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Review of Machine and Deep Learning Model for Smart Manufacturing

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***Abstract*: Smart manufacturing refers to using advanced data analytics to complement physical science for improving system performance and decision making. With the widespread deployment of sensors and Internet of Things, there is an increasing need of handling big manufacturing data characterized by high volume, high velocity, and high variety. Machine and Deep learning provides advanced analytics tools for processing and analysing big manufacturing data. This paper presents the review of machine and deep learning model for smart manufacturing.**

***Keywords*: Smart Manufacturing, AI, Deep Learning, Machine Learning.**

I. INTRODUCTION

Smart manufacturing integrates big data, advanced analytics, high-performance computing, and the industrial Internet of things to manufacturing systems and industries to improve manufacturing processes, resulting in better quality products that are available at lower costs [1]. In smart factories, devices, machines, and processes are interconnected monitored, and optimized to enhance productivity and efficiency. Time-series forecasting is applied to many areas of smart factories, including machine health monitoring, predictive maintenance, and production scheduling. In smart factories, machine speed prediction can be used to dynamically adjust production processes based on different system conditions, optimize production throughput, and minimize energy consumption. The traditional manufacturing industry uses decades-old technology and manual processes that are expensive, laborious, redundant, and a slight human error can cost millions of dollars. With the industrial revolution 4.0, industries are adopting intelligent additions and modifications into their systems involving robotics and internet of things (IoT) based technology, which can help in their operations. Artificial intelligence and machine learning have revolutionized every field, and the manufacturing industry has also started to reap its benefits[2].

Securing critical infrastructure networks requires a detailed understanding of the devices that are connected to the network and how networking resources are being used.

In this paper, we present a novel technique that focuses on describing device behavior by analyzing and classifying the observed network traffic patterns, and demonstrate how this technique augments existing Machine Learning (ML) models for the detection and classification of networked devices.

Figure 1: The role of data driven intelligence in smart manufacturing

The prevalence of IP networks within manufacturing and industrial sites adds a layer of vulnerability and makes it a primary target for attacks by malicious actors. By design, the IP network often carries critical SCADA traffic as well as other Information Technology (IT) traffic with different security constraints. We will share our initial results obtained using an optimized implementation of a Bayesian Neural Network (BNN) used to classify SCADA devices and alternatively, to characterize networked devices behaviors for unknown protocols [3]. In smart manufacturing, multivariate time series (MTS) data from interconnected sensors and actuators have been collected to model the product quality. However, high dimensional MTS data associated with complex functional structures has posed significant challenges for classical machine learning and statistical learning methods. As alternatives, deep neural networks (DNN) with highly non-linear structures and various data augmentation, pre-processing, and tuning techniques have been investigated for MTS data modeling [6].

Self-optimizing robots and machines in future factories are an exciting next step towards an ever more efficient industry. To achieve this goal, robots used in production must gain an understanding of the quality of their behavior.

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Machine learning can help us move closer to this goal. In this paper, we provide insights on the feasibility of self-optimized laser welding robots and show how accurate quality analysis based on deep learning and smart computer vision algorithms provide a reliable input for quality evaluation and ultimately a scoring function [8]. The findings of the last years regarding the deep and machine learning algorithms provided the substantial impetus to the discovery of heretofore unknown data. The future of mechanical/electromechanical engineering lies in the design of smart materials and technologies. In this paper, the problem of material design in particular for applications in mechatronics industry and additive manufacturing-based production has been considered. Developed high-entropy alloys could outreach limited properties of conventionally used steels, ceramics and superalloys[9].

II. BACKGROUND

M. A. Essien et al.,[1] However, making accurate data-driven machine speed forecasts is challenging. Given the complex nature of industrial manufacturing process data, predictive models that are robust to noise and can capture the temporal and spatial distributions of input time-series signals are prerequisites for accurate forecasting. Motivated by recent deep learning studies in smart manufacturing, in this article, we propose an end-to-end model for multistep machine speed prediction. The model comprises a deep convolutional LSTM encoder-decoder architecture. Extensive empirical analyses using real-world data obtained from a metal packaging plant in the United Kingdom demonstrate the value of the proposed method when compared with the state-of-the-art predictive models.

H. M. Ahmad et al.,[2] In this case study, we have explained the applications of deep learning-based approaches contributing to the automation of surveillance of production lines. Several cameras are installed to collect live feeds on the floor lines where the manually operated cranes and different tasks it performs are detected and tracked by state-of-the-art Convolutional Neural Network-based YOLOv3, an object detection model, and DeepSORT tracking algorithm. The post-processing is done on the matrices generated. It varies based on the use case and helps the manufacturers with automated inspection, quality control, and labor productivity. This process will save millions of dollars per year just in the crane maintenance operation for our industry partner's client. The developed technology can be replicated in almost every manufacturing industry using traditional methods and provide them better key insights into their production lines.

M. Touma et al.,[3] We will present two scenarios and discuss the performance of BNN: In one scenario, we use an application protocol parser for Building Automation Control Network over IP (BACnet/IP) and show how the specific protocol features can be used for classifying devices. In a second scenario we assume that we cannot parse the application protocol messages and use features derived from the underlying User Datagram Protocol (UDP) for our classification. We will discuss the benefits and shortcomings of each method and discuss how the method for analyzing UDP can be used to quickly formulate an initial point of view on the network being studied by classifying devices based on their pattern of behavior independent of what application protocol they use. This approach presents a significant advantage when the messages between the devices cannot be decoded.

H. Ghorbel et al.,[4] The aim of the Social Network of machines (SOON) project is to investigate the impact of using of autonomous social agents to optimize manufacturing processes in the framework of Industry 4.0. In this article, we present the multi-agent SOON architecture and the built solutions aiming at optimizing the scheduling of tasks. Two different scheduling approaches are proposed. The first approach is based on an ‘auction’ paradigm where the task assignment is decided according to the capability of a machine agent to bid for a task. The second approach is built on a heterarchical agents network where agents learn the acquisition of cooperative tasks. Both solutions are capable of managing and synchronizing the communication between agents while performing their tasks. To describe each approach, two industrial use cases are illustrated: wire rod mill manufacturing and mechanical part manufacturing. Finally, in the heterarchical network, agents are trained with reinforcement learning to maximize the cumulative reward and optimize the manufacturing scheduling. Results show that reinforcement learning allows learning the optimal behavior in multiple scenarios.

M. Leier et al.,[5] Elevator manufacturing companies make great effort to provide better user experience and to reduce elevator waiting time. Deep learning for visitor profiling offers more options for personalised service and enables the elevator to learn about its usage. In this paper, we present a solution that integrates conventional elevator with facial recognition, voice assistant and unsupervised learning and discuss some insights gained during the development. In the 3-month testing period, we experienced different social reactions that help us to examine people's readiness to accept new technologies in their daily life.

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The novelty of the solution lies in a combination of different cognitive technologies like facial recognition, unsupervised classification of persons, recognition of voice commands and statistics-based prediction of passenger destinations.

P. Shojaee et al.,[6] The recent transformation of step-by-step offline data analytics to the fast end-to-end computation pipelines motivated us to investigate DNN pipelines for MTS classification problems. However, execution of all the candidate DNN pipelines is computationally expensive, which calls for an effective approach. Thus, the adaptive top-N linear generative-discriminative (AT-LinGD) method is proposed as a learning to rank method that learns top-N ranked pipelines by iteratively exploring a small subset of all possible pipelines. It generates latent variables to describe pipelines and explore them to update the exploration set in a sequential manner. Thus, the adaptively generated latent variables enable the efficient and accurate ranking of the top-N pipelines with limited execution. A real case study of aerosol® jet printing process demonstrates the merits of the AT-LinGD model.

S. R. Pokhrel et al.,[7] We consider a fifth-generation (5G)-empowered future Industrial IoT (IIoT) networking problem where IIoT machines are capable of communicating and sharing their data networking knowledge gained (and experiences) with other neighboring devices/tools. For such an IIoT setting, deep-learning (DL)-based communication protocols are known to be highly efficient but having a computationally complex training procedure in terms of both time/space and volume of data sets. One solution for such training is to be completed offline for each equipment and machines of IIoT before deployment. A better approach would be to replicate the model from the expert existing machine and implant it into new machines. Such training for the transfer of knowledge can be done by manufacturers using high computational power, even for large-scale DL models. After sufficient training and the desired level of accuracy, the trained machines can be deployed in the smart factory equipment to perform life-long collaborative learning. We design a novel distributed transfer learning (TL) framework to maximize multipath communication networking performance for Industry 4.0 environment. To conduct seamless sharing of knowledge gain by the multipath TCP (MPTCP) agents and tackle retraining issues of DL-based approaches, we investigate TL for MPTCP from the IIoT networking perspective. With relevant insights from transfer and collaborative learning, we develop a distributed TL-MPTCP framework to accelerate the learning efficiency and enhance the performance of newly deployed machines.

Our approach is validated with numerical and emulated NS-3 experiments in comparison with the state-of-the-art schemes.

M. Schmitz et al.,[8] Furthermore, the suggested scoring function can capture the defining properties of a weld. In turn, the score can be used as feedback to define a reward for a reinforcement learning agent's action, which then optimizes the robot's behavior accordingly. Our experiments show that we can achieve very good accuracy and consistency when evaluating the quality of the weld with deep learning and statistical modeling. Finally, we provide a production-oriented learning architecture that considers the scoring component in a reinforcement learning pipeline.

V. Buranich et al.,[9] The thermal and mechanical properties of refractory metals-based high-entropy alloys has been studied using a complex of analytical algorithms (linear, random forest and gradient boosting regression). The highest accuracy has been achieved by applying the gradient boosting model (above 91%). Performed calculations allowed to verify the properties of different alloys, hence simplify their further selection for the manufacturing. From the developed ranking of overall properties make the TiNbHfTaW, CrNbHfTaW and VNbHfTaW alloys demonstrated the best results for being used in applications for mechanical and electromechanical engineering.

S. Dhir et al.,[10] This creates a necessity for the integration of ML and cyber security in CPS, where it makes the skilled people to track threats on web within a less time period. The proposed research study is performed on the different frameworks used for Cyber-attack detection using learning approach, this proves the importance of machine learning and deep learning in Cyber physical system for detecting the threats in a better way. Security analytics is used by various researchers and also by using it one can prioritize the signals and alerts. The proposed study on different attacks has also highlighted the researchers to be more aware about uncommon attacks that can become very dangerous. Further, the study of various works done in analyzing different attacks are done using various approaches and dataset that is covered along with pros and cons to help in choosing the best approach according to the requirement.

M. Kozek et al.,[11] Modern technology lines in Industry 4.0 standard use many complex smart systems to improve the speed of production. Manufacturing becomes more flexible and, on the other hand, more demanding for a process operator. This article presents mixed reality glasses that supports the work of the operator integrated via a cloud with a technology line.

Transfer learning algorithm is shown in a set of artificial neural network algorithms belonging to the Deep Learning class to analyze the image from ML headset. This algorithm is designed to recognize the current occupation of the storage tray with direct transmission of information to the control and measurement system.

L. U. Khan et al.,[12] propose a novel dispersed federated learning (DFL) framework to provide resource optimization, whereby distributed fashion of learning offers robustness. We formulate an integer linear optimization problem to minimize the overall federated learning cost for the DFL framework. To solve the formulated problem, first, we decompose it into two sub-problems: association and resource allocation problem. Second, we relax the association and resource allocation sub-problems to make them convex optimization problems. Later, we use the rounding technique to obtain binary association and resource allocation variables. Our proposed algorithm works in an iterative manner by fixing one problem variable (for example, association) and computes the other (for example, resource allocation). The iterative algorithm continues until convergence of the formulated cost optimization problem. Furthermore, we compare the proposed DFL with two schemes; namely, random resource allocation and random association. Numerical results show the superiority of the proposed DFL scheme.

III. CONCLUSION

Deep learning provides advanced analytics and offers great potentials to smart manufacturing in the age of big data. By unlocking the unprecedented amount of data into actionable and insightful information, deep learning gives decision-makers new visibility into their operations, as well as real-time performance measures and costs. To facilitate advanced analytics, a comprehensive overview of machine and deep learning techniques is presented with the applications to smart manufacturing. In future the deep learning based model will be implemented to prediction of smart manufacturing based on the dataset.

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