Six-Layer Industrial Architecture Applied to Predictive Maintenance

Fernanda Pereira Guidotti[1][a], Jesimar da Silva Arantes[2][b], Márcio da Silva Arantes[3][c], Albeiro Espinosa Bedoya[4][d] and Claudio Fabiano Motta Toledo[1][e]

[1]*Institute of Mathematics and Computer Science, University of São Paulo, São Carlos, Brazil*
[2]*Institute of Exact and Technological Sciences, University of Lavras, Lavras, Brazil*
[3]*SENAI Institute for Innovation in Embedded Systems, ISI-SE, Florianópolis, Brazil*
[4]*Department of Computer Science and Decision, University of Colombia, Medellin, Colombia*
fl

Keywords: Systems Architecture AI, Industry 4.0, AI Industry Framework, Digital Transformation.

Abstract: In the context of digital transformation defining Industry 4.0, the integration of Industrial Artificial Intelligence (I-AI) emerges as a transformative element, promoting the development, validation, and deployment of machine learning algorithms in industrial applications. As sensor technologies advance, reducing costs and expanding the capability for direct data collection from machines, there arises a need for system architectures that not only support but also optimize these data collection and analysis processes. This paper introduces an innovative reference architecture for I-AI, which stands out by advancing beyond the traditional 5-layer (5C) framework through the addition of a sixth layer, named "Consciousness". This innovative layer is designed to retroactively feed the knowledge acquired back to the previous layers, significantly enhancing control and optimization through AI systems. The proposed architecture, termed 6C, comprises the layers of Connection, Conversion, Cyber-Physical, Cognition, Configuration, and finally, Consciousness. The introduction of the Consciousness layer marks a significant innovation in the literature, offering a mechanism by which the architecture is capable of autonomously perceiving the state and needs of the industrial system. Validated in an industrial case study, the 6C architecture demonstrated performance improvement by incorporating the Consciousness layer, highlighting its effectiveness in enhancing operational efficiency and decision-making within complex industrial contexts.

1 INTRODUCTION

Artificial Intelligence (AI) has profoundly impacted industrial production, revolutionizing work environments and production chains. This transformation is driven by technological advancements that facilitate the integration of diverse features, such as embedded systems, cloud resources, big data processing, and AI techniques (Van Kranenburg, 2008). Such integration empowers industrial systems with autonomy, enabling them to make informed decisions through knowledge-based reasoning.

Access to information has been crucial for enhancing productivity and quality in the production process, achieved through intelligent machine adjustments. The Industrial Internet of Things (IIoT) exemplifies this by bridging the digital and physical worlds in factories, utilizing advances in local sensing and reliable communication protocols.

As a result, we are witnessing the 4th Industrial Revolution, Industry 4.0, characterized by enhanced communication between equipment and computer systems. This communication facilitates improved production management through the generation of valuable information. The growing recognition of AI's critical role in smart industries is evidenced by numerous national AI initiatives (Lee et al., 2020a).

In this evolving landscape, industries are reevaluating their approaches and exploring new possibilities. However, the challenge remains to develop intelligent systems capable of addressing complex and varied problems. This has led to the emergence of Industrial Artificial Intelligence (I-AI), which focuses

[a] https://orcid.org/0000-0001-5913-9371
[b] https://orcid.org/0000-0002-1776-1514
[c] https://orcid.org/0000-0002-9309-7678
[d] https://orcid.org/0000-0001-7292-987X
[e] https://orcid.org/0000-0003-4776-8052

Guidotti, F., Arantes, J., Arantes, M., Bedoya, A. and Toledo, C.
Six-Layer Industrial Architecture Applied to Predictive Maintenance.
DOI: 10.5220/0012767000003753

In *Proceedings of the 19th International Conference on Software Technologies (ICSOFT 2024)*, pages 123-130
ISBN: 978-989-758-706-1; ISSN: 2184-2833

on the development, validation, and deployment of machine learning (ML) algorithms for industrial applications, as noted by (Lee et al., 2018).

Industries seeking technological advancements have begun leveraging ML solutions to optimize processes. However, a significant gap exists between constructing ML systems that function in a development environment, such as notebooks, and creating ML solutions robust enough for deployment in industrial production environments (Ng, 2021). Addressing this gap necessitates a systematic framework for I-AI.

This paper introduces a reference architecture for I-AI that builds upon the 5C layers described by (Lee et al., 2020b), with the addition of a novel Consciousness layer. This layer enhances the architecture by feeding acquired knowledge back to the previous layers and improving the auto-tuning of AI systems as a whole. Termed the 6C-layer, this architecture has been validated in an industrial case study, showing improved performance with the integration of the Consciousness layer, aligning with the proposed 6C architecture.

The paper is structured as follows: Section 2 reviews related works; Section 3 describes the proposed software architecture; Section 4 reports on the case application; and Section 5 presents our conclusions.

2 RELATED WORK

We review studies related to AI in industry addressing software architecture projects, development of AI solutions and their application in an industrial setting as show in Table 1.

The article by (Liu et al., 2018) introduced a framework for industrial AI applied in high-speed rail networks using a 5C architecture. This framework creates digital twins to monitor and optimize real-time performance, predicting potential failure anomalies and supporting maintenance decisions. The authors reported a case study to monitor train traction, engine condition, and railway line using sensors. They highlighted the versatility of applying industrial AI beyond railway transportation, suggesting an iterative process. This article is directly related to our work due to its innovative approach in applying industrial AI to optimize cyber-physical systems, a methodology we also employ to address similar challenges in our study. The use of the 5C architecture and the emphasis on scalable and predictive solutions for operations and maintenance resonate with the goals of our own framework, underscoring the relevance of this work as a valuable precedent in related literature.

(Guo et al., 2019) presents an AI framework tailored for the manufacturing sector to facilitate the development and operation of AI models, especially for device health management. This framework, known as I-AI DevOps, addresses challenges such as predictive maintenance, lifecycle management, and uncertainty in AI models. The authors highlight three major engineering challenges in predictive maintenance applications: data scarcity, real-world uncertainties, and interdisciplinary collaboration difficulties. The I-AI DevOps framework follows a cyclical model that encompasses requirements understanding, data collection, exploratory analysis, model training, validation, and seamless integration with software during the operations stage. Continuous monitoring ensures users receive valuable insights. The authors emphasize the importance of model forecast updates due to inevitable long-term structural changes. This study's focus on the AI model life cycle in industry resonates with our research objectives.

In their study, (Lee et al., 2020b) explore Industrial AI and predictive analytics for smart manufacturing systems. They highlight how AI techniques enable pattern recognition, learning from past experiences, and making informed predictions to enhance decision-making processes. The authors identify key challenges faced by factories in the Industry 4.0 era, including issues with transmission, storage, security, connectivity, standardization, integration complexity, and context awareness. They present a case study on an intelligent bandsaw system using a 5C architectural model. Data is collected and processed in a fog layer before being analyzed in the cloud using analytical models. This process updates the cyber twin models of the bandsaw machines, providing insights into blade integrity. Finally, the optimized operational parameters are sent to the machine, enabling the blade to self-configure to improve or predict its lifespan. Lee et al.'s (2020) study aligns with our research on AI-driven solutions for industry. Their emphasis on predictive analytics and use of a 5C model offer insights for designing AI architectures in manufacturing.

(Peres et al., 2020) conduct a systematic literature review on artificial intelligence in the industry, proposing an adapted framework from (Lee et al., 2020b). The purpose of this adaptation is the addition of a Human-Machine Technology (HT), expanding the 4 enabling technologies of the 5C architecture to 5. The HT technology aims to facilitate system interaction with people. The goal of such interaction is to assist maintenance and diagnostic operations through virtual or augmented reality means. The authors also outline future challenges in three areas: data, models, and infrastructure. This study contributes to the

Table 1: Comparison with related works.

Autor	Software architecture	AI deployment	Application case
(Liu et al., 2018)	5C	✔	Prognostics and Health Management for Rail
(Guo et al., 2019)	I-AI DevOps	✗	Prognostic model lifecycle management
(Lee et al., 2020b)	5C	✗	Intelligent bandsaw system
(Peres et al., 2020)	Adapted 5C	✗	✗
(Calabrese et al., 2020)	Big Data Architecture	✔	Predictive Maintenance
(Granlund et al., 2021)	✗	✔	Medical scenario
Our proposal	6C	✔	Predictive Maintenance

proposed research by considering the analysis of application context.

The study by (Calabrese et al., 2020) introduces an application that employs a data-centric approach utilizing machine learning in industrial machinery. They present a three-step architecture involving data acquisition from machine logs through sensors, followed by data processing, analysis, and predictive modeling, and finally, information display on a dashboard. The authors illustrate a case study in a woodworking shop, demonstrating the prediction of potential machine failures based on historical log data. Emphasizing the need for intelligent systems to comprehend machine integrity status, they focus on developing a computational pipeline for predictive maintenance. This study significantly contributes to research in constructing a pipeline for predictive maintenance, addressing one of the major challenges in the industry.

The authors (Granlund et al., 2021) conduct a case study on AI systems deployment, focusing on challenges faced in a medical scenario. They employ DevOps and MLOps to integrate organizations and describe a pipeline involving data scientists, software developers, and experts. Oravizio software provides risk information regarding hip and knee surgery, utilizing three prediction models for infection, revision, and mortality risks. Challenges included dataset organization, model definition, and training. This study contributed to the proposed research concerning the construction of pipelines and system integration.

In Table 1, it's observed that out of the related studies, 6 employ some form of software architecture, with three of them utilizing the 5C architecture (Liu et al., 2018; Lee et al., 2020b). The study by (Peres et al., 2020), although not directly using the 5C architecture, is based on it to propose a new framework with Humana technology. Meanwhile, (Guo et al., 2019) introduces a DevOps cycle in the industry, and (Calabrese et al., 2020) describes a pipeline architecture for data acquisition, processing, and monitoring.

Most of the studies present industrial application cases, except for (Peres et al., 2020), which conducts a systematic review of AI challenges and prospects in the industry. However, none of the studies comprehensively address the interaction between layers. In contrast, our study proposes a 6-layer architecture, including the ability to acquire domain consciousness.

The reviewed studies indicate a growing adoption of AI frameworks to optimize industrial operations. Our proposed 6C architecture represents a progression beyond existing architectures, enabling autonomous knowledge acquisition and smarter interaction between layers. This pioneering approach aims to fill gaps in the literature on assertive implementation of AI models in industry, establishing a new paradigm for intelligent industrial systems.

3 PROPOSED ARCHITECTURE

The 5C architecture provides a solid foundation for integrating Artificial Intelligence into the industry, establishing a structured framework for data processing and analysis through its five layers: Connection, Conversion, Cyber-Physical, Cognition, and Configuration. These layers facilitate everything from data acquisition to the self-configuration of machines, promoting efficient interaction between physical and digital systems. However, to fully embrace the dynamic challenges of the modern industrial environment, there is a recognized need to evolve beyond these fundamentals. This work proposes an evolution of the 5C architecture by incorporating an innovative sixth layer: Consciousness. This new layer not only compiles all relevant information generated in the previous stages but also employs knowledge-based reasoning, providing active feedback to the preceding layers. The addition of the Consciousness layer expands the system's ability to learn autonomously, enabling a deeper understanding and adaptation to industrial scenarios. This evolution does not diminish the importance of the 5C architecture; on the contrary, it builds upon its robust structure, integrating enabling technologies and promoting synergy that elevates industrial AI to a new level of effectiveness. By retaining the original five layers, our framework expands its functionalities to include a continuous and interactive learning cycle, where the generated intelligence is used not only for diagnostics and configurations but also to constantly enhance the system based on operational insights.

The present paper advances from the 5C architecture in (Lee et al., 2015; Lee et al., 2020a; Lee et al., 2020b) by adding the Consciousness layer and the enabling knowledge technologies as shown by Figure 1. We keep the previous 5C-levels described in (Lee et al., 2015):

- Connection identifies equipment and mechanisms for acquiring data.
- Conversion decodes the collected data into meaningful information.
- Cyber integration analyses the information through the digital twin concept.
- Cognition provides diagnostic information to identify failures.
- Configuration executes auto-tuning becoming the machines self-configurable.

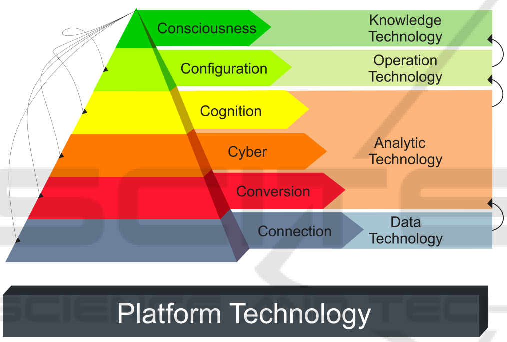

Figure 1: Industry AI architecture with 6 layers.

We introduce the Consciousness layer that assembles all relevant information generated through the previous step, reasoning from the acquired knowledge and sending feedback to the previous layers. The idea is to allow a whole self-learning that goes beyond those addressed by the configuration level.

Figure 2 illustrates the overlap between the 6C-levels and the respective enabling technologies in our architecture.

The 6C architecture states a pipeline to guide the development process: development, validation, and deployment at each layer. In this context, we consider the four enabling technologies from (Lee et al., 2020b) and include the Knowledge Technology as described next:

- The **Platform** layer provides the framework for selecting, organizing, and integrating hardware and software at each level, tailored to specific industrial scenarios where I-AI is required. This enables device connections, data analysis, and integrated knowledge acquisition reliably.
- **DT - Data Technology** is linked to the Connection layer, defining the technology for data acquisition and communication, and its relation to databases, tables, sensors, or cloud storage.
- **AT - Analytical Technologies** encompass three other layers: in the Connection layer, data adjustments and conversion into information occur; in the cyber-physical layer, the concept of a digital twin is utilized to create a reliable virtual model of the industrial process or machine; and in the cognition layer, machine learning methods are employed to predict failures or changes, leading to self-configuration of machine behaviors.
- **OT - Operation Technology** enables the configuration layer, allowing control and optimization of the industrial process based on findings from analytical technologies.
- **KT - Knowledge Technology** covers the consciousness layer, monitoring the entire process and utilizing learning and decision-making models to evaluate feedback and adjustments, enabling continuous optimization of the I-AI process in the industry.

Our proposal of a Consciousness layer, enabled by KT, includes some OT duties as previously stated in (Lee et al., 2015), which now will help to reason from acquired knowledge through the development process. The authors in (Lee et al., 2015) mention feedback following a closed-loop to redesign the lifecycle or manage the manufacturing system. However, our proposal sees the self-adjust, self-configure, and self-optimize features in (Lee et al., 2015) working here as a more immediate adjustment tool from analytic outcomings. The KT will lead such analysis to another baseline at the knowledge level by employing a fusion of information and deeper analysis. The complete information will be evaluated based on, e.g., some time series from data and result profiles, and the knowledge learned will feedforward the other layers.

The knowledge learned can be sent back considering three categories, representing the level of concscientiousness reached by the system. The first category is the production estimation and evaluation, which share relevant information for connection and conversion levels. The second is the evaluation and monitoring that feed cyber and cognition levels. Finally, life cycle monitoring makes fine-tuning adjustments for machines, methods, and monitoring systems.

The 6C architecture represents a significant advancement in the integration of Artificial Intelligence in the industry, surpassing the limits previously established by the 5C architecture. By introducing the Consciousness layer and associating it with enabling

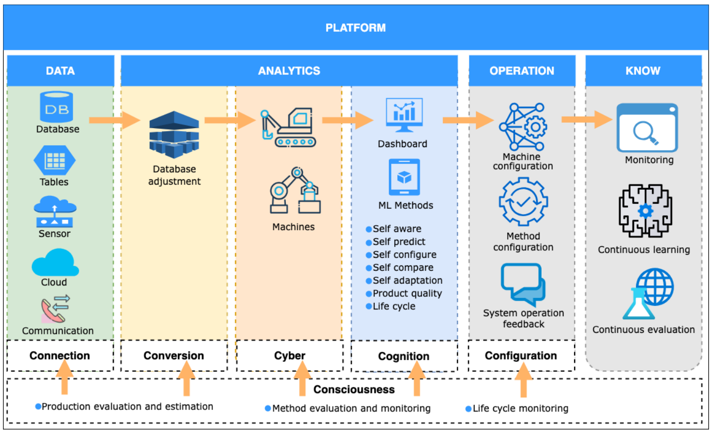

Figure 2: Industry AI architecture highlighting the six layers.

knowledge technologies, our proposal establishes a new paradigm for autonomous and adaptive systems. This innovation not only enhances operational efficiency and predictive capabilities but also opens new avenues for research and technological development, fostering a deeper integration between AI and industrial processes.

4 APPLIED CASE STUDY

The case study considers a vegetal oil production industry with machines and sensors generating thousands of daily data. We extend the approach proposed by (Arantes et al., 2021) for the same industry, which was the first attempt to include an intelligent system in its production process. The industry still needs strategies to efficiently manage all devices and sensors to take advantage of the information available. However, the mentioned industry has software technologies for production control and management, such as Manufacturing Execution System (MES), Supervisory Control and Data Acquisition (SCADA), and Systems Applications and Products (SAP). However, the company does not use such systems to create an I-AI environment.

A relevant issue for the industry is machine maintenance, where there was no predictive or intelligent system to detect or avoid failures besides the amount of available data. The authors in (Arantes et al., 2021) addressed the predictive issue, and we advanced from them by deploying our 6C architecture in the production process. The problem of predictive maintenance seeks to identify potential failures in machines even before they show an apparent signal. When minimal signs of an eventual failure are neglected, severe damages to the company's assets can cause the stop of activities that leads to financial losses.

The model proposed by the authors (Arantes et al., 2021) detects whether the machine is operating in a degraded state and, if necessary, interrupts its operation before a critical condition arises. The main idea of such a method is to use time-series data for anomaly detection. Figure 3 illustrates the previous intelligent system flow developed for the industry, with three main modules:

- **Data**: performs data acquisition from sensors, store in the database, and create a fault history.
- **Analytics**: performs the predictive maintenance by monitoring, diagnosis, and prediction.
- **Interface**: displays the results of alerts, reports, and register of information about detected faults.

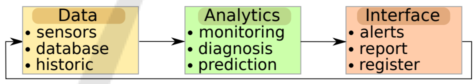

Figure 3: The conceptual flow of predictive maintenance.

The data from the sensors and maintenance history provided by the SAP system feed an account of the monitored equipment. From these and other information sources, Analytics can carry out the processes to determine the information required to predict a failure. This integration occurs through an API, and the information becomes available to the user through a dashboard. Thus, the system allows us to keep track of the equipment, proactively executing preventive maintenance measures. From this current pipeline, we make changes with Figure 4 illustrating the 6C architecture adaptation to the vegetal oil industry under study.

The connection layer executes the data acquisition and communication by the machine's sensors through ethernet communication. We obtain the electrical current, temperature, vibration, and pressure data, among other features, from machine sensing.

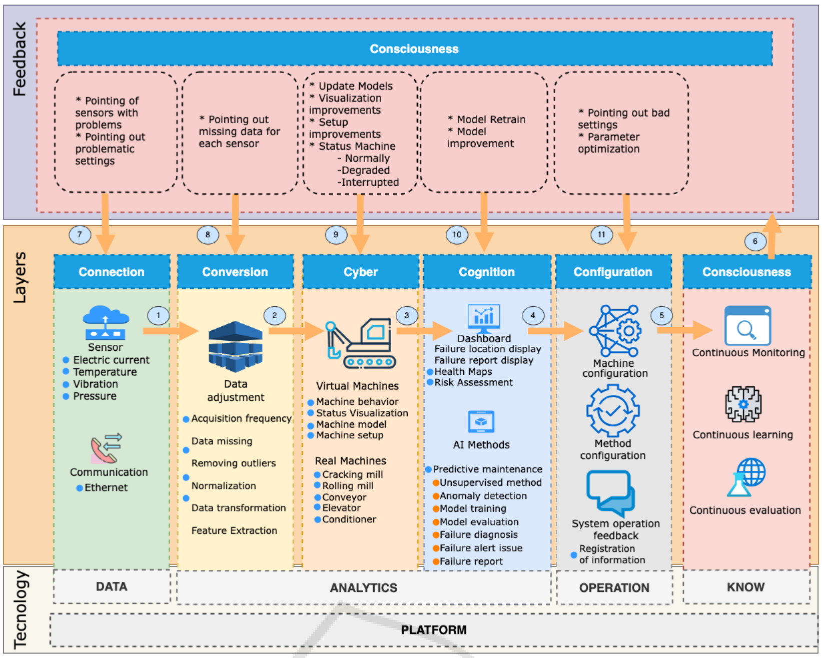

Figure 4: 6C Architecture of AI in vegetal oil industry.

Next, the database adjustments take place in the conversion layer, where standardization of the sensor frequency during data acquisition occurs, as well as the treatment of missing data, the removal of outliers, and the normalization of the input data for the next level.

In cyber-physics, we have a virtual representation of the machine that allows adjusting its configuration. We have the prediction model developed in (Arantes et al., 2021) extended for the following machines in the industry: cracking mill, rolling mill, conveyor, elevator, and conditioner. The cognition layer handles previously processed data by applying the unsupervised method for predictive maintenance from (Arantes et al., 2021). At this layer, it is possible to train and validate the model, providing the fault diagnosis through a dashboard for the user. Such visualization of results allows the user to find the fault location and access the machine-related fault report. Thus, the failure detection and prediction happen in the cognition layer, where the prediction model specifies the probability (%) of the current failure. The operator access such evaluation through the Dashboard, learning about what happened to the sensor or machine and being able to make decisions for more proactive maintenance, saving resources. In the configuration layer, the eventual changes to the configuration parameters happen based on the models' prediction results.

Finally, the Consciousness layer becomes possible to monitor data and machines, map the system's health, and enable continuous learning. We can now iterate among the previous layers, estimate the production, and determine if the devices are operating normally or in a degraded state. All the reasoning over such information leads to more robust adjustments in the previous levels.

The Consciousness layer is where the understanding of the process as a whole takes place. In the configuration layer, there is feedback to the process whenever the operator modifies the industrial relevant features, either because the AI warned or because the operator may have done preventive maintenance. The operator informs the system, which learns from such changes in the production process. Moreover, the next time the same pattern of behavior occurs, the algorithm will notice and be more assertive about it. The Figure 5 illustrates a general flow in which the system identifies possible anomalies. If the system does not identify anomalies, it takes no action, but when it does, a failure signal is issued, and the dashboard is updated, reporting the failure in the dashboard. When the operator visualizes the failure on the dashboard, she/he opens a maintenance call, the maintenance team goes to the machine, performs corrective actions, and reports to the operator the action taken at the end. If the failure occurs, the operator informs the system about the corrective action; otherwise, the operator adds false positive feedback to the system. However, the system learns in both cases by retraining the related models.

We state four scenarios of our applied case study based on Figure 5:

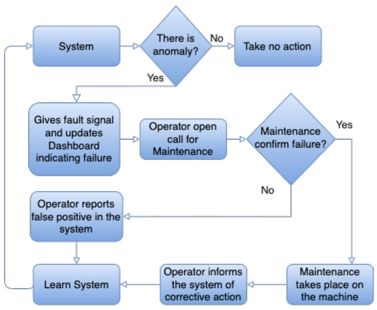

Figure 5: General system flow.

Scenario I - False Negative. In this case, the system does not find any anomalies and does not take any action, which means do not inform the operator. However, let's suppose that the operator identifies a strange noise in the engine when next to the machine. The operator decides to schedule maintenance and verifies a problem in the machine, e.g., the maintenance team changes the engine's bearing belt. It informs the operator, who feeds the system, about the problem and the corrective action taken. The system learns by receiving a time window with the data related to the problem, which allows learning by adjusting the weights or other parameters in the system model during the retraining. Next time, the system becomes more sensitive to the sensors and metrics that led to this problem, thus increasing the chance of detection.

Scenario II - True Negative. The system does not find any anomalies and does not take action to notify the operator. When passing through the machine, the operator does not notice anything abnormal, and she/he does not give any feedback to the system, which understands that everything is right. As the forecast was correct and the information is complete, nothing needs to be done in the Consciousness layer.

Scenario III - False Positive. The system identifies an anomaly, triggers a failure signal, and updates the Dashboard to show the failure. As soon as the operator checks the Dashboard and sees the fault, she/he goes to the machine but does not identify anything wrong with it. The operator decides to open a call for maintenance anyway. The maintenance team checks the machine and does not identify anything wrong with it, informing the operator that it works correctly. The operator tells the system that the machine does not have a failure at that period, allowing the system to learn from this operator's feedback by adjusting the weights and parameters of the prediction models.

Scenario IV - True Positive. The system identifies an anomaly and issues a failure signal, updating the Dashboard. The operator visualizes the failure in the Dashboard, but he doe not identify the problem at the machine. She/he opens a call for maintenance, and the maintenance team identifies a problem. For instance, the team changes the bearing and replaces it, informing the operator later about the action taken. The operator updates the system with such information about the failure and the corrective action done. In the Consciousness layer, the system learns by adjusting the weights and other parameters to identify such failures regarding the corrective actions. When a similar fault happens again, the system will inform about the most likely fault type and the related actions.

To visualize the cases, refer to Table 2, which demonstrates the results where machine failures occurred. A total of 17 lines report favorable conditions, which makes sense once we have 14 true positives (TP) and three false negatives (FN).

Table 2: Results obtained in the case study.

time ID	did the problem happen?	did the model predict?	failure intensity	failure classification
10	yes	yes	28.89%	light
12	yes	yes	95.98%	warning
14	yes	yes	89.12%	warning
15	yes	yes	64.55%	warning
16	yes	yes	30.34%	light
18	yes	yes	30.93%	light
20	yes	yes	15.47%	light
37	yes	yes	34.23%	light
54	yes	no	-	-
56	yes	no	-	-
57	yes	no	-	-
66	yes	yes	40.74%	light
73	yes	yes	41.25%	light
110	yes	yes	23.66%	light
135	yes	yes	19.00%	light
136	yes	yes	16.50%	light
141	yes	yes	27.08%	light

We employed the same metrics defined in (Arantes et al., 2021) as shown in Table 2 for evaluation of the results achieved by the machines' models. Table 3 presents the confusion matrix with the results obtained in the experiments. These results show the great precision of the method that, in this context, was able to predict all the failures that occurred. The recall was 82.4 %, precision 100%, accuracy 98.1%, F1-score 90.3%, and the Area Under the Receiver Operating Characteristic Curve (AUC) was 91.2%.

Table 3: Confusion matrix with the results.

Total population	Cond. positive	Cond. negative
Predicted positive	[TP] 14	[FP] 0
Predicted negative	[FN] 3	[TN] 141

The implementation of the 6C architecture not only addressed specific challenges in the vegetable oil industry but also showcased a model applicable to other domains, providing valuable insights for the adoption of intelligent practices across various sectors of Industry 4.0.

This interactive and visual approach to data management not only streamlines the maintenance process but also significantly contributes to the prevention of unexpected downtimes and associated costs of emergency repairs. This case study confirms the feasibility and effectiveness of the 6C architecture in optimizing predictive maintenance in industrial environments. The implementation of this innovative architecture not only overcame challenges identified with previous approaches but also demonstrated a significant improvement in the accuracy of fault detection and prediction.

5 CONCLUSION

This article introduced an innovative AI architecture for the industry, based on the 5C framework described in (Lee et al., 2015), and advanced by adding a sixth layer called Consciousness. A case study in the vegetable oil production industry, which already implemented an intelligent system for fault prediction, served to evaluate the proposed 6C architecture. The 6C architecture facilitated interaction across all layers of the process, promoting the exchange of discoveries from the Consciousness layer and enabling comprehensive monitoring of the system's lifecycle, as well as continuous learning and evaluation. Applications of AI in industry are vast and diverse, covering different processes and sectors. Further validation in new industrial scenarios is essential to reinforce the versatility of the 6C architecture. While this study focused on predictive maintenance, the proposed architecture has the potential to be implemented in any AI application in the industry, underscoring industrial AI as a promising approach to overcoming operational and maintenance challenges. The 6C architecture, with its continuous iterations and ability to acquire domain consciousness, promises to revolutionize industrial systems, offering a path to enhanced innovation and efficiency.

ACKNOWLEDGMENT

The authors thank SENAI Institute for Innovation in Embedded Systems for supporting the research.

REFERENCES

Arantes, J., Arantes, M., Fröhlich, H. B., Siret, L., and Bonnard, R. (2021). A novel unsupervised method for anomaly detection in time series based on statistical features for industrial predictive maintenance. *International Journal of Data Science and Analytics*, 12(4):383–404.

Calabrese, M., Cimmino, M., Fiume, F., Manfrin, M., Romeo, L., Ceccacci, S., Paolanti, M., Toscano, G., Ciandrini, G., Carrotta, A., Mengoni, M., Frontoni, E., and Kapetis, D. (2020). Sophia: An event-based iot and machine learning architecture for predictive maintenance in industry 4.0. *Information*, 11(4).

Granlund, T., Kopponen, A., Stirbu, V., Myllyaho, L., and Mikkonen, T. (2021). Mlops challenges in multi-organization setup: Experiences from two real-world cases. In *2021 IEEE/ACM 1st Workshop on AI Engineering - Software Engineering for AI (WAIN)*, pages 82–88.

Guo, Z., Bao, T., Wu, W., Jin, C., and Lee, J. (2019). Iai devops: A systematic framework for prognostic model lifecycle management. In *2019 Prognostics and System Health Management Conference (PHM-Qingdao)*, pages 1–6. IEEE.

Lee, J., Bagheri, B., and Kao, H.-A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3:18–23.

Lee, J., Davari, H., Singh, J., and Pandhare, V. (2018). Industrial artificial intelligence for industry 4.0-based manufacturing systems. *Manufacturing Letters*, 18.

Lee, J., Singh, J., Azamfar, M., and Keyi, S. (2020a). Industrial ai:a systematic framework for ai in industrial applications. *Zhongguo Jixie Gongcheng/China Mechanical Engineering*, 31:37–48.

Lee, J., Singh, J., Azamfar, M., and Pandhare, V. (2020b). Industrial ai and predictive analytics for smart manufacturing systems. In *Smart Manufacturing*, pages 213–244. Elsevier.

Liu, Z., Jin, C., Jin, W., Lee, J., Zhang, Z., Peng, C., and Xu, G. (2018). Industrial ai enabled prognostics for high-speed railway systems. In *2018 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pages 1–8.

Ng, A. (2021). A chat with andrew on mlops: From model-centric to data-centric ai. Available in: https://www.youtube.com/watch?v=06-AZXmwHjo.

Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., and Barata, J. (2020). Industrial artificial intelligence in industry 4.0 - systematic review, challenges and outlook. *IEEE Access*, 8:220121–220139.

Van Kranenburg, R. (2008). *The Internet of Things: A critique of ambient technology and the all-seeing network of RFID*. Institute of Network Cultures.