Lecture Notes in Mechanical Engineering

Achim Wagner
Kosmas Alexopoulos
Sotiris Makris *Editors*

Advances in Artificial Intelligence in Manufacturing

Proceedings of the 1st European Symposium on Artificial Intelligence in Manufacturing, September 19, 2023, Kaiserslautern, Germany

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Preface

This volume of Lecture Notes in Mechanical Engineering contains selected papers presented at the 1st European Symposium on Artificial Intelligence in Manufacturing (ESAIM 2023), held in Kaiserslautern, Germany, on September 19, 2023. The conference was organized by the German Research Center for Artificial Intelligence (DKFI) and the Laboratory for Manufacturing Systems & Automation (LMS) of the University of Patras, Greece.

Artificial intelligence (AI) technology becomes mature, and at the same time researchers and manufacturers discover new applications in which AI can support manufacturing operations. The real benefit from AI in manufacturing will not just be by automating tasks but provide new levels of autonomy and human assistance that will make possible entirely new applications and introduce new business processes in manufacturing. In contrast to consumer applications, well known from mobile device, media and automotive domains, industrial AI applications in general cannot refer to a big data availability collected during operation and interaction with the users. Additional challenges arise related to the industrial conditions such as privacy, safety, interoperability and physics-induced real-time requirements. Due to the lack of a huge amount of centralized data and the requirements on the shop floor, new approaches for data collection, processing and modeling are required, which are reflected by various AI methods and technologies applied to digitized factories.

The scope of the ESAIM'23 symposium was around recent developments of AI in manufacturing, advancing key concepts and technologies, as well as understanding the benefits and the barriers when applying such technologies in industrial practice. The symposium has welcomed contributions focusing on theoretical, applied research and industrial case studies.

ESAIM'23 covered topics such as AI in manufacturing processes, robots, machines and operations support in manufacturing and AI in manufacturing systems. It also considered research work on cross-cutting aspects such as information systems, regulation, education, systems engineering and data augmentation.

ESAIM'23 received 26 contributions from organizations and researchers in Europe. After a thorough peer-review process, the Program Committee accepted 19 papers. Thank you very much to the authors for their contribution. These papers are published in the present book, achieving an acceptance rate of about 73%.

We would like to thank members of the Program Committee and invited external reviewers for their efforts and expertise in contributing to reviewing, without which it would be impossible to maintain the high standards of peer-reviewed papers.

Many thanks to keynote speaker Prof. Martin Ruskowski, Department of Machine Tools and Control Systems (WSKL), University of Kaiserslautern-Landau for sharing his knowledge and experience in the topic of AI in manufacturing.

The book "Advances in Artificial Intelligence in Manufacturing" consists of three parts. The first part aims at recent developments in "Artificial Intelligence at Manufacturing System Level". A manufacturing system can be considered a combination of machines, cells, intra-logistics devices and other peripheral devices, used on the factory floor as well as in logistics. A range of topics such as AI for production planning and scheduling, AI for condition monitoring and digital platforms and frameworks for AI were discussed. Active learning frameworks for the deployment of machine learning development can be used for learning efficiently from limited labeled data, allowing manufacturers to optimize production processes with better accuracy and reduced data annotation efforts. Machine learning algorithms for fusing and making sense of big multi-channel data gathered in discrete manufacturing applications to anticipate the detection of anomalies are also being discussed. In a similar manner Asset Administration Shell (AAS) and Industrial Data Spaces (IDS) can be used for setting up architectures and supporting interoperability for AI applications in manufacturing value chains. Going more into shop-floor applications, skill-based production by means of incorporating automated fault detection can be used for modeling the behavior of Cyber-Physical Production Modules. Runge-Kutta Neural Networks (RKNN) are used to detect rare fault cases for mobile robot applications, while Physics-Informed Neural Networks (PINNs) can be used in parameter identification for continuum models of manufacturing systems and deep reinforcement learning agents can be trained for optimal dispatch rules selection in production scheduling.

The second part is based on recent developments in the field "Artificial Intelligence at Manufacturing Equipment Level". There is a wide range of topics addressed in this chapter such as AI for flexible and precise robotics, AI for exoskeletons, AI for enhanced human-robot collaboration, AI for quality assessment and defects detection. In the field of quality assessment, unsupervised machine learning is investigated for blind rivet inspection and a set of tools for defect detection tasks within a factory, based on deep learning methods as elements of different quality control are presented. In the field of AI for robotics, the use of Large Language Models (LLMs) for enabling Human-Robot Collaboration is being discussed as a means of improving human-robot collaboration performance. AI can be introduced for monitoring and optimization of robot-assisted adhesive deposition in large parts while compensating for disturbances during the path following process. In a similar manner, semi-active exoskeletons can be made autonomous by increasing their awareness using AI-powered computer vision techniques. Deploying collaborative robots in manufacturing presents diverse challenges, thus integrating multiple risk factors into task sequencing models can improve efficacy and adaptability to diverse risk levels. Training a single model for bin picking proposes a challenge due to high-mix low-volume situations, and for that purpose a modular pipeline, which splits the problem into sub-questions, each of which refers to a separate component of the picking process, can help address this challenge. In most industrial use cases, it is difficult to collect and annotate data for small objects, as it is time-consuming and prone to human errors. Thus, synthetic data generation is discussed as a means for collection and annotation of small object datasets.

The third part is devoted to "Artificial Intelligence at Manufacturing Process Level". A manufacturing process can be defined as the use of physical mechanisms to transform the shape or properties of a material. This chapter discusses AI topics, related to manufacturing processes. A mapping is sketched between AI territories and manufacturing process-related operations by considering different aspects of the processes, such as monitoring, modeling, optimization, design and preparation, as well as control, twinning and operation. Moreover, specific cases are studied such as metal forming process with the use of AI and AI-supported vision systems for fabric defect detection and process monitoring purposes in steel factories.

We appreciate the partnership with Springer, Turnitin, EasyChair and the members of the Artificial Intelligence in Manufacturing Network (AIM-NET, www.aim-net.eu) for their essential support during the preparation of ESAIM 2023.

November 2023

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Artificial Intelligence at Manufacturing System Level

An Integrated Active Learning Framework for the Deployment of Machine Learning Models for Defect Detection in Manufacturing Environments

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Abstract. The digitalization of factories has triggered a humongous number of applications of Machine Learning techniques to optimize manufacturing processes. In the last years, different methodologies have been suggested for tasks like predictive maintenance, defect detection, or advanced perception systems that might contribute to a better performance of entire production lines optimizing their different steps. However, one of the main issues for the deployment of these technologies in real manufacturing environments is the management of complex tools that need, in many cases, specific AI-related knowledge from workers that are not used to work with AI-based systems. In this work we present a set of tools for defect detection tasks within a real factory based on deep learning methods and we demonstrate their performance as parts of different quality control systems. In addition, to integrate all these tools, we introduce MINT a modular intelligent framework for deep learning model management. MINT uses active learning to learn efficiently from limited labeled data, allowing manufacturers to optimize production processes with higher accuracy and reduced data annotation efforts. This framework makes more accessible to non-experts steps like model training,performance evaluation and model traceability while providing an explainability module for classification models that encourage trust and adoption of AI between factory workers. Meaning that our tool contributes to the deployment of AI techniques in real manufacturing scenarios making more accessible the management of the entire life cycle of AI models.

Keywords: Deep Learning · Quality Control · Active Learning

1 Introduction

In the current scenario of modern manufacturing, artificial intelligence (AI) has emerged as a transformative technology, revolutionizing production processes and unlocking unprecedented opportunities for efficiency, productivity, or innovation. By harnessing the power of advanced algorithms and machine learning techniques, AI has become an indispensable tool for manufacturers seeking to stay competitive in an increasingly dynamic and data-driven landscape.

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The impact of AI on manufacturing spans a wide range of areas, from optimizing supply chains with advanced quality control methods, to enhancing predicting maintenance needs enabling intelligent automation. By analyzing vast amounts of data in real-time, AI systems can identify patterns, anomalies, and insights leading to better decision-making and resource allocation [1] [2]. While AI brings immense potential, its successful implementation and management pose a remarkable set of challenges. The management of AI models has emerged as a critical issue that manufacturers must address. As models become more sophisticated and complex, ensuring their accuracy, reliability, and ethical use becomes paramount.

One major challenge lies in the continuous training and retraining of AI models. Manufacturing environments are subject to ever-changing conditions, requiring models to adapt and evolve accordingly. Managing the vast amounts of data needed for training, as well as the computational resources and infrastructure to support the training process, demands careful planning and investment.

Another crucial aspect is the need for robust governance frameworks surrounding AI. Manufacturers must navigate ethical considerations, such as bias mitigation, privacy protection, and transparency, to ensure that AI systems operate in a fair and responsible manner. Additionally, securing AI models against potential cyber threats and ensuring compliance with data protection regulations pose additional complexities that demand diligent management.

This work introduces MINT (Modular Intelligent Network Trainer) as a solution for managing AI models in manufacturing environments, specifically focusing on its deployment in an automotive factory. MINT serves as a versatile tool for managing different AI models used in quality control across various piece types and references along the production line. The integration of active learning capabilities empowers manufacturing teams to efficiently fine-tune AI models with minimal labeled data, enabling continuous improvement and adaptability to varying production scenarios. To ensure usability for a wide range of technical knowledge, the development of MINT involved collaboration with workers from diverse backgrounds, resulting in a user-friendly tool that doesn't require expertise in AI.

The paper is structured to showcase the modularity of MINT and its practical applications. It begins by providing context, highlighting the necessity for a tool like MINT and explaining its benefits in managing AI models (active learning, deployment, monitoring and explainability). Subsequently, the paper presents several AI use cases implemented within the same factory, illustrating the diverse problems encountered and the wide array of models that MINT can handle. Each use case is introduced briefly, outlining the approach taken for image-based defect detection. Next, the paper briefly presents the main results achieved with the AI models in each use case, offering insights into their performance and how MINT facilitates their management. Finally, the paper concludes by discussing the current improvements made to the tool and outlining future perspectives for its development. The use cases covered in this work primarily revolve around binary classification tasks, specifically Tripods and Cages, as well as Tab Slots and Crack Detection in metallic parts (Fig. 1).

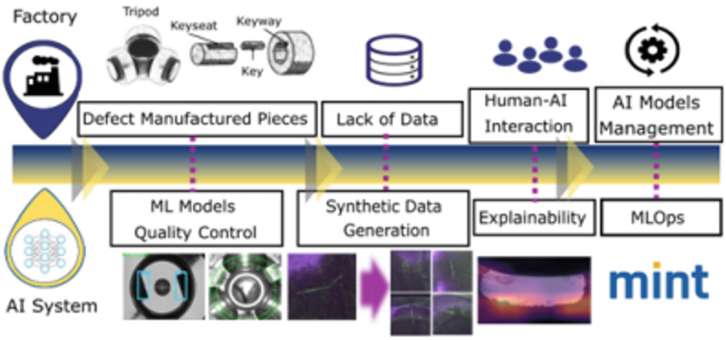

Fig. 1. Factory-AI system path. The factories within their production lines represent living labs for AI systems, generating large amounts of data. The inspection of such pieces can be addressed through different ML models. MINT allows non-experts to manage these models (training, evaluation, deployment and monitoring).

2 The Problem

Within robotic inspection cells, robotic arms, PLCs, cameras and locally running machine learning models are employed to classify pieces, ensuring quality control efficiently. Just like robots, machine learning models also require maintenance with some frequency as they may degrade over time and reduce their performance. Furthermore, the complexity of managing models in a factory escalates as their number increases. In this context, MINT is a custom application designed to ease and optimize the management of models deployed in a production plant. It provides a unified solution to various stages of the model development such as labelling, training and deployment in a centralized manner for binary and multiclass classification use cases. Additionally, MINT integrates with manufacturing cells as shown in Fig. 2, enabling communication with PLCs, and facilitating the management of data generated during automatic inspection. One of the causes of model degradation is concept drift [3]. This phenomenon refers to changes in the underlying distribution of streaming data over time (emergence of new defects, introduction of new piece references, changes in the cell environment, etc.), leading to a deviation from the original data distribution observed at the time of training. The following sections explain the modules of MINT and how they help users to manage the models deployed in multiple inspection cells of a factory.

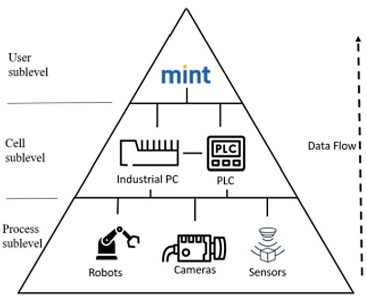

Fig. 2. Hierarchy of a robotic inspection system

2.1 Active Learning

MINT uses active learning to reduce the reliance on indiscriminate labeling [4], which is extremely resource consuming, by selectively choosing the most informative samples [5, 6]. It has three phases:

1) User feedback loop: Users are presented with batches of images which have been predicted by models in production. They are requested to provide feedback to determine, according to their expertise, whether they have been correctly classified or not. The criterion followed to present samples is based on their least confidence score [7], an uncertainty-based querying strategy that selects data whose most likely label has the lowest posterior probability. Pieces with the lowest score are considered suspicious of being misclassified.
2) Training: Once several batches have been evaluated and new samples are added to datasets, the user is given the opportunity to start a retraining cycle. Training cycles freeze the last layers of the current model and fine-tuned them.
3) Evaluation: This process involves computing the F1-score metric for the overall expanded test set to check if the new model outperforms the previous one.

2.2 Deployment

It is necessary to deploy new models in the shortest possible time, since manufacturing cells are working steadily, and production cannot be halted. MINT takes advantage of factory network to communicate with cells. When user decides to update a model, the weights file is sent through the network to the cell computer, and it starts a communication protocol with the PLC that allows real-time updating.

2.3 Monitoring

In the monitoring phase of a robotic inspection process, the calculation of metrics has two primary purposes, i.e., detecting potential deviations in the inspection process and monitoring concept drift. To identify process deviations, variables of the control process such as illumination levels and position of the inspected pieces are calculated. If any of these metrics exceed predefined thresholds, an alarm is triggered to warn manufacturing engineers to inspect the cell. Concept drift is monitored by examining the average least confidence score over a specific period. A decrease may indicate a potential model degradation.

2.4 Explainability

Explainable methods are designed to provide insights into the learning process of a neural network [8]. For classification models managed by MINT, the class activation mapping has been used [9]. In this method, the last dense output layer is removed and replaced by an average global pooling. This layer outputs a heatmap that shows which parts the network is looking at for each class.

The utilization of class activation mapping serves as a valuable tool for debugging, as it enables users to identify potential biases introduced by the model. By analyzing the heatmaps, users can gain a better understanding of how the model attributes importance to different parts of the input data, ensuring transparency and interpretability in the decision-making process.

3 Use Cases

3.1 Binary Classification

Tripods. Tripods have a key role in vehicle's movement transmission since they allow to connect two longitudinally arranged discontinuous axes. This small piece has two positions, the face and the chamfer, which are assembled by a robot. The robot picks the tripod from a conveyor belt and deposits it in a press (it must be with chamfer up) to insert it with pressure inside a joint. To date, the operator had to deposit tripods over the conveyor in a concrete way (chamfer up) to avoid wrong assemblies (those made with face up) (Fig. 3).

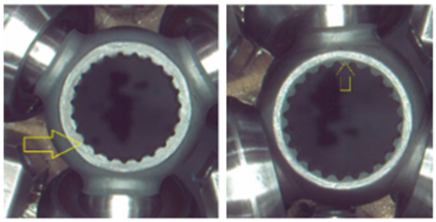

Fig. 3. (Left) Arrow pointing to tripod's face, (Right) Arrow pointing to tripod's chamfer.

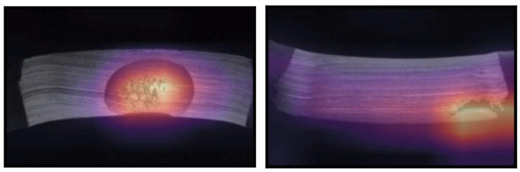

Fig. 4. Class defect heatmaps. On the left, a drop activates the neurons, while on the right it is the lack of material.

Cages. A ball cage refers to a component used to guide and retain ball bearings within the transmission system. It helps to maintain proper spacing and alignment of the balls, ensuring a smooth movement within the transmission assembly. Ball cage manufacturing involves several steps on different machines, including the punching of the ball pockets, which generate stress in the material and may lead to the appearance of defects. Defects in this piece appear on the window-like ball pockets, which will be the future interaction surface with some rolling balls. The current method of addressing this problem is visual inspection. A trained operator is responsible for checking every window manually and separate defective ones, which is a very time-consuming task. In Fig. 4 two surface heatmaps from explainability MINT module are shown.

Models. In order to address this task, a binary classification algorithm was used to detect if a piece was deposited faced up or chamfer up over the conveyor, and depending on that, the robot will pick the piece with a specific path to carry it onto the press. This involves training a convolutional neuronal network (CNN) with all used references