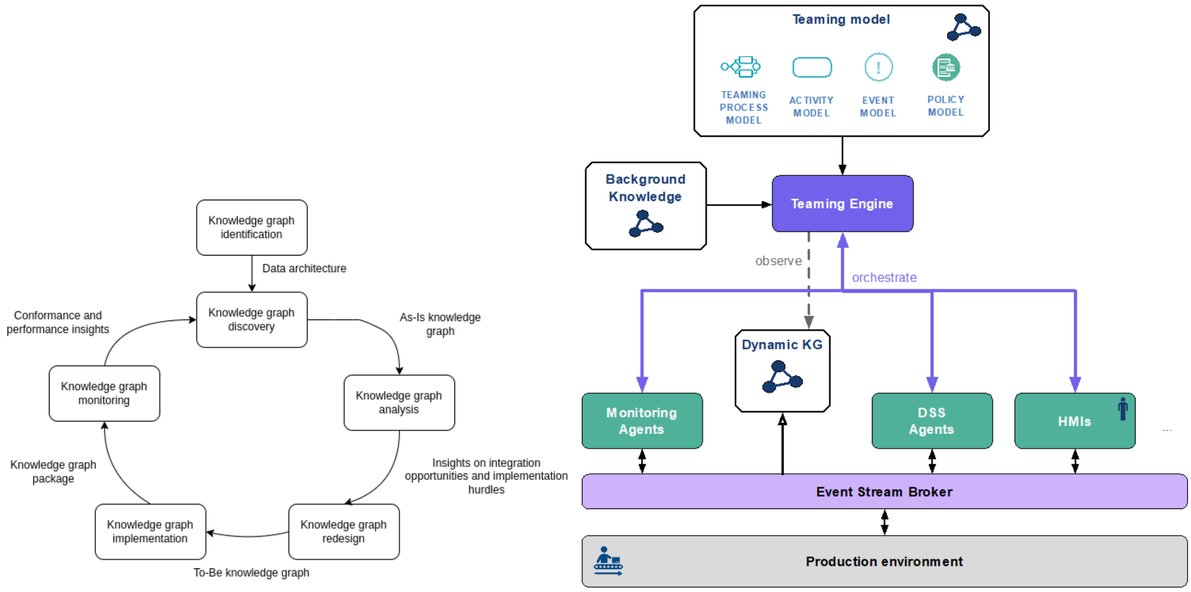

Fig. 2: KG Management Lifecycle (left), TEAMING.AI architecture [3,4] with Dynamic KG as central component (right)

The setup and implementation of the KG follows a **knowledge graph management lifecycle** (see Fig. 2, left) that structures KG population activities as well as the monitoring of the KG once it is deployed. Specifically, we developed methods supporting KG analysis and re-design/repair by means of maintaining constraints in SHACL (self-diagnosis), and automatically generating repairs for constraint violations. With respect to the TEAMING.AI Engine, component for orchestrating dynamic human AI tasks assignment, and its implementation in the use cases, it should be noted that updates in the **knowledge graph must necessarily be synchronized with the embedding space**, so that changes in the KG can be immediately applied to the embeddings of the affected nodes **to handle downstream relational machine learning tasks**. Thus, a service should exist that manages the embeddings of the nodes in the KG and adjusts them as soon as facts are updated in the knowledge graph. The system architecture of TEAMING.AI, as illustrated by Fig. 2, right, takes these aspects into account. In particular, to address the dynamic adjustment also of the downstream relational machine learning tasks we developed the NaviPy framework [2]. Finally, we concentrated on methods for the fusion of KGs obtained from use case domain knowledge with traditional ML models to improve prediction performance and efficiency.

The Teaming Intelligence Aspect of Human-AI Collaboration

The teaming intelligence aspect is central for the project. Therefore, we not only reviewed existing literature about human-AI collaboration but dig deeper into social science and physiology to develop a concept of a digitalized teamwork that is based on knowledge modeling and model-process synchronization at the level of team interactions among team members as well as between human

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and AI (communication, interaction), knowledge transfer from human (cognition) to AI and team and task scheduling and synchronization (workflow).

In TEAMING.AI the human-AI teaming is centered on a coordination mechanism that supports teaming intelligence for human-AI collaboration by means of operationalization of the 4S framework[4] based on the **interdependence analysis of teamwork**. We developed concepts for its technical realization in the use cases. The main components are the **Teaming Model** based on the **Dynamic KG** and its sub-meta-models for **representing and modeling activities, events, processes, and high-level policies** as basis for synchronizing and aligning human-AI communication, reciprocal learning (AI assists human in decision making and, vice versa, KG enhancement by humans) and task assignment between humans and AI. The sub-models of the Teaming Model are tightly integrated with the KG and are envisioned to support the fusion of KGs obtained from use case domain knowledge with traditional ML models to improve explainability of predictions/decisions made by the ML algorithms, so that outputs of ML algorithms are easier to debug and process by human operators.

Development and Integration of Components for a Proof of Concept

The development of the Use Cases started with a requirement engineering and the description of user stories that will be used as anchor points for validation tests of teaming scenarios. The requirement engineering included an importance evaluation of an extended list software quality attributes (scalability, robustness) that also included attributes towards teaming aspects (trustworthiness, explicability, …). Based on this assessment a software architecture for the TEAMING.AI platform has been developed that has a special focus on scalability and timing requirements of ML components and the KG runtime layer. The **reference architecture** serves as a blueprint for deriving the software architecture for a particular manufacturing context.

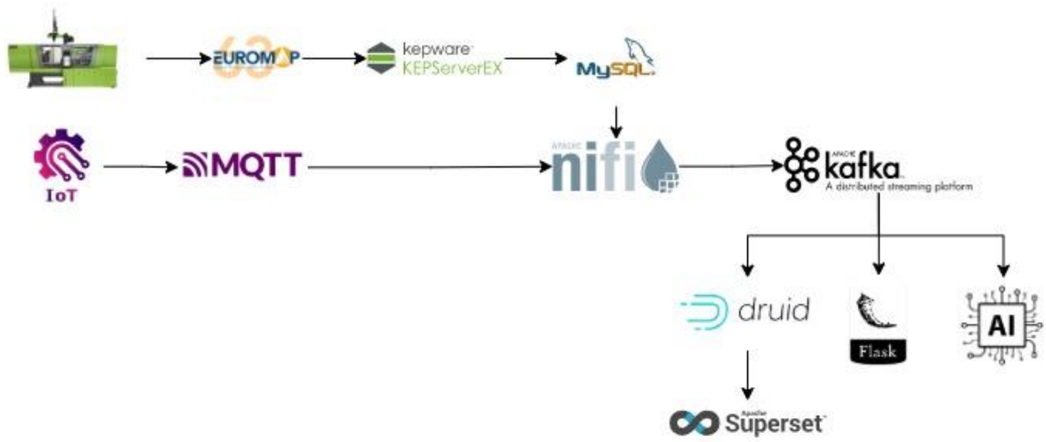

Fig. 3: Example of a production site data pipeline used in TEAMING.AI

In parallel, the use case providers concentrated on the digitalization of the manufacturing processes. This includes upgrades of IoT and monitoring equipment as well as the implementation of data extraction modules that can act as a **streaming node for data transmission to the TEAMING.AI platform**, see Fig. 3. Data collection efforts led to several datasets that are used now to train alpha versions of the ML services for KG population (e.g., visual fault detection, parameter change detection, fault prediction, pose estimation, ergonomic risk assessment). For example, in use case 3 the TEAMING.AI platform supports the **ergonomic risk assessment** of manual activities performed by operators. The ML components consist of an automatic scene analysis tool that allows us to extract

[4] Johnson and Vera, No AI Is an Island: The Case for Teaming Intelligence, AI Magazine, 40(1), 16-28, 2019

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behavioral patterns and postures of workers (Rapid Upper-Limb Assessment, RULA; Rapid Entire Body Assessment, REBA) to be assessed in terms of an ergonomic risk score.

Dissemination and Exploitation of Results

TEAMING.AI has worked early on a Corporate Identity and a Communication and Dissemination Master Plan (CDMP) that includes a distinct visual identity and a clear communication strategy. TEAMING.AI is following the timeline for the dissemination activities which is structured in four main phases according to the AIDA model (Awareness, Interest, Desire, and Action). During the first two phases the consortium participated in numerous events (Data Week 2021, IJCAI 2022, ICT-38/ICT-48 activities, …) and engaged with the scientific community with conference participations (ICSE 2022, ESWC22, …) and publications.

For further exploitation of key results, we conducted a thorough literature analysis to identify market barriers for AI in manufacturing. Based on the literature analysis and our previous work on pains in TEAMING.AI, an online questionnaire was developed and circulated to our end-users that participate in the Teaming.AI consortium. The questionnaire had two respondents from each End-User (of which 3 are operators/technicians and 3 are managers) and revealed that all three companies are still at an early phase in digitalizing their manufacturing processes. Main improvements are envisioned towards decision making and increased agility through automation and up-skilling. Based on the end users' feedback and an additional market analysis we identified the following five key market segments and use cases as promising for further exploitation of TEAMING.AI results: a) Quality Control, b) Process Control, c) Safety features, d) Design & Maintenance, and e) Augmenting human capabilities.

Progress beyond the State-of-the-Art

Operationalizing Teaming Intelligence Concepts from the Social Sciences

To enable the AI to take part in the human-AI coordination activities, we follow concepts from social sciences and utilize **knowledge modeling techniques by means of knowledge graphs to analyze and model the teaming interdependence relationships** along the team and task structure and link teaming activities to the skills of the team actors, addressing the challenges outlined for situation awareness and its reasoning within the model and about it. At the most granular level, we expect that an activity is either performed by a human team member or an automated AI service. However, the performer of this activity can be supported either by a human or the AI by providing additional insights the performer can rely on. Our knowledge graph based approach introduces a **concept of abstract activities** as a mechanism to model this performer/supporter pattern. We envision the supporter role as a more passive role that monitors the current state of the production process and interacts if needed. The final outcome of the interdependence analysis is a description of the teaming processes and activities as well as teaming events that trigger interactions. They form the basis of the Teaming Model that allows the TEAMING.AI engine to keep track of the activities of the other team members. The concept was presented at the conference on Interoperability for Enterprise Systems and Applications (I-ESA) 2022 [1].

Knowledge Graph Modularization

Industrial production is currently undergoing a major paradigm shift, often referred to as Industry 4.0, and its extension in terms of human values and sustainability as Industry 5.0. Advances in digital and manufacturing technologies are strongly driven by data as a key enabler, creating opportunities beyond classic monitoring and predictive applications. In this context, **Knowledge Graphs** (KGs) have strong application potential to create an **integrated multi-perspective machine data space** from heterogeneous data silos, lift and contextualize machine generated data, and facilitate cooperation between various domain experts and Artificial Intelligence (AI) agents based on shared concepts.

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Compared to other domains, however, KG techniques have seen limited adoption in this field so far. We argue that the construction of KGs in the context of cyber-physical production systems requires a systematic methodology grounded in domain-specific abstractions. Consequently, we introduce a **KG modularization framework based on the well-established RAMI 4.0 architecture model**. A key benefit of the proposed approach is that the resulting KGs support **navigation across abstraction hierarchies**, enabling bottom-up contextualization of raw data on the one hand, and top-down explanations by linking to lower levels of granularity on the other hand. Thus, such a structured KG can be used

- to support the delivery of a trustworthy, auditable, integrated datastore that preserves the inherent heterogeneity of manufacturing data,
- to combine different types of AI and human reasoning in an integrated platform, and
- to improve decision-quality in the manufacturing and selection of parts by taking all available information into account.

This view was presented at the International Semantic Web Conference (ISWC) 2021 [2].

Dynamic Knowledge Graph Embeddings

Knowledge graph embeddings and successive relational machine learning models represent a topic that has been gaining popularity in recent research. These allow the use of graph-structured data for applications that, by definition, rely on numerical feature vectors as inputs. In this context, the transformation of knowledge graphs into sets of numerical feature vectors is performed by embedding algorithms, which map the elements of the graph into a low-dimensional embedding space. However, these methods mostly assume a static knowledge graph, so subsequent updates inevitably require a re-run of the embedding process. In this work the **NaviPy Approach** [2] is introduced which aims to maintain advantages of established embedding methods while making them accessible to dynamic domains. Relational Graph Convolutional Networks are adapted for **efficient reconstructing node embeddings based solely on local neighborhoods**. Moreover, the approach is independent of the original embedding process, as it only considers its resulting embeddings. Preliminary results suggest that the performance of successive machine learning tasks is at least maintained without the need of re-learning the embeddings nor the machine learning models. Often, using the reconstructed embeddings instead of the original ones even leads to an increase in performance. The research results were presented at the Extended Semantic Web Conference (EWSC) 2022 [3].

TEAMING.AI Software Architecture

With the proliferation of AI-enabled software systems in smart manufacturing, the role of such systems moves away from a reactive to a proactive role that provides context-specific support to manufacturing operators. In TEAMING.AI we focus on **knowledge graphs** (KG) to capture product and process specific knowledge in the manufacturing process and on **relational machine learning** to utilize the information in the KG for context specific recommendations for the optimization of product quality and the prevention of physical harm. In multiple workshops over the course of six months, our research consortium identified two main challenges relevant for a reference software architecture for human-AI teaming in smart manufacturing [3,4]. The first challenge relates to the required **scalability of the architecture** when processing data in near-realtime, particulary in combination with relational machine learning, i.e., the statistical analysis of graph-structured data. The second challenge relates to examining a suitable framework to **explicate the knowledge** for effective teaming in the manufacturing process. Shared mental models capture the common ground knowledge in the collaboration between humans and AI services. We use knowledge graphs and ontologies to formalize these shared mental models of the manufacturing process and the semantics of trust factors for human-AI teaming in an operational manner.

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Based on these challenges, our research consortium developed a reference software architecture that serves as a blueprint for our subsequent research activities and validations. Though this architecture merges different viewpoints from researchers with software engineering and machine learning backgrounds, we expect subtle changes with further progress of the research project.

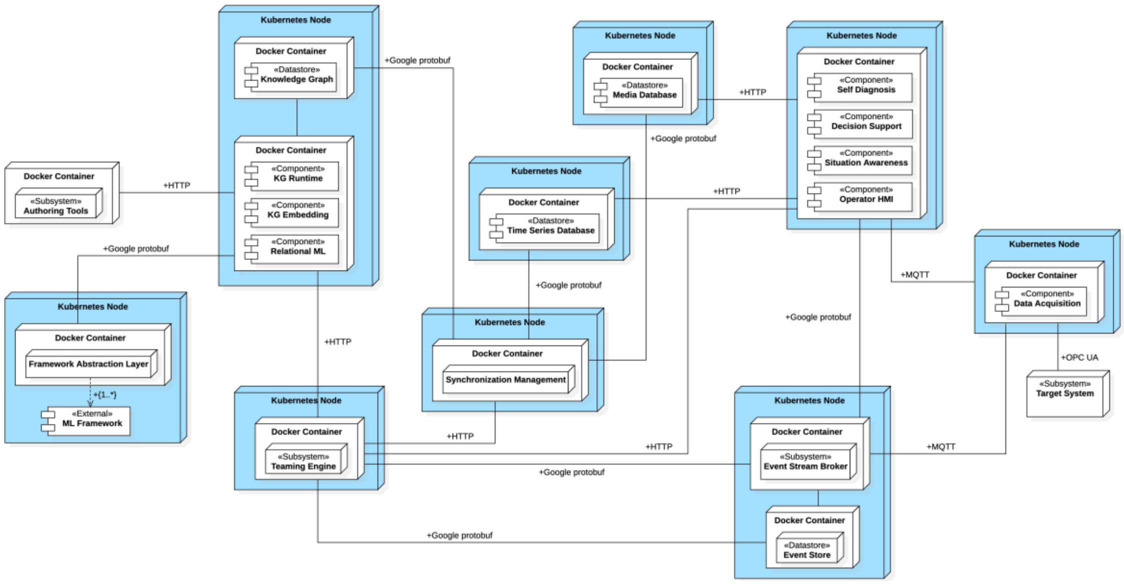

Fig. 4: Deployment view of TEAMING.AI Software Architecture

Above figure shows the different components of this **reference software architecture**. To account for the different latency requirements of the components to process the data in a streaming-like manner, we followed the Lambda architecture pattern and group the components based on their latency requirements into three layers. The **batch layer** (model authoring) ingests and stores large amounts of data, the **speed layer** (knowledge graph, graph-based ML and teaming engine, production line systems) processes updates to the data in low-latency, and the **serving layer** (operation support, ML experimentation, introspection & policy monitoring) provides pre-calculated results also in a low-latency fashion. The empirical validation of this software architecture will be conducted in cooperation with three large-scale companies in the automotive, energy systems, and precision machining domain. The reference software architecture was presented at the International Conference for Software Engineering (ICSE-2022) and is described in detail in [4].

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[2] Stefan Bachhofner et al. "Knowledge Graph Modularization for Cyber-Physical Production Systems." *ISWC (Posters/Demos/Industry)* (2021).

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