

## **Contemporary Trends and Challenges and Advances, in the Manufacturing Industry, with a special focus on applications of Artificial Intelligence and Deep Learning**

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### **Abstract:**

In the last few years' artificial intelligence (AI), has begun to make its appearance in our everyday life. Even though it is still in its early stage of development, AI has proved beyond human intelligence. DeepMind's AlphaGo is an illustration of how the AI could provide amazing benefits, particularly in industries such as manufacturing. At the moment there are attempts to connect AI technology with precision engineering and manufacturing in order to change classical production methods.

This research paper focuses on some notable milestones that have already been attained in the realization of AI for manufacturing and how it will change the face of any manufacturing facility. There are several challenges in the AI manufacturing application; these include data acquisition and management, human resources, infrastructure, security risks associated with trust issues as well implantation of hurdles. For instance, the collection of data required to train AI models can be challenging for rare events or expensive in large datasets that require labeling.

The introduction of AI models into industrial control systems can also pose risks to the security, and some players in industry may be reluctant to use AI because they don't trust it or understand what is going on. However, these hindrances do not deter AI from becoming an effective solution for predictive maintenance and quality assurance in the sector of manufacturing. Therefore, one should ponder over each manufacturing case and its needs before deciding if or how to adopt AI.

The aim of this research paper is to analyze the current progress, problems and prospects in AI-ML across manufacturing entities. Its aim is to enhance knowledge of accessible technologies, support decision-making in choosing appropriate AI/ML technologies and determine where further research needs are possible centered on latest developments. Initial findings indicate that the combination of AI/ML technologies with advanced data collection capabilities from manufacturing networks can produce massive cost and efficiency gains.

Though the accurate representation of complex phenomenon in manufacturing is problematic, AI can revolutionize this industry. Other areas where AI is intensively studied include medical image analysis, bioinformatics, recommendation systems and finance. Many notable AI products such as Amazon's Alexa, IBM Watson and DeepMind AlphaGo have already integrated into our daily use. To address limitations such as interpretability and degraded performance with

insufficient data, several sub-branches of deep learning are currently researched namely; Physics - Informed Deep Learning (PIDL), Explainable AI(XAI), Domain Adaptation, (DA) Active Learning (AL), Multi Task Learning MTL , Graph Neural Network GNN.

Convergence of AI with other engineering industries have a potential issue that should not be ignored. The aim is to enable an effective use of AI by the precision engineering and manufacturing community for future-oriented manufacture.

**Keywords:** *Machine Learning, Artificial Intelligence, Manufacturing sector, AI challenges in manufacturing sector, deep learning, deep learning in manufacturing sector*

### **Prolusion of the title of this paper:**

The emergence of the Industry 4.0 has seen a sector within manufacturing boom into existence known as Smart Manufacturing This industry capitalizes on the technology that is embodied by both IoT and technologies connected to the internet, leverages such accessibility not only in creating products but also monitoring different processes. The major goal of Smart Manufacturing is to make manufacturing operations more automated, improve efficiency; reduce environmental factors and so on. This is done by creating, optimizing and deploying huge heaps of data. The implementation of advanced analytics to manufacturing data allows manufacturers, through this process both individual assets and the whole industrial operation can be optimized in terms of productivity. This is achieved by combining AI and ML technologies.

At present, a major shift is taking place in the manufacturing sector. The latest developments in Big data and ML are shifting the old manufacturing age into the smart era of I4.0 that is Industry 4.0 (I). This change is opening up new avenues for the businesses. The IIoT, which is a facet of the IoT also has an important role to play in this revolution. It includes the set of digitally intercommunicating physical objects that allow communication and data transportation over the web. Through the fusion of sensors, RFID tags, software and electronics with machines IIoT provides possibility to collect information in real time. This great volume of smart sensors and IoT technology makes possible the collection-storage process for massive amounts of industrial data, which is pivotal to numerous production aspects.

A digital twin is one of the several concepts that form part and parcel of this paradigm shift. A digital twin is a virtual duplicate of physical product, machine process or system. It provides companies with an opportunity to understand their processes more, and continually optimizing them using live simulations based on data that gets sent in from IIoT. The digital twin paradigm depends on cloud computing. It uses internet connections to store, access and process data which forms the basis of operations for digital twin simulations.

In addition, the current generation of manufacturing is being facilitated by modern technologies like robotics; augmented reality and virtual reality, as well as additive manufacturing. The use of such technologies along with ML techniques under AI subfield can help reveal hidden production patterns and offer timely decision support in different manufacturing scenarios.

Such examples include predictive maintenance, process optimization, task scheduling, quality improvement, supply chain management and sustainability. The efficient utilization of technology and AI has now become critical for business development as well as its progress. Companies across the world are pouring a large number of finances on creating AI and ML in manufacturing.

### **Analysis and Review of Literature:**

In the manufacturing industry, among other applications of machine learning is computer vision for inspection and monitoring part process. We can realize advanced part inspection by using low-cost sensors such as RGB cameras along with machine learning algorithms. Combining computers vision with machine learning, products can be monitored throughout the

In addition, computer vision-based methods also make process monitoring an effective and continuous approach. In the paper under discussion, a data-driven approach for wire bonding defects inspecting using image based automatic

inspection is offered. The method outlined in the paper (refer to the citation) consists of three steps: Data pre-processing involves finding and segmenting IC chip image patches from raw images along with feature engineering for obtaining geometric features of the wires, followed by classification using machine learning algorithms including CNN and SVM.

The authors (refer to the citation) prove the usefulness of such an approach employing a set of X-ray images collected in a semiconductor factory. In the paper "Soft sensor of flotation froth grade classification based on hybrid deep neural network," there is mentioned about developing a soft-sensing system, which may classify the iron ore tailings according to its quality by looking at images from flotation process tails. The paper highlights two key contributions: The development and validation of a database containing froth images from the flotation tailings and an accuracy comparison between various deep neural network (DNN) models for this task. According to the results of comparative analysis, authors present a fine tuned hybrid DNN model with high prediction accuracy and build software around it. The experimental findings show that DNN may be a useful tool in the study of iron ore froth flotation.

The prompt and accurate diagnosis of process faults in a manufacturing plant's equipment is paramount for industrial companies to remain competitive by minimizing machine down times. Increasing demand for quality products with low production costs forces machine learning to become a core element in manufacturing industries, which makes fault diagnosis essential. In their paper titled 'A deformable CNN-DLSTM based transfer learning method for fault diagnosis of rolling bearing under multiple working conditions', Wang et al. (2020) present a TL approach that integrates the use of deformable convolutional neural networks and deep long short term memory to achieve the rolling bearing fault diagnosis. In particular, bearing faults that take place in multiple work environments are considered by the authors as it is difficult to build a large-scale labeled dataset. They can use data samples of one working condition to pre-train a fault diagnosis model and then transfer it, along with further fine tuning using only few data samples, to another working condition.

As the developed structure proves, it is more efficient than standard methods if applied to an experimental dataset. In a similar study referred to as "New Applications of Deep Learning for Detection Faults in the Industrial Cold Forging Process," Glaeser et al. (2021) address how deep learning methods can be applied within the field coil detection faults industrial cold forging domain using The authors pose two techniques using CNN and DT on the impact of machine signals upon various deficiencies. Such methods show better accuracy when applied to data obtained from the vibration of readily occurring faults within industrial cold forging.

### **Application of the data observed:**

The curious case of semi-conductor----

The technological development of fast computing chips in the semiconductor sector creates various engineering applications' current state of AI. But this relationship is no longer unilateral and moves towards a bi-directional one. The increase in AI and the development of semiconductors is interdependent as it seems that changes through Artificial intelligence for semiconductor industry. In general, the semiconductor manufacturing process includes various steps that take place on a silicon wafer. These processes include the oxide insulator formation, photolithography patterning. Etching using etchant followed by thin film creation through evaporation or sputtering among other things. Any source of defect, including dust particle must be eliminated since these processes involve such extreme precision.

In an attempt to keep a nearly dust-free environment in most semiconductor fabs, defects which greatly diminish yield are still detected from the manufacturing lines due to malfunctions of machines and human blunders. There are two main approaches to detecting and localizing defects on wafers: Signal-based and image based fault detection. The most common practice of discovering a fault in wafers makes use of complex image-based detection through deep learning. Not only do defects reveal the site of fault, but their grouping and patterning can shed light on how malfunction is caused. Imoto et al. automated classification by transfer learning using CNNs to monitor the incidence rate of defect types, which helps in pinpointing process failure causes. Because of the presence in storage a significant amount of inconsistent input labeled data, the author proposes use transfer learning as an option for weakly supervised task.

The proposed methodology consists of two steps: pre-training and fine-tuning. The amount of data used for pre-training contains a large number of wrong labels. After which only the last layers' parameters are then fine-tuned on a relatively

small highly reliable labeled data set. Yang obtained accuracies of 99.2 percent and XGBoost, respectively for CNN. This high accuracy is achieved by a careful examination of the wafer map and finding out that spatial correlations exist in background have defect signature for this wafer. As a result, the pictures are modified to improve contrast between signal and background. SVD is used to perform preprocessing on the images in order to remove noise surrounding defects. Furthermore, data augmentation methods including random cropping, rotation, resizing and flipping are also employed to enhance the performance of this.

Tello et al., however, applied the RGRN and CNN to categorizing both single-defect pattern as well mixed-defect patterns. It is stated that previous researches on defect classification were mainly dedicated to the single-defect patterns and involved lower models. The traditional method for visually inspecting defects using a high-resolution camera presents certain challenges. The major disadvantage is that it assumes the knowledge of all types and their possible shapes beforehand. In other words, many defects of different forms need to be pre-labeled which is usually a slow and inaccurate process. To address this issue, it is helpful to use the multitude of unlabeled wafer maps for training.

In this work, Yu et al. introduced a new approach known as the stacked convolutional sparse denoising autoencoder (SCSDAE). This approach integrates CNN and SDAE. A significant feature of SAE's is its capability to learn sparse features by introducing a penalty term that promotes sparsity during the learning phase. Due to the addition of SAE into the network, SCSDAE is a more effective optimizer of weights in comparison with PBAE. Additionally, the network's denoising property makes it robust in representation of features despite corruption on input data.

The proposed SCSDAE incorporates two SDAEs employed in the feature extraction steps, which are further enhanced by convolution and max-pooling operations to learn more abstract features. This collection of methods generates the name SCSDAE. Even like Nakazawa et al. created a deep convolutional encoder-decoder structure that not only identifies abnormal defect patterns but also segments them. This network runs on the FCN architecture mainly composed of convolutional layers for segmentation.

Segmentation of defect patterns makes it possible to extract additional info such as location, size, major and minor axis length, and orientation. Compared to base architectures such as FCN, SegNet and U-Net in terms of defect detection performance, the proposed network excels. This also shows that the method is successful in correctly determining and describing defects on wafer maps.

Although the image detection is currently becoming more and more popular, there still are many researchers working on signal-oriented schemes. According to the research carried out by Lee et al., it was established that fault diagnosis aimed at identifying root cause process failures could be successfully performed with a black box CNN model. In this way, the adaptive receptive field across multivariate sensor signals over time customizes CNN that correlates extracted features from hidden layers with physical meaning of raw data. As a result, this leads to determining the variable and time of process failures. Lee et al. aimed at suppressing the noise while retaining information enough to ensure accurate fault detection using other study.

For this purpose, the author suggested using Stacked Denoising Autoencoders (SDAE), in which several DAEs are pretrained on latent representations from previous time step as an input. After initial training, the last layer is adapted for defect classification followed by further fine tuning. The study showed how the model was relatively more resilient when considering increasing noise set in their study, Kim and his colleagues used status variable identification (SVID) data of different lengths for early detection.

One of the major differences between this suggested approach and other studies is its potential to process sequences with SVID variations by using the robustness. Motivated by text classification strategies that transform variable-length series into fixed vectors, the author introduces a self-attention mechanism to distribute attention over a constant vector length and thus allow these models access selected instants of time when fault emerges. Speaking of the problem with data drift, Azamfar et al. created a solution to take into account changes in distribution of data due to changing conditions during operations.

In real-life scenarios, operators meet with contrasting testing environments that occur as a result of various disturbances hence deviations in the distribution pattern between training and test datas. The proposed model is a variant of standard

CNN with an additional loss term known as maximum mean discrepancy (MMD) This loss function determines the distribution's difference between source and target domains. It is asserted that the incorporation of this loss term considerably increases classification accuracy. Unlike previous works that mostly rely on CNNs, Kim et al. showed the use of RNN method for early-stage anomaly detection.

This approach has the primary strength of its capacity to detect outliers even without prior training with defective data. The model DeepNAP consists of a detection module and a prediction module. The prediction module uses the capabilities of LSTM to predict next signals, which are then given as input into detection module for latent representation and anomaly identification. The detection module refers to the first output of LSTM, which is used as a target signal for optimization using partial reconstruction loss function. This loss function assigns a higher anomaly score to the defective segment of the signal, making it appropriate for this application. The proposed model outperforms other baseline architectures in the pre-detection of anomalies.

#### **Ratiocination and research summary:**

The application of AI in the field of manufacturing has been complex due to high-dimensional and highly nonlinear processes that almost necessitate perfect modelling. Though AI is still young, a lot of arguments have been made about it recently and these industrial sectors so that even technology deserves revolution in production industry soon while it has already thoroughly studied for medical image analysis contributing bioinformatics drug development recommendation systems financial frauds detection visual art processing military aside from above mentioned industries. Alexa from Amazon, Watson from IBM, AlphaGo by DeepMind and many other very successful commercial products are demonstrations of the practical application AI.

Manufacturing industry is in the midst of a major evolution with machine learning technology integration and application. This special issue brought together an array of different experts that try to describe the recent developments in core theoretical and, respectively experimental aspects of ML as well as their application in manufacturing systems with a focus on production lines to explain this change at the beginning of 2019s. In this special issue, these themes like computer-vision based inspection and monitoring, defect detection, cloud manufacturing process optimisation and optimization comprehensive state of the art review paper are covered in papers.

In the process of development and implementation of Industry 4.0 in factories, artificial intelligence will be crucial as it concerns data analysing and decision-making processes. With machine learning (ML) feeding into manufacturing applications, it is therefore evident that ML may be utilized in every step of the production process within a factory environment. Furthermore, it is important to note that the very basis of physics governing physical phenomena can improve decision-making in ML manufacturing applications. In various manufacturing settings, data generation can be prohibitively costly and hazardous; convergence of machine learning with physics thus becomes crucial.

**To add:** While supply chain management plays a very critical role in the manufacturing operations, it can be highly complex due to many countries and continents being involved. The use of AI and ML in applications such as the supply chain can considerably improve its efficiency. Through predictive analytics and real-time data analysis, AI and ML can use inventory levels for both production planning. The forecasting of vital parameters in the supply chain, including demand to final products and lead times on critical components is among key benefits offered by AI IML. Real-time data analysis from AI allows companies to make decisions about the purchase of feedstock or selling product based on spot market signals in a timely manner.

Contrasting with conventional approaches, AI/ML-based predictive models can work on a larger quantity of historical data and features leading to more precise predictions. Further, NLP may efficiently process the news feeds to generate valuable information which will provide market insights for the concerned agent and digitizing physical data like invoices faster than a human operator. Under minimal supervision, industry robots and drones with AI/ML-based computer vision can be utilized in warehouses and perform with a very high level of accuracy. The can efficiently monitor inventory and help locate items from the store.

Also, AI and ML have other uses in supply chain management. But it can --- aid in the tracking and minimizing waste for instance, provide real-time monitoring during logistical operations; as well automatize routine tasks to minimize errors said productivity. RL has also been shown to be beneficial in simplifying the production routes and improving productivity by reducing delays and enhancing scheduling.

The remarkable developments in AI/ML technology create a unique opportunity for wholesale change to the industrial sector. This in-depth analysis presents a wide range of manufacturing use cases and demonstrates the way AI/ML can enhance production, efficiency, sustainability and safety for manufacturers.

It discusses several dimensions in which AI/ML can be used such as product design, automation; security and safety, operations, planning quality assurance energy consumption fore casting human-machine interface. The assessment also points out new developments, current challenges and possible directions in AI/ML relevant to manufacturing sector. It also emphasizes the use of AI/ML technologies to solve industrial problems, mentions aspects that future study can have a revolutionary impact on the industry.

## References

1. Chen, Junling, Zijun Zhang, and Feng Wu. 2020. "A data-driven method for Enhancing the image-based automatic inspection of IC wire bonding defects." *International Journal of Production Research*. doi:10.1080/00207543.2020.1821928
2. Zhang, Dingsen, and Xianwen Gao. 2021. "Soft sensor of flotation froth grade classification based on hybrid deep neural network." *International Journal of Production Research*. doi:[10.1080/00207543.2021.1894366](https://doi.org/10.1080/00207543.2021.1894366).
3. Wang, Zheng, Qingxiu Liu, Hansi Chen, and Xuening Chu. 2020. "A deformable CNN-DLSTM based transfer learning method for fault diagnosis of rolling bearing under multiple working conditions." *International Journal of Production Research*. doi:10.1080/00207543.2020.1808261
4. Imoto, K., Nakai, T., Ike, T., Haruki, K., & Sato, Y. (2018). A CNN-based transfer learning method for defect classification in semiconductor manufacturing. In 2018 International Symposium on Semiconductor Manufacturing (ISSM), IEEE, pp. 1–3.
5. Glaeser, Andrew, Vignesh Selvaraj, Sooyoung Lee, Yunseob Hwang, Kangsan Lee, Namjeong Lee, Seungchul Lee, and Sangkee Min. 2021. "Applications of deep learning for fault detection in industrial cold forging." *International Journal of Production Research*. doi:[10.1080/00207543.2021.1891318](https://doi.org/10.1080/00207543.2021.1891318).
6. Yuan-Fu, Y. (2019). A deep learning model for identification of defect patterns in semiconductor wafer map. In 2019 30th Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC), IEEE, pp. 1–6.
7. Tello, G., Al-Jarrah, O. Y., Yoo, P. D., Al-Hammadi, Y., Muhaidat, S., & Lee, U. (2018). Deep-structured machine learning model for the recognition of mixed-defect patterns in semiconductor fabrication processes. *IEEE Transactions on Semiconductor Manufacturing*, 31(2), 315–322.
8. Yu, J., Zheng, X., & Liu, J. (2019). Stacked convolutional sparse denoising auto-encoder for identification of defect patterns in semiconductor wafer map. *Computers in Industry*, 109, 121–133.
9. Nakazawa, T., & Kulkarni, D. V. (2019). Anomaly detection and segmentation for wafer defect patterns using deep convolutional encoder-decoder neural network architectures in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, 32(2), 250–256.
10. Lee, K. B., Cheon, S., & Kim, C. O. (2017). A convolutional neural network for fault classification and diagnosis in semiconductor manufacturing processes. *IEEE Transactions on Semiconductor Manufacturing*, 30(2), 135–142.
11. Lee, H., Kim, Y., & Kim, C. O. (2016). A deep learning model for robust wafer fault monitoring with sensor measurement noise. *IEEE Transactions on Semiconductor Manufacturing*, 30(1), 23–31.
12. Kim, E., Cho, S., Lee, B., & Cho, M. (2019). Fault detection and diagnosis using self-attentive convolutional neural networks for variable-length sensor data in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, 32(3), 302–309.
13. Azamfar, M., Li, X., & Lee, J. (2020). Deep learning-based domain adaptation method for fault diagnosis in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, 33(3), 445–453.
14. Kim, C., Lee, J., Kim, R., Park, Y., & Kang, J. (2018). DeepNAP: Deep neural anomaly pre-detection in a semiconductor fab. *Information Sciences*, 457, 1–11.