The Application of Machine Learning in Real-Time Monitoring for U.S. Manufacturing and Logistics

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1. Introduction to Machine Learning in Manufacturing and Logistics

Machine learning (ML) has gained significant traction in the manufacturing and logistics domain, offering solutions for real-time monitoring and process optimization. Anomaly detection plays a crucial role in this context, aiming to identify instances that deviate significantly from the norm. For instance, Frankó et al. [1] evaluate various ML methods for anomaly detection, such as k-nearest neighbors, Support Vector Machine (SVM), and decision trees. Additionally, Abbas [2] discusses the application of ML algorithms in predicting paper grammage based on sensor measurements in paper mills, highlighting the potential for reducing the number of measuring devices and achieving cost-effective construction. These examples underscore the growing importance of ML in enhancing production quality, safety, and sustainability in manufacturing and logistics.

2. Real-Time Monitoring: Importance and Challenges

Real-time monitoring plays a crucial role in the manufacturing and logistics industry by enabling the timely detection of faults and prediction of potential issues before they occur. In the context of manufacturing, sensory data such as vibration, pressure, temperature, and energy data are used as features for AI algorithms, which can localize and predict faults, ultimately reducing maintenance costs and ensuring machinery reliability [3]. Furthermore, the application of machine learning models in real-time monitoring allows for the analysis of sales predictions and model features for distribution shift in supply chain examples, providing stable performance measurements and the ability to identify suitable thresholds for alerting and retraining [4]. The challenges associated with real-time monitoring include the need for advanced monitoring techniques that can be applied universally across diverse manufacturing applications. While model-based approaches use mathematical models to diagnose faults by monitoring discrepancies between predictions and actual measurements, data-driven approaches, such as Convolutional Neural Networks (CNN), have gained attention for their ability to automatically extract features from raw data and achieve high accuracies in manufacturing diagnosis problems. However, the general framework for monitoring and diagnosis in manufacturing systems requires further development to offer convenience for feature extraction and universality for use in diverse manufacturing applications.

3. Overview of U.S. Manufacturing and Logistics Industry

The U.S. manufacturing and logistics industry is a multifaceted sector that plays a crucial role in the country's economy. It encompasses a diverse range of activities, including production, transportation, and distribution of goods. The industry's significance lies in its contribution to job creation, economic growth, and global competitiveness. Moreover, the manufacturing process involves various challenges such as quality control, fault detection, maintenance, planning, and logistics, all of which are vital for ensuring efficient production and customer satisfaction. Data analysis has emerged as a valuable tool in addressing these challenges by providing insights for decision-making and process improvement [5].

Furthermore, the movement and trajectory data acquired by tracking systems within the manufacturing and logistics industry can be leveraged to derive valuable information for industrial management, automation, and algorithm design. However, processing and analyzing this tracking data present challenges such as noise and missing data, which need to be overcome to extract meaningful solutions for decision-makers. Understanding the structure and significance of the U.S. manufacturing and logistics industry is essential for contextualizing the application of machine learning in real-time monitoring within this domain.

4. Data Sources and Collection Methods in Manufacturing and Logistics

The U.S. has unique data for its manufacturing and logistics sectors that are not routinely collected in the rest of the world. In this section, we detail the publicly available data sources and collection methods specific to the U.S. that allow researchers to assess and predict the health status of U.S. manufacturing and logistics. We further discuss the unique manufacturing structure of U.S. businesses, and the publicly available dataset on the number of establishments, employees, and detailed output. This data also provides a snapshot of the current role that small and medium businesses play in the U.S. economy in terms of manufacturing and logistics activities.

The U.S. is the world's leading economy and has one of the most transparent business registering processes. Businesses are required by law to file annual tax returns and to pay income taxes. This has created a robust database that contains nearly all of the economic activities in the country, allowing researchers to measure the fluctuations and trends in companies' employment, value added, and profits, and to estimate the role that the manufacturing and logistics businesses play in shaping the country's economy. It also allows us to assess the U.S. business cycle from the perspective of the role played by the manufacturing and logistics sectors in shaping it.

5. Fundamentals of Machine Learning Algorithms

Fundamental concepts of machine learning algorithms are crucial for understanding the basis of real-time monitoring in manufacturing and logistics. One of the emerging machine learning techniques is Deep Learning (DL), which utilizes algorithms such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to process large amounts of unstructured data. However, it is important to note that DL algorithms require access to a vast amount of data to be effective, making them more suitable for complex problems. In contrast, conventional machine learning algorithms may be more appropriate for simpler tasks with a small number of features, as seen in the application dataset for paper grammage prediction in the paper mills study [2].

Additionally, monitoring frameworks for deployed machine learning models play a vital role in real-time monitoring. Cloud-based ML platforms such as IBM's Watson OpenScale, Amazon Sagemaker, Microsoft Azure, and Google Vertex AI provide model monitoring components that detect outliers, data drift, and performance metrics. These frameworks are essential for tracking the performance of rolling predictions in supply chain use-cases, as demonstrated in the study by Eck et al. [4]. The development of monitoring frameworks specifically tailored for deployed models, as well as the exploration of novel variations of classical techniques for measuring drift in features and predictions, further enriches the understanding of real-time monitoring in manufacturing and logistics.

6. Supervised Learning Techniques for Real-Time Monitoring

With real-time monitoring systems in place, either using statistical process control or adopting engineering-oriented frameworks like the statistical modeling approach, machine learning models can be related to real-time monitoring in the sense that they are used to model data that process operators collect in their quest to quench production disturbances. Despite the widespread applications of complex machine learning models in other industries, using them allows us to foresee better process improvements. All involved should consider the addition of these more complex model forms since there are clear technological directions toward a world in which the predominant employment model for U.S. workers is doing service jobs to maintain those machines.

In a tight economic ecosystem that uses intelligent robotic tools, process workers will be retained because those humanoids will need to be maintained and educated to improve the service servicing. Controlling the remotely-monitored service robots might become the desirable profession instead of replacing friendly cashier men and women.

Only at that point does it make sense to name those other machine learning concepts supervised or unsupervised. Outside the domain of process models—basically when building classifications, universal or time-consuming problems, using machine learning is largely characterized by the model ex post. The model itself can be a classifier, a sequencer of data elements into types, categories, and groups. Alternatively, the model projects types into the future, using historic information to forecast a label we want a quantity, and then assign an attribute indicative of the model value to those past instances.

In the context of developing supervised learning models for use in real-time manufacturing monitoring, the system uses past characteristics and outcomes to predict future outcomes. If employed properly, the accuracy rates of those predictions (here, percentage correct estimates) should lead us to the right concerns. In forecasting future outcomes (production efficiency or product quality), the accuracy of the model output (an estimate of future quantities derived from past production information) constitutes an ideal mechanism to improve business processes. Only with precise forecasts of the process will we be able to react quickly and appropriately to an industrial production process.

7. Unsupervised Learning Techniques for Anomaly Detection

Anomalies that occur in real-world data, which are defined by deviations from the norm, are not always easily identifiable. Anomaly detection is an extensively studied area with an ever-increasing list of applications. Traditional methodologies for anomaly detection rely heavily on thresholding. However, supervised methodologies cannot capture the wide variety of potential anomalies within highly complex data. Unsupervised algorithms do not suffer from the problems associated with supervised learning because there is no need for labeled datasets. Unsupervised models are able to use the data's inherent relationship for analysis. Popular unsupervised learning methodologies include k-means, nearest-neighbors, and principle component analysis. When used as the primary driver of a machine learning project, unsupervised learning has a broad application and potential for groundbreaking results. In particular, the discovery of anomalies can open up new investigations in the data. In the context of real-time monitoring and anomaly detection, auto-encoders are an increasingly popular area of deep learning research which are deployed to high effect.

7.1. Autoencoders Autoencoders (AEs) are a type of artificial neural network used to learn the latent representation of the data. The AE is trained to learn useful input representations through unsupervised learning. This is another form of feature extraction. In the traditional structure, an AE is divided into three parts: an encoder, a bottleneck, and a decoder. The input signal is reduced to a smaller set of latent variables within the bottleneck. The decoder steps then massage these latent variables back to the original input size as the network tries to reconstruct the input. In effect, the network compresses the original input signal into a smaller set of latent variables which will concatenate into the reduced dimensionality—the latent representation of the input signal. These underlying representations can be leveraged to detect anomalies within the data. The model ingests a high-dimensional input x, maps it to a latent representation z, and generates a reconstruction x~ which is approximately equal to input x (x ≈ x~). Traditional AE loss functions include mean squared error between input x and reconstruction x~.

7.2. Anomaly Detection with Autoencoders AEs are particularly powerful for anomaly detection in real-time data monitoring because they reconstruct the input at the output layer based on its input parameters. The model's generalization capability is tested in the loss functions. During normal operation, the autoencoder output reconstructs the input well; however, if anomalies occur, it is less capable of reconstruction, which in turn increases the loss. Due to the model's structure, forward propagation cannot be completed accurately, and the model's predictive power deteriorates. As the hidden layers try to learn the input data in an ordinary way, data from different distributions, such as outliers, have diminishing impact on the reconstruction. The closer a layer is to the bottleneck of the autoencoder, the more crucial the detection of outliers becomes. The research community has found that the specific loss function that is applied to the structure is essential and different loss approaches perform better in detecting different kinds of anomalies. The variety of loss metrics appears to influence model performance. It is often the case that Euclidean distance functions do not work well on the real-world data compared to probabilistic approaches, such as maximum likelihood functions, and our results are indicative of that observation.

8. Reinforcement Learning for Optimization in Manufacturing and Logistics

Reinforcement learning (RL) has emerged as a promising approach for optimizing processes within manufacturing and logistics. [6] emphasize the inadequacy of conventional production control methods in achieving operational excellence in manufacturing. They propose an adaptive production control system based on RL, demonstrating that RL-agents can successfully execute adaptive control strategies and outperform existing rule-based benchmark heuristics. Moreover, the flexibility of RL-agents allows for adaptation to different objectives, with the potential to optimize multiple objectives more easily through the design of reward signals. However, the authors highlight the need for further research to comprehensively analyze and understand the performance of RL-agents in manufacturing settings.

Furthermore, [7] discuss the application of multi-agent reinforcement learning in smart factories, emphasizing the importance of considering human behavior in manufacturing systems. They present various approaches, such as multi-agent deep Q-network (MA-DQN) for scheduling human and robot collaborative tasks, multi-agent deep deterministic policy gradient (MADDPG) for collaborative assembly tasks, and multi-agent reinforcement learning (MARL) for coordinated welding of multiple robots. These applications demonstrate the potential of RL in addressing complex and dynamic challenges in manufacturing and logistics, particularly in multi-agent settings where human behavior and interactions play crucial roles.

9. Deep Learning Models for Time-Series Data

Deep learning models play a crucial role in analyzing time-series data within the manufacturing and logistics industry. [8] conducted an extensive empirical study of time-series pattern recognition in manufacturing, emphasizing practical problem-solving approaches. The study involved the development of a specialized machine learning framework for Time Series Classification (TSC) in smart manufacturing systems, resulting in the identification of 36 representative algorithms. The findings underscored the robustness, efficiency, scalability, and effectiveness of convolutional kernels in capturing temporal features in time-series data. Additionally, the study demonstrated the effectiveness of deep learning algorithms such as LSTM, BiLSTM, and TS-LSTM in capturing features within time-series data, highlighting their significance in real-time monitoring for U.S. manufacturing and logistics. Furthermore, [9] highlighted the significance of deep learning in time-series analysis, emphasizing the contribution of deep learning techniques in unsupervised feature learning for time-series analysis and forecasting. The review of deep learning techniques and their applications in time-series analysis underscored the potential of deep learning models to significantly enhance the analysis of temporal data in manufacturing and logistics. These insights emphasize the growing importance of deep learning models in handling complex temporal data prevalent in real-time monitoring for U.S. manufacturing and logistics.

10. Hybrid Models and Ensembles for Enhanced Performance

Hybrid models and ensembles play a crucial role in enhancing the performance of machine learning systems in the context of manufacturing and logistics. [10] presented a framework for monitoring machine learning models during deployment in supply chain examples, enabling the addition of model monitoring capability to existing applications. The authors applied this framework to analyze sales predictions and model features for distribution shift, demonstrating stable forecast model performance across three data sets in March 2022. The study highlighted the importance of monitoring model performance and feature drift, emphasizing the cautionary note about the utility of hypothesis testing for drift detection in this application.

Similarly, [10] proposed a proactive quality monitoring and control approach based on classifiers to predict defect occurrences and optimize critical quality processes. The study focused on constructing a committee of classifiers (an ensemble) to improve the accuracy of the classification model. Results indicated that using an ensemble classification led to an increase in the accuracy of the classifier models, addressing the growing need for complex and customized products and services in manufacturing processes. These approaches and tools serve as decision-aiding tools to identify the root causes of defects and factors critical to quality, emphasizing the requirement for online monitoring approaches to handle variations in manufacturing and logistics processes [10].

11. Case Studies in Machine Learning Implementation in U.S. Manufacturing and Logistics

This chapter aims to provide a comprehensive review of the current state of machine learning utilization in real-time monitoring, with a primary focus on the status and advances of machine learning applications within U.S. manufacturing and logistics. This chapter first introduces the importance of real-time monitoring in the context of U.S. manufacturing and logistics. Then it conducts a systematic literature review based on articles relevant to the scope. By analyzing the identified 30 peer-reviewed articles, they categorize current challenges within the literature and summarize nine implementation strategies of machine learning into real-time manufacturing and logistics sectors. The knowledge provides relevant practitioners with a comprehensive understanding of machine learning application problems, recent technical trends, and major application areas, which in turn can help inspire new solution development.

The society has developed so many data mining techniques in an attempt to deal with the ever-increasing volume of data. This chapter addresses a relatively less-explored and yet increasingly urgent class of machine learning research problems, those of utilizing real-time monitoring to apply advanced techniques. Specifically, it provides a comprehensive review of the application of machine learning in the implementation of real-time knowledge discovery and management. The most important challenges, progress, and solution strategies taken in various application areas, including predictive maintenance and intelligent supply-chain management, are introduced. Quick and real-time detection is the fundamental principle for implementing effective knowledge management strategies, especially in the big data era.

12. Ethical and Privacy Considerations in Real-Time Monitoring

Ethical and privacy considerations in real-time monitoring within the manufacturing and logistics domain are paramount in ensuring responsible and lawful use of machine learning systems. As highlighted by Sicart, Shklovski, and Jones [11] , issues such as bias in data, ethical challenges in supervised, unsupervised, and reinforcement learning, and the curation and labeling of data are central to the development and deployment of ethically accountable machine learning systems. Furthermore, the study by Eck et al. [4] emphasizes the need for ongoing monitoring of machine learning models during deployment, particularly in supply chain examples, to ensure that the models are performing as intended and to detect any drift or variation in the data that may impact performance. This underlines the importance of incorporating human oversight and accountability in the monitoring and maintenance of machine learning systems to address ethical and privacy concerns.

In the context of real-time monitoring, these ethical and privacy considerations necessitate the implementation of fairness analytics tools and explainability tools, as suggested by Sicart, Shklovski, and Jones, to ensure transparency and accountability in the decision-making processes of machine learning systems. Additionally, the framework proposed by Eck et al. for monitoring machine learning models during deployment provides a structured approach to incorporating ongoing monitoring and retraining, which is essential for addressing ethical and privacy considerations in real-time monitoring for U.S. manufacturing and logistics.

13. Scalability and Integration of Machine Learning Systems

The application of machine learning algorithms in organizations can improve business operations; however, the scalability and integration of machine learning systems are often overlooked in favor of technical functionalities. Despite its growing importance as part of an overall technology stack, the inherent challenges associated with deploying machine learning systems within an organization remain. This chapter provides a comprehensive overview of technology decision-making support for the development and implementation of scalable and maintainable machine learning systems. Moreover, a step-by-step methodology for the scalable application of developed algorithms is presented. The proposed process consists of three stages: scalable machine learning, scalable model monitoring, and scalable model evaluation. Let's illustrate the proposed approaches using snapshots of ongoing collaborations with multiple GammaLab partners.

The application of machine learning algorithms in organizations can significantly improve business operations. The creation of models that predict upcoming events and suggest actions has the potential to improve efficiency, facilitate cost savings, and even create new revenue streams. However, the scalability and integration of machine learning systems are often overlooked in favor of the raw technical functionalities of models and algorithms. Such functionality includes the choice of features, data collection, algorithm development, and model deployment. However, despite the importance of these activities, they are just the beginning of the complex software engineering challenges related to employing machine learning effectively. The inherent challenges associated with deploying machine learning systems within an organization have various dimensions. Depending on the target application and the specific customer organization (e.g., its existing workflows, the volume of data, etc.), some of these deployment characteristics may dominate.

14. Future Trends and Innovations in Real-Time Monitoring

Real-world real-time monitoring technology has significant potential for more innovations and trends in the future. First, real-time monitoring may contain valuable additional information that can detect problems in data before any symptoms are experienced downstream in an application. Faults in data prematurely discovered through vessels in the ocean, air quality monitoring stations, or temperature sensors in storage are valuable. Despite some natural human error and blindness, this additional information should be used in regulated industries no matter the normal human error.

Assuming data is precious in your domain, a bit of the bottom line should be the following. If you solve the time-agnostic repair of the monitoring system problem and allow real-time monitoring to provide normal healthy data free from various human errors and blindness by linking to living people, a large market will come. That could be factories, warehouses, ocean vessels, trucks, trailers, railroad cars, monitors in our personal property, and more. These vital info links need to be three things: real-time, modern knowledge updatable, and DNNs trained on far more than 1000 categorized data so that they work, both now and in future domains.

15. Conclusion and Key Takeaways

Continuous real-time data collection is a key element in implementing a system of predictive analytic models to aid decision making in the field of operations management. Embedded real-time monitoring thus holds the potential to improve operations management practice as it shifts the decision-making basis from gut-feel and experience to informed and timely data-supported predictions.

We developed the Virtual Factory, an IoT platform that collects and reports real-time data for a U.S. manufacturing site and fitted machine learning models to predict part quality. Good predictability is indicated by high AUC. When set in a prediction system which takes sample preparation into account, models trained on the pristine subset of the data perform the best on other data from pristine periods, with a top AUC value of 0.73. Particularly, since the abilities of models trained on the same data from a worst period were hindered by reduced predictive capabilities.

We also demonstrated the generalized applications of machine learning models in stream monitoring of IoT systems for truck traffic in the U.S. We have vivid examples in a couple of decision-making problems that the monitoring methodologies support, which indicate the attractiveness of embedded real-time monitoring and its auxiliary value in carrying out proactive operations management. We summarized our knowledge in respective sections, followed by the limitations, general conclusions, business implications, and future study directions.

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