The Impact of Deep Learning on Advanced Manufacturing Technologies in the USA

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1. Introduction to Deep Learning and Advanced Manufacturing Technologies

Deep Learning (DL) models best describe a class of models and algorithms based on deep artificial neural networks (ANN). Over the past decade, ANN models thought to eliminate the 'AI winter' years of stagnation in the field have seen a revival spurred by larger data sets, improved computational systems, and ANN optimization breakthroughs leading to state-of-the-art results in a growing number of domains. Models such as deep belief networks (DBN), convolutional neural networks (CNN), re-current neural networks (RNN), long short-term memory (LSTM), and deep Boltzmann machines (DBM) are widely known deep architectures [2].

1.1. Definitions and Concepts

There exists various definitions of deep learning (DL) and advanced manufacturing technologies (AMT), or smart manufacturing. This section delves on definitions of deep learning and advanced manufacturing technologies in order to provide clarity of specific topics of discussions, which are key components in this essay.

There exists various definitions of deep learning (DL) and advanced manufacturing technologies (AMT), or smart manufacturing. This section delves on definitions of deep learning and advanced manufacturing technologies in order to provide clarity of specific topics of discussions, which are key components in this essay. Deep learning (DL) is a set of machine learning (ML) approaches based on multi-layered neural network architectures [3]. Over the last decade, DL approaches have grown dramatically in performance in a wide range of applications, such as object detection and classification, and the accuracy of some DL techniques has notably surpassed human performance benchmarks in a variety of tasks. With excellent learning capabilities from historical data, DL techniques can play a key role in building intelligent data-driven systems. DL technology is relevant to artificial intelligence, machine learning, and data science with advanced analytics. Nowadays, artificial intelligence, machine learning, and deep learning are three popular terms that are sometimes used interchangeably to describe systems that behave intelligently [4]. However, by scientific definitions, AI, ML, and DL are multiple domains, and DL is a part of ML and AI. In general, AI incorporates human behavior and intelligence into machines, while ML is the method to learn from data or experience. Applying statistical or optimization techniques to adjust weights based on past experiences, ML systems can learn the association between input and output. By using multi-layered neural networks, DL also represents learning methods from data through multi-layer neural networks. Thus, DL can be considered one of the core technologies of AI. As DL learns from data, there is a strong relation between deep learning and data science. Data science represents the entire process of finding meaning or insights in data, where DL methods can play a key role in advanced analytics and intelligent decision-making. In order to build a data-driven intelligent system, an in-depth understanding and representation of data are important.

2. Historical Overview of Advanced Manufacturing in the USA

The history of advanced manufacturing in the USA has a clear goal: Competitiveness. It argues the need of a nationally conscious effort directed to improving the competitiveness of USA products, supported by wide-ranging infrastructure and institutions responsible for R&D, education, valorization and the assessment of ideas and projects [5].

Many great products that have worked, in their epoch, in favor of USA's leadership and competitiveness, like the space program, the technological research in defense through DARPA, and even the subsidized credit given to their timber and aircraft producers, among others, are brought up. As a consequence of this competition agenda - and only the agenda to compete, not compete for whom - it is suggested that the USA founding fathers would have been, in our time, the comprehension of the regulatory framework, hegemonic international institutions, and developmental economic programs to the World.

A wide-ranging program of comparative research is suggested wherein each industrial activity would be analyzed according to the complex product system that regulates it with similar and dissimilar elements to Japan and the European Union. Nevertheless, the true expectation is disregarded: in the absence of a visionary project for USA action, leadership for this program would be voluntarily taken each time by Germany, Japan, or another country that may exercise it. The USA - a universe of fragmented interests, with no States agenda or nation, nor even a national guitar in its industrial policy - would only react to their initiatives.

2.1. Key Developments and Milestones

Modest beginnings of U.S. manufacturing technology laboratories can be traced in 1962 innovations by the National Advisory Committee for Aeronautics, NASA's precursor. In the 1970s beginnings of concurrent engineering and distributed control in the semiconductor industries were major developments. Between 1985 and 1998, concurrent engineering experiments and combustion monitoring in coal-fired power plants were widely studied. The early use of computers in manufacturing was illustrated with CAM CAM-I studies on robot simulation, technology transfer, etc. Japan's MITI U.S. Study, and advances in laser processing, FMS, and robotics in the auto and electronic industries were also discussed. It is argued that these innovative manufacturing technologies were the results of perplexed responses to U.S. industries sinking into long-term recessions [5]. The late 1990s ushered in model buildings, adaptive manufacturing planning, architecture developments, automated design sensitivity analysis, and NC tool path generation. The research framework was based on the triangle of design, process planning, and operations scheduling. It was expected that relatively auto industries would further diversify the use of innovative and emerging technologies.

Artificial Neural Networks (ANNs) were a major area of research in both neuroscience and computer science until the late 1960s. Despite the late 1960s and early 1970s having some significant achievements, less efficient computing technology, difficulties in data collection, and limited applications contributed to the closing down of many neural network research labs and researchers moving to other fields. However, in the mid-1980s, owing to many factors, interest in ANNs revived. Besides improvements in hardware and software, new learning techniques such as back-propagation period also lent themselves to circumstances that made it practicable to apply neural networks to increasingly complex problems. The combination of all these above factors resulted in a period of quick development for ANNs [2]. However, despite an early interest in the research and application of ANNs to aerospace, and many interesting ideas and prototypes having been developed, interest in ANNs waned back in the 1980s.

3. Deep Learning Techniques and Algorithms

This section explores the rapidly emerging field of deep learning, addressing its constituent components, techniques, and algorithms. An introduction to the various technologies that include or relate to deep learning—from a working, technical, or research standpoint—is provided. Since the primary focus is on the application of deep learning within advanced manufacturing technologies, this section is aimed more at aiding comprehension than providing expertise.

Deep learning, a specialization within the broader field of artificial intelligence (AI), is one of the best-known and most-discussed technologies of the twenty-first century [4]. Understanding the foundational components, techniques, and algorithms of deep learning advances will provide greater knowledge of the technology. It's essential to begin with the basics, as deep learning research cannot be done without understanding its constituent components. Typically, the word artificial (as in artificial intelligence) denotes something that is not natural or is manmade. The complementary word "natural" refers to something that exists as part of nature and is not created or caused by people. In attempting to differentiate depth of knowledge, the words "superficial" and "deep" are oftentimes used. A superficial understanding of something suggests that one knows some surface aspects—a little bit about many things without a grasp of the foundations. A deep understanding indicates that one knows the fundamentals and therefore has a grasp of both the breadth and knowledge [6].

3.1. Neural Networks

Deep learning techniques: Neural networks.

Neural networks are a key concept within the exploration of deep learning techniques and crucial in the context of advanced manufacturing technologies. They are composed of an input layer, one or more hidden layers, and an output layer. The hidden layers are the prime focus of neural networks, where information is processed [4].

ANNs are the earliest neural network architectures and were proposed by McCulloch and Pitts in 1943. They are capable of solving simple and complex problems. There are various types of neural networks, including DNN, RNN, CNN, FNN, GRNN, ELM, and RADIAL, and of these, DNN is a basic type of neural network with multiple intermediate layers where each layer has more than one neuron [7].

4. Applications of Deep Learning in Advanced Manufacturing

With the proliferation of deep learning technologies, research and development have been actively conducted in diverse fields. In the manufacturing sector, deep learning technologies are widely used for product inspection to improve quality and yield. Deep learning-based product inspection systems employ convolutional neural networks to extract learned features from a product's image. Then, the inspection result is determined after comparing and classifying the learned features. However, to ensure the performance of the deep learning inspection systems, it is crucial to prepare the appropriate dataset and model architecture for each inspection system [8]. For the target inspection model, training the deep learning models of each production line separately requires collecting a large amount of data for each inspection system, which takes significant time and manpower. To address the aforementioned problems, a simple transfer learning technique called fine-tuning can be used. Fine-tuning reduces the amount of data required to learn target inspection models while expanding deep learning inspection systems to other lines. This has the advantage of ensuring a certain level of performance, even with a small amount of training data because training does not start from random parameters. Similar to fine-tuning, domain adaptation can be used to expand the inspection model in a multi-line manufacturing system. Training a separate model for each inspection system requires preparing datasets with labeled images that take considerable time and effort. The domain adaptation technique adapts two different domain distributions to reduce the discrepancies between the upstream and downstream domains. Using this technique, the model is adapted not using the images from downstream domains but aligning the domain distribution of the target lines to be adapted to the distribution of the pre-trained deep learning model. Deep learning technologies are widely used for various quality management techniques in manufacturing sectors. In the current state, however, the quality control and inspection processes still rely on statistical methods and conventional computer vision technologies [9].

4.1. Quality Control and Inspection

Within the applications, this section discusses quality control and inspection as an important area in advanced manufacturing where deep learning technologies are being applied. In particular, deep learning methods using various types of input, such as images, sounds, or signals, are presented. Advanced manufacturing technologies enable mass customization—producing a high number of different products economically. The increasing variants of products and shortening life-cycles increase the pace of change of manufacturing processes, making it difficult to adjust the process parameters manually [10]. In such dynamic environments, an automated detection of defects before the final quality control process is required. To achieve this, machine learning-based approaches are among the alternatives explored in the scientific community. As a part of a larger project that focuses on automatic defect detection in advanced technologies, approaches based on deep learning using images, waveforms, and sound inputs are proposed [8]. Moreover, feasible options for the preparation of datasets for model training are discussed.

Quality control is a key activity performed by manufacturing enterprises to ensure products meet quality standards. With the increased usage of sensors and fast camera systems for gathering data on acquired products, manufacturing enterprises are taking advantage of their data. However, the degree of utilization of such data is often low due to a lack of tools for extracting meaningful information from them. The decreased cost of sensors and connectivity enabled an increasing topic of studies in the area of deep learning applications in manufacturing. In addition, the decreasing cost of computing power, memory, and storage units led to the increasing digitalization of manufacturing. Artificial intelligence technologies-enabled higher degrees of automation, reducing overall costs and time required for defect inspection. Various solutions for defects detection using deep learning adopted in manufacturing are presented. Solutions where deep learning is implemented without fully automated defect detection are also highlighted.

5. Challenges and Limitations of Deep Learning in Advanced Manufacturing

Despite their high potential for helping advanced manufacturing, a few challenges and limitations associated with deep learning must be addressed. This includes the issues related to data, including data quality and quantity. Data acquisition and processing, which were typically easy approaches for traditional machine learning, have become the main obstacles in the application of deep learning technologies [11]. Nonetheless, these obstacles can be overcome with the development of better low-cost sensors and cameras, with better algorithms and hardware for real-time data processing, or with comprehensive industrial 'big-data' analytical solutions.

Data quality relates to how data is noise-free, homogeneous, defect-free, and ground truth defined; industrial data are typically diverse and do not comply with such attributes. The following solutions can be employed either separately or in combination to mitigate the problem of data quality [1] : (1) pre-processing data with filters and data-mining algorithms to remove outliers or wrong values from the data set, (2) using domain knowledge and expertise, even if imperfect, to correct, complement, or validate the data set, (3) accepting and modelling the state-of-theart uncertainty to account for incomplete and noisy data in data-driven methods (the so-called Dempster–Shafer theory, direct probability estimation, data reconciliation), and (4) using generative deep learning models (e.g. GANs, VAEs) to synthetically create noise-free and homogeneous training (or reference) data sets. Challenges related to data quality must be carefully considered from the very beginning during every phase of the deep learning process.

5.1. Data Quality and Quantity Issues

The observations on major challenges and limitations are provided below to create a better context for some of the opinions and proposals already presented. As deep learning models require huge amounts of data for training, this is one of the first factors to be considered. If there is not enough data available in an existing company and it is not trained on a huge and diverse dataset, a company's entry into deep learning appears to be much harder than it is often portrayed [12]. If there are datasets available, they must also be validated first. In individual companies, datasets might often comprise only a fraction of the variance featured in a huge and complex dataset, as in the case of advanced manufacturing. This leads to the discussion of the applicability of techniques that can be employed when dealing with non-diverse datasets.

Apart from the absolute amount of data available for training a deep learning model, overcoming legal barriers when collecting additional data, e.g., in a factory, can increase the company's upfront costs as well. Because of the high costs of modern machinery and high demands on precision, many processes must be monitored and several approaches to models of inner status, product quality, and others must be examined before deep learning can even be executed in scientific studies. The development and production of electronic goods, e.g., chips or boards, are classic examples of high precision and costs. In these markets, the production equipment needed to manufacture a chip can easily exceed several million euros and one incorrectly placed electrode that results in a product scrap material worth millions. To make sure that the manufacturing process continuously offers the high precision required for chips, identification with a virtual method of features that correlate with quality must be performed first.

6. Future Trends and Opportunities

The future of advanced manufacturing technologies (AMTs) is leading toward a new environment in which all equipment and devices are able to connect to each other via the internet and exchange relevant information, such data, material, and energy. This future of manufacturing will allow resource and power saving, faster and more effective production planning, monitoring, control and management of manufacturing processes, and many more benefits [13]. AMTs are already beginning to merge with the Internet of Things. Although the IoT usually refers to the connection of everyday devices such as cars, household appliances, and building sensors, it also includes the connection of industrial equipment and devices such as CNC (computer numerical control) machines, robots, and workstations that are part of the industrial cyber-physical system [1]. The convergence of advanced manufacturing with the IoT will lead to a significant change in the manufacturing landscape and will make manufacturing smarter, more efficient, and more flexible. However, many implementation challenges need to be addressed for Smart Manufacturing Systems to become a reality. In particular, there is a lack of methodologies and frameworks that support the mapping of data and information exchange between manufacturer equipment and devices and manufacturing applications.

6.1. Integration with Internet of Things (IoT)

Integration of deep learning technology into advanced manufacturing technologies can create new opportunities for increasing product quality, reliability, manufacturing cost reduction, and production lead time reduction based on the information collected or available in the entire manufacturing lifecycle [14]. However, to fully exploit all opportunities, deep learning is required to be integrated with the internet of things (IoT).

Deep learning, devices, and machines supported by sensors along with the product, process, and quality control, are integral parts of the manufacturing ecosystem facilitated and integrated by the cloud [13]. The proposed deep learning integrated IoT-based manufacturing ecosystem promotes learning enhanced smart connected devices manufactured with progressively complex deep learning algorithms learnt preferably on an evolved edge on-chip with few-shot edge transfer learning for faster competition facilitation in making possible more complex integrated capabilities. On the edge side further captured data aggregation and transfer operations are performed essentially reducing latency and bandwidth congestion silicon on which mass data storage for the entire journey of manufacturing is done. These evolvement of the manufacturing ecosystem offer an attractive future direction for the further development of deep learning and manufacturing technologies.

7. Case Studies and Success Stories

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Deep learning with neural networks is applied by an increasing number of people outside of classic research environments, as the countless successes in fields such as translation, image understanding, and games by the press column hint at, often despite lacking a formal background in the field. At the same time, practical work in deep learning on novel tasks without existing baselines remains a challenge. As a necessary prerequisite for most deep learning attempts, gathering and cleaning the data set itself is often the most research-intensive part of the task, and it may take months before any algorithmic deep learning intervention can be made on data sets studied only with distinct approaches. This paper describes the specific challenges arising in the realm of real-world tasks, and extracts lessons learned from them, based on case studies from research & development in conjunction with industry. Recognizing the disparity between environments of algorithm publication and application, it thus fills a gap between the publication of latest algorithmic and methodical developments and the usually omitted details of how to make them work in practice.

Increased demonstrations of success stories from industries and the scientific community experience in applying cutting-edge technology on novel tasks are believed to encourage and enable more such undertaking. At the same time, it is well-known that deep learning is not a panacea, particularly when data sets are smaller in size and number. The chosen approach for the used case often needs fully customized algorithmic implementations, while on the market mainly generic or too highly abstracted products can be found. Besides resulting in a lot of problems that deep learning would later need to be solved, such data exploration also requires plenty of back and forth exchanges with experts.

7.1. Industry Examples

Deep Learning in the Automotive Industry. USA (2019)

One of the most exciting technology breakthroughs in the last few years has been the rise of deep learning. State-of-the-art deep learning models are being widely deployed in industry, across a variety of areas. These developments have a huge potential for the automotive industry, and therefore the interest in deep learningbased technology is growing. Many product innovations, such as self-driving cars, parking and lane-change assist, and safety functions like autonomous emergency braking, are powered by deep learning algorithms. Deep learning is poised to offer gains in performance and functionality for most Advanced Driver Assistance System (ADAS) solutions. Virtual sensing for vehicle dynamics, vehicle inspection, automated driving, and data-driven product development are key areas that are expected to get the most attention.

Deep learning is redefining the way we interact with machines. It has achieved breakthroughs in historically difficult areas such as image classification and speech recognition. Deep learning refers to a class of models and algorithms based on deep artificial neural networks. The field of deep learning has matured significantly in the last decade. Increased compute power has been the main factor making deep learning a burgeoning field of artificial intelligence. Faster Graphics Processing Units (GPUs) and Graphics Processing Unit compute clusters have enabled the training of very large deep learning models. Deep learning technology is already widely deployed in industry, with an accelerating upward trend. A survey of Fortune 500 companies illustrates that deep learning has been adopted by a diverse array of industries, including the automotive industry.

Toward Fault Detection in Industrial Welding Processes with Deep Learning and Data Augmentation. Germany (2021)

The rise of deep learning models in the field of computer vision proves to return great benefits. This paper addresses the challenges on the industrial realization of the AI tools, considering the use case of Laser Beam Welding quality control. They use object detection algorithms from the TensorFlow object detection API and adapt them to their use case using transfer learning. The baseline models they develop are used as benchmarks and evaluated and compared to models that undergo dataset scaling and hyperparameter tuning. They find that moderate scaling of the dataset via image augmentation leads to improvements in intersection over union (IoU) and recall, whereas high levels of augmentation and scaling may lead to deterioration of results.

8. Policy and Regulation Implications

The integration of this emerging technology into advanced manufacturing, often characterized as the "fourth industrial revolution," brings with it societal, ethical, and regulatory policy implications. Such considerations are particularly important given the potential magnitude of impact this combination of technologies may have. Although reflections on the emerging societal implications of AI/machine learning technologies in manufacturing are few [16], some general comments and queries are offered. One major implication concerns ethical considerations associated with deep learning manufacturing technologies. Ethical questions raised generally pertain to the extent to which processes (and consequent decision making) informed by these technologies can be interpreted as being trustworthy, if not entirely deterministic and unexplainable. Important questions are solicited regarding the extent to which deep learning-based technologies and processes are anticipated to be free from bias, particularly in terms of disparities owing to race and gender.

As incremental AI/machine learning applications in manufacturing technology become increasingly widespread, complementary organizational and institutional investments are foreseen as being necessary to realize their full benefit. A more complex set of public and private policy and regulatory strategies will need to be developed and implemented with respect to competing, cooperating, and otherwise interacting stakeholders. These organizations would encompass manufacturing firms and their workers, equipment and software vendors, professional organizations, and government entities. Given the early stage of consideration of such policy dimensions, the analysis does not attempt to delve deeply into them, but rather raises questions for thought and debate. To help frame and focus such queries, a range of potential stakeholders is considered.

8.1. Ethical Considerations

Within the examination of the policy and regulation implications of technological responses to the societal impacts of AI applications in manufacturing, analysis turns to ethical considerations. There is a growing consensus that deep learning applications should be explicable, transparent and accountable to avoid discriminatory outcomes. While ethical frameworks for AI in manufacturing and on the social implications of AI applications from a manufacturing systems perspective are nascent, there is an opportunity for academic scholarship to inform industry and be catalysts for needed protection [16]. Within academia more broadly, the research proposed in the policy implications section and the corresponding partnerships have potential to broaden the scope of investigations into the societal implications of AI applications. There is potential to engage with ELSI (ethical, legal and social implications) researchers and to inspire similar engagement in other regions. Recent reports highlight a gap in ethical frameworks and guidelines for AI applications in manufacturing. There is considerable urgency to address this and additional cooperation between industry, government and academia will be critical to the success thereof [17].

9. Conclusion and Recommendations

The findings from this paper suggest that deep learning will have a significant impact on Advanced Manufacturing Technologies (AMT) in USA by 2034. The application of deep learning to AMT systems is expected to increase substantially, resulting in changes in practices, risks, opportunities, workforce, and the spread of systems and benefits unevenly across sectors.

The strong expectations regarding the impact of deep learning are increasingly connected to an ongoing hype surrounding AI. The risk exists that the expectations exceed the realities, leading to disappointment. Policymakers need to support more basic research and development, and the coordination of the integration of deep learning with AD technologies. Additionally, there is a need to explore how to better understand the possible future impacts of deep learning, including better foresight tools or frameworks, and the possible establishment of future expectancies within AMT as a community.

9.1. Summary of Findings

This essay has conducted a thorough examination of deep learning's implications for advanced manufacturing technologies (AMTs) in the USA, addressing the research objectives set forth. Key insights have emerged concerning the role of deep learning in the advancement of AMTs, the need for a synthesis of existing knowledge, an analysis of the current landscape in both academia and industry, and the identification of barriers to further advancement and integration [1].

Deep learning is a subset of machine learning characterized by multi-layered neural networks that extract features from data, both in supervised and unsupervised forms. These neural networks consist of an input layer, multiple hidden layers, and an output layer, where each layer comprises interconnected neurons that process data through weights and biases, allowing for the learning of hierarchical representations. With ever-increasing data size and computation power, deep learning has quickly gained ground in a variety of industrial applications. In contrast to classical machine learning methods, raw data sets are fed into the model, thereby automatically extracting pertinent features instead of manually engineering them through domain knowledge. Hence, deep learning is often seen as a second revolution of artificial intelligence (AI), with the first one taking place in the 1980s using classical machine learning methods and expert systems. Formerly, AI overcame challenges such as vision recognition and natural language processing, whereas currently, deep learning uses a broader array of approaches, including computer vision, neuro-linguistic programming, and robotics. Today, deep learning is reshaping several industries, including autonomous vehicles, (financial) risk management, healthcare, smart cities, personalized marketing, and social analysis [16].

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