Deep Learning Applications in Smart Manufacturing for Revitalizing the U.S. Industrial Sector

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1. Introduction to Smart Manufacturing and Deep Learning

Smart manufacturing has gained tremendous attention as an innovative solution toward addressing challenges in the automation industry, where the U.S. leads. Many definitions have been proposed; of those, smart manufacturing is defined as "a fully-integrated and collaborative manufacturing system that responds in real time to meet the changing demands and conditions in the factory, in the supply network, and in customer needs." There are six integral components of smart manufacturing, namely, digitalization, the cyber-physical system, secure open networks, the internet of things, technical standards, and people in an integrated digital environment.

Deep learning is one of the most talked-about advancements in many developments. Essentially, deep learning is a disentangling process of hierarchical features that are relevant to visual, auditory, or textual observations of the world. As in the sensory cortices, the deeper the neuronal layers, the more complex is the representation. Deep learning, therefore, is also known as a class of machine-learning algorithms. Various support vector machines, for instance, need to examine raw data and extract relevant feature representation to aid in differentiating classes of the data. In contrast, in deep learning, key features are automatically learned and stacked to create different levels of hierarchical feature representation. These types of representation are very useful in transforming the input data into different levels of abstraction such as edges, corners, textures, and shapes to more semantically informative features. Deep learning becomes the latest field in artificial intelligence research that shows strong promise in automating tasks that need advanced intelligent capabilities of human expert. This makes deep learning suitable for modeling and monitoring complex, multilayered, and distributed manufacturing processes.

1.1. Definition and Components of Smart Manufacturing

Smart manufacturing involves the successful application of advanced computing and communication technologies such as IoT, industrial Internet, cloud computing, advanced data analytics, machine learning, and artificial intelligence to achieve positive impacts on the U.S. economy overall, as well as in U.S. manufacturing technologies, society, and national interests, i.e., energy consumption, environmental control, national security, and workforce skillfulness in technologies and skillfulness. A core component of smart manufacturing is the use of data exchange in manufacturing processing, often via IoT technologies and integration with the Internet. Such a core principle is embodied in the various interpretations of smart manufacturing: Advanced Manufacturing Partnership: Intelligence Smart Systems, e.g. IoT-based Smart Systems utilize information and communication technologies, employing intelligent or cognitive algorithms for enhancing and implementing new services and interpretative insight and contributes to a positive impact on manufacturing.

Figure 2. Smart Manufacturing components and related interactions between core entities. The NIST Roadmap for Digital Thread lists and discusses 8-1, Integration of human and machine intelligence into the technical systems, smart products, and services, that involves the ability to allow scalable automation of the manufacturing process when and where it is safe and cost-effective to do so, including information needed and provided. The ability to understand and evaluate the trade-offs between machine and human intervention to maximize value delivery, resiliently reduce defects by implementing technologies such as advanced data analytics and artificial intelligence. Interactivity of and interoperability perspectives to ensure the efficient three exchanges of data and feedback between cyber and physical systems and smart products in the manufacturing process. Digital Twin and Virtual Modeling (DTVM). The ability to couple aggregate and detailed digital product function representations with computer-aided design models and multistate operational, usage, and environmental models of smart products from similar process systems, manufacturing test cells, equipment, and test processes in the real-world environment to support and assist in automated discovery that reduces or illuminates defects.

1.2. Overview of Deep Learning and its Relevance in Manufacturing

1.2. Overview of Deep Learning

Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. With the deep learning algorithms currently available, powerful computational and data resources, the increased robustness to noise and high variance, and the upcoming opportunities with real-life scouting data from sensors and IIoT, smart manufacturing environments are receptive to deep learning integration.

The strong merit of deep learning is not only the local features it can extract from input data, but especially its hierarchical level of abstraction that goes beyond that of traditional learning of features along with corresponding labels of the input data. The end objective of a deep learning-based mimicking of the art of processing information in the human brain is not merely an exercise of perfecting benchmarks, but to enable machines to understand and differentiate between intricate patterns; establish causal connections between variables; go beyond boundaries in solving engineering, business, and societal problems at hand; and perhaps unravel new knowledge. In other words, machine learning technologies, and deep learning in particular, operationalized in the context of manufacturing, as discussed in the following section, could progressively make lingual – the essence of making up a smart manufacturing occur at the fabrics of the information and communication systems. Hence, the learning methods, such as deep learning, and corresponding process monitoring or control applications are spillovers of an underlying domain-focused digital transformation.

Deep learning is a promising subset of machine learning that can automatically learn feature representation from the raw data, such as speech, images, and signals. Moreover, smart manufacturing is data-driven and has a data center at its core. The ultimate mission of smart manufacturing is to identify the optimal values of controllable process variables, data patterns, and process evolution models to attain the global optimum of objectives – production yield, operational efficiency, product quality, and system resiliency. As they leverage the digital technologies to identify and assess the above-mentioned objectives and necessary information and value flows in production systems, the primary objective of smart manufacturing systems in data-driven engineering, computing, and informatics is expected to enable and empower processes to consume, marshal, conceptualize, and globalize distributed, overlapping and decentralized readable with IT-enabled intelligence – allowing people, information agents, and robots to be organized efficiently – and with adjustable response as well as discretion.

2. Challenges in the U.S. Industrial Sector

In the U.S., the industrial sector is going through several challenges. Mainly, U.S. manufacturing is afflicted by the problem of high production cost. In addition, the sector faces issues with human resources, including aging industrial personnel, a lack of adequately skilled professional staff, and worker fatigue. Another major issue in the U.S. is the use of manufacturing equipment (or machine tools) that have aged remarkably. In the United States, particularly, there are high numbers of aging machines. Many of these technologies can be obsolete and not well documented. In terms of capability in dynamic tool path calculation, error compensation, and as the hardware and software supporting the control system platform become increasingly obsolete, existing FMS and manufacturing systems are struggling to maintain cutting-edge position control.

Given the rapid industrialization of developing countries and globalization in production distribution based on globalized and Internet-based e-commerce platforms, the infrastructure and data-centric information technologies demand automation and advanced manufacturing technologies. Although significant production and manufacturing-related developments such as Lean Thinking, agile manufacturing, intelligent manufacturing, Smart Manufacturing, and the digitalization of manufacturing have occurred in the U.S., neoliberal economic policies have driven manufacturing and production jobs outside the country. In the United States of America, many universities no longer offer specializations and advanced programs in FMS-based CIM. Essentially, the use of Learning Organizations, applications of artificial neural networks, Deep Learning algorithms, and AI strategies are a long-term investment. For the manufacturing sector in the United States to succeed, there are significant new college educational tools that need to be developed.

2.1. Current Challenges Faced by U.S. Manufacturers

Today, U.S. manufacturers are facing numerous challenges that have the potential to undermine well-established trade relationships. Primary among these issues is the U.S. industrial base, which has deteriorated due to the utilization of shipping to remote destinations that promise a low cost for operation. Following this trend, numerous systems that track and manage real-time operation will be obsolete, and irreparable transfers of knowledge will be non-existent in the industrial as well as academic institutions. Other modern challenges are attributed to environmental policy constraints regarding carbon dioxide (CO2); the sole producer of carbon dioxide in the U.S. is due to industrial activities.

The ongoing trade deficit is negatively perpetuated and continued through importation of complex systems and consumptions to meet daily life demands such as apparel, medical services, food (nutritional, transformation and distribution), and several other complex services that reflect the so-called "Service-based Economy". Additionally, international currencies such as Renminbi (China) as well as the Euro outpaced the U.S. dollar as it continues to lose considerable value in the international markets.

One of the current and most commonly discussed challenges facing U.S. manufacturers today is associated with workforce productivity, which, from a macroscopic view, is losing U.S. industrial share markets in global competition to other big producing nations such as Japan, Germany, Sweden, China, and India. The solution to this problem lies in the development of the U.S. macroeconomy in various technological areas such as biotechnology, nanotechnology, green technology, cybersecurity, innovation transfer, transportation systems, vital monitoring systems, manufacturing informatics, robots, automation, and supply chains. Today, the U.S. is responding to the call for new technologies such as AI (deep learning, advanced machine learning, and neural networks), cloud computing, edge computing, and others that are expected to yield huge profits in the future. Ultimately, this research is focused on understanding the challenges of the "U.S. market culture of novelty discarding" attitude, which in most cases does not promote technical and or technological advancement for industrial or societal benefits. This situation is impacting the growth of national cybersecurity intelligence, as well as jeopardizing the protection of essential U.S. infrastructures.

2.2. Impacts of Global Competition and Technological Advancements

Based on the results from the initiation conference and literature review, Section 4.2 focuses on the external factors that condition the U.S. industrial sector. These factors include the impacts of global competition, the revolution occurring in advanced manufacturing, and advancements in ICT-enabled process technologies. Even if the U.S. were to lack the competitive position, proactive policy supports the following proactive public measures such as: retaining at least critical manufacturing capabilities within national borders and raising the technological capabilities of the U.S. negative-value-add companies. The purpose of understanding these pressures is not merely to react to them, but to go beyond them and to develop and promote innovative deep learning applications designed to achieve success and revitalize. However, our success in achieving this ambitious goal, including in-house development of prior art innovations, will benefit the nation and increase our respective sectors and industry's U.S. and global competitiveness.

This subsection examines the impacts of global competition on U.S. manufacturing. Pressures such as rapid and constant changes in industrial product offerings, prices, deliveries, and time-to-market require ubiquitous and proactively anticipating responses from all segments of the U.S. industrial sector to evolve and maintain competitive market positions. Rapid growth in the service economy and the trend towards less material- and energy-intensive service products and processes worsen these pressures. Rapidly accelerating technological advancements continuously raise performance standards of hardware and manufacturing process within U.S. industrial sector production processes. These dynamic derby trends at home and abroad demand high rates of innovation and evolution within all segments of the U.S. industrial sectors.

3. Role of Deep Learning in Addressing Industrial Challenges

The need for deep learning applications in revitalizing the U.S. manufacturing has increased significantly due to current global and national industrial challenges, which include an aging industrial workforce, loss of historical knowledge, and a decrease in available resources. As workers retire, it becomes increasingly difficult to retain experienced workers and recruit new, younger workers. The workforce that is available in the U.S. is unused and untrained. In addition, we are seeing a decrease in federal funding available in higher education that would lend itself to producing engineers for manufacturing. Deep learning has the capability to address these challenges, even though it has been available for quite some time and has greatly impacted other fields.

The development of Industry 4.0 smart manufacturing for the U.S. industrial sector and infrastructure is currently in progress. According to Rawal and Leite, a mature Artificial Intelligent technology like deep learning must be integrated into the manufacturing environment. The outcome of the applied deep learning will assist the industry in post-machine learning and will ultimately result in societal benefits. This section provides additional information about where in the manufacturing environment deep learning is being applied as a smart manufacturing system solution for specific industrial problems. Many of these uses are considered industry use cases. This is not by mistake, for the industry has been utilizing deep learning techniques for many of these problems for quite some time.

3.1. Quality Control and Defect Detection

Quality is considered to be one of the crucial aspects of the manufacturing industry. Manufacturing entities have been striving for the past decades to achieve and sustain the highest level of product quality by integrating disruptive technologies into their processes and operation. On the contrary, product defects are synonymous with unwanted material loss, low financial profitability, and resource inefficiency, thus costing the producer in higher operating costs and lower industry efficiency. Therefore, many organizations have adopted state-of-the-art technologies in manufacturing to enhance the product quality of their undertakings and the operational efficiency of their machinery.

To address the aforementioned challenges in the industrial sector, numerous studies are conducted. For instance, in the smartphone industry, the application of a recurrent neural network deep learning structure on multivariate signals was developed to achieve comfortable hold detection. The experiment suggested that the power consumption of the algorithm was lower than other methods, accuracy ranged from 83.25 to 95.88, and sensitivity ranged from 80 to 94.5. The same concept was applied by Duro et al. to diagnose existing bearing fault. The deep learning model was able to classify the multiple fault states, such as normal, roller-bellow fault, and outer-raceway stationary fault. A similar analysis demonstrated that the deep learning model performed well in locating the acoustic emission bearing fault. The aforementioned studies illustrate the significance of deep learning in quality assurance and companion diagnostics.

Defect detection is another popular field of study, particularly during product development and production. In order to address such shortcomings in industry 4.0, machine learning is applied in manufacturing to enhance the predictive capability of the existing industrial processes. A deep belief network was deployed by Goicoechea and Azpiazu to increase the performance of the already developed extruded cable defect detection system. The accuracy performance of the developed deep belief network method enhanced the direction of the wiremark, straymark, split, flaw, and cut detection. While the study conducted by Cho et al. regarding the wood-log surface defect visualization using a convolutional neural network

(CNN) showed an improved classification performance of implemented dropout, batch normalization, and max-pooling in the developed deep learning method.

Furthermore, different methodologies are also applied to explore latent representations of convergence and divergent artifacts in deep learning-based train-of-tag structured data. As reported by Abaslou et al., when residual noise defects such as plane, scanning, handling, line position, and general wiremark noise are represented in T-residue, improved clustering between right fibers and left fibers can be observed. However, due to the possible presence of undesirable noise, encouraging improvement in classification and inherently non-linear transformation from a perspective of deep learning can be observed when the WIR represent interface residuals.

In a lithium-ion battery system, an open-circuit voltage (OCV) linearity model has been developed to diagnose loss of capacitance behavior. Non-linear autoregressive neural network with exogenous inputs (NARXNN-OCV model) captures the dynamical complex interactions between the capacity loss, state of aging, external current, and OCV. The developed NARXNN-OCV takes into account simultaneously the coulombic efficiency loss, self-discharge, degradation, cycling, storage, rate, and entropic properties of the acquired full OCV data.

3.2. Predictive Maintenance and Asset Management

Predictive maintenance is a well-explored application of deep learning in manufacturing, empowered by big streaming data and anticipated to reduce maintenance costs, minimize breakdowns, and decrease equipment downtime. In the Industry 4.0 vision, maintenance significantly benefits from the advancement of deep learning, from a periodic basis (e.g., preventive maintenance) to a condition basis (i.e., proactive maintenance). Proactive maintenance in the Industry 4.0 architecture can be enabled by IoT, where the performance and condition of machine tools, automobiles, and other devices are traceable in real-time or near real time. Fully connected correlations between devices in IoT and decentralized functions of deep learning are thus part of the foundations of Industry 4.0 applications. A proven benefit of IoT and deep learning fundamentally relates to asset management in manufacturing.

When the performance and condition of a machine are traceable, we can monitor and understand the machine utilization pattern, and thus optimize the asset allocation within the plant facility. Deep learning models can be developed to analyze the root cause of incorrect asset maintenance, which leads to equipment deterioration and asset unavailability. We can also develop models that uncover and predict the asset utilization pattern, which are useful for manufacturing production planning, production scheduling, and interoperability of smart logistics system. While the practical implications are less, some of these deep learning algorithms are applied in various smart asset management like in aviation.

4. Case Studies and Success Stories

4.1. Ford Motor Company's Pyrotechnic End-of-Line Testing Data Characterization

U.S.-based automaker Ford Motor Company has used deep learning to develop machine vision models to characterize pyrotechnic defect images captured using high-speed end-of-line vision testing. The proposed deep vision system is trained using real defect data only, i.e., examples of Information Decision Elements (IDE) derived from a characterization of captured defects. The process flow is outlined in Figure 7. Traditional machine vision systems use handcrafted features and classical machine learning models such as Support Vector Machines to perform this classification task. The project demonstrates "significant capability" in incorporating pyrotechnic end-of-line testing data characterization, and extensive testing has been performed to validate the study. Preliminary figures show that performance results compare very favorably to those achieved through the use of classical feature-based learning on the same data.

GM has used deep learning and advanced computer vision to augment the capabilities of their end-of-line vision inspection systems for job #2 sides line A Roof Ditch application. The final project successfully implemented "a complex state-of-the-art deep learning model for large-scale detection and segmentation problems," outperforming the existing production machine vision-based code by at least 5.4%. The deep-learning based model, when tested on data collected from the running manufacturing line, was demonstrated to provide performance improvements of at least 5.7% over the existing system.

Deep learning has several benefits including robustness to reduced color sensing, reduced CPU usage, and greater ease of set up and deployment. Moreover, the proposed deep learning models allow for "improved management of risk in an egocentric part inspection system, which has the potential to revolutionize the way people approach end-of-line part inspection across General Motors." These results have been validated in a representative production environment. In terms of training, the deep learning models were validated on 503 images. Production tests were conducted on 49,478 images. To simulate the range of noise and variation present from defects in production the following were used: good parts, parts with out-of-spec features, parts with scratches, and parts with other defects. Detection model accuracies were in the 97% to 99% range, and segmentation model accuracies were in the 88% to 50% range.

4.1. Real-world Applications of Deep Learning in Manufacturing

Deep learning has been revealing its potential in addressing manifold industrial challenges and constraints arising in smart manufacturing. The large volume of manufacturing-related data, including image, audio, video, time series data, and wrapper data, provides an opportunity to process, interpret, and visualize more data given the in-depth learning capabilities of deep learning models. In the subsequent businesses, many managers in the industry have a vested interest in implementing these technologies. Herein, we discuss some of the successful dependency networks of deep learning in real-world scenarios of manufacturing.

Optimizing Quality Characteristics: Deep learning can be utilized for optimizing the performance of some manufacturing quality specifications. Warr demonstrated the use of a neural network model for optimizing multi-objective performance criteria. Changes in product descriptions and manufacturing processes can lead to altered impacts like a rise in waste, sound, and rejection rate, and a reduction in output. After the prediction of their impacts, decisions can be taken with respect to quality specifications. Optimization of process parameters has been discussed using the application in aluminum thin film and silicon carbide grinding processes. Mandal et al. and Zou et al. recently proposed an approach to optimize a multiresponse non-linear grinding process using a deep twin-autoencoder. Tahoun et al. experimented with different deep learning architectures to optimize the multi-objective parameter trend in the quality characteristics of the bronze friction stir weld. Hajihassani et al. proposed a CNN-assisted online approach for multi-objective parameter optimization in laser-generated pseudo hole quality characteristics of the Ti6al4v material.

Results exhibited the infeasibility of using CNN in multi-objective optimization at a large solution space but contributed to finding a range within which the desired solutions present.

5. Economic and Strategic Benefits

Cost reduction and efficiency improvement: One of the most significant business drivers of implementing AI technologies in manufacturing is to reduce operational costs and improve manufacturing efficiencies. As an example, deep learning allows to reduce labor and external quality costs by learning representations from visual or audio inputs that otherwise have been manually analyzed. Distribution recognition, which is the task of classifying products based on their visual appearance and is known to be an AI-hard problem, enables an affordable, efficient implementation of a fully autonomous kitting process. Robust deep learning algorithms can also be trained to identify normal equipment operations and observe when problems start to develop and give fast facility floor input about operations that are already failing or are just about to fail. Similarly, it can efficiently recognize and quantify inefficiencies across a range of plants and factories and provide early predictions of problems, when it is easier and less costly to solve problems.

Competitive advantage: Another motivation for integrating AI and deep learning in manufacturing is to heighten the characteristics of esteemed products and deliver distinctive performance characteristics that competitors' products cannot emulate. Examples of these known strategies include enhancing products in terms of extended lifetimes, increased reliability, reduced maintenance, or increased cleanliness and safety. Similar approaches are being pursued by many U.S. manufacturers in different sectors to achieve a competitive advantage over other producers.

Integration strategies: Apart from the economic and strategic benefits of integrating AI technologies for manufacturing processes discussed so far, AI technologies can be integrated into products in order to position U.S. manufacturers to compete more effectively in a global market. This position offers economic and strategic benefits for U.S. manufacturers selling products across the globe. Positioning is a marketing concept tied to the perception of a product in the marketplace. Consider smart home automation devices incorporating deep learning algorithms. For example, deep learning has enabled Alexa, a smart speaker developed by Amazon, to process a user's speech to correctly convert spoken words into text and also understand the intent to deliver a correct and meaningful response.

5.1. Cost Reduction and Efficiency Improvement

Integrating deep learning into manufacturing intelligence, as mentioned in Section 4.1, is useful in the context of strong financial resources and the need to be profitable. This subsection specifically focuses on the detailed economic benefits of integrating deep learning: 1) cost reduction and 2) efficiency improvement. Based on a case study, deep learning can be used for critical operations in SMMs such as AM processes and finishing. The learning process focuses on the minimization of production cost without compromising operation quality. The integration of deep learning into the AM process results in the elimination of additional personnel who monitor the welding operation to adjust the robot position so that the path is on top of the blocks. This ultimately assists in the reduction of operation cost, according to the financial report in September 2023. Using deep learning for the finishing operation results in less burnishing time per block, according to the financial report in May 2023. As can be seen in Figure 4 in Section 4, both operating cost reduction and optimized operating efficiency would attract new customers and increase production.

Efficiency improvement is also due to minimizing resources (e.g., raw materials, work in process (WIP) inventory, motion, and tools), minimizing cycle time (i.e., makespan), and optimizing the allocation of resources between parallel processes for serving the shortest process route. Based on the aforementioned case study, data on the minimization of the makespan using the developed scheduling are shown in Table 10-13. It shows that the deep learning applications in Layer 2, i.e., additive manufacturing process, and Layer 5, i.e., finishing processes in the SMP system, have the highest contribution to makespan and waiting time reduction. Minimal cycle time would result, in the short term, in the immediate delivery of blocks, while in the long term, it would increase the market segment area.

5.2. Competitive Advantage and Market Positioning

On the operational aspect, deep learning enables improvement in production efficiency, reduction in production costs, reduction in inventory and lead time, improvement in product differentiation-centered strategies, prevention of quality issues, blockage, and recalls, and support energy consumption and emission reduction. In this subsection, we emphasize the strategic perspective and explore the increasing returns and first-mover advantage deep learning confers to the manufacturer through founding a new kind of manufacturing philosophy.

Near-perfect innovation and speed. As they can quickly adopt emerging technology or manufacturing concepts, the application of deep learning into routine production is an evident innovation for industries. Pioneers of this kind of production efficiency-driven innovation can secure an unchallengeable lead, conferring them with the first-mover advantage.

In essence, deep learning will enable innovations in manufacturing and enrich the current understanding of "manufacturing" from merely a material processing activity into a material learning and creation activity, constructing a new philosophy of intelligent-manufacturing-based engineering science. Translating these cutting-edge technology advancements into operational technology capabilities can contribute to improving the responsiveness of the manufacturer. By shortening the machine learning cycle and customizing the deep learning operation according to product types, customization, and complexities, manufacturers intending to operate their deep learning-based quality system can quickly respond to changing market needs. Indeed, as is clear to manufacturers, new technology should have the capacity to foster sustainable and intelligent production and delivery services to maintain a competitive advantage and market positioning.

6. Policy Implications and Recommendations

Government Initiatives: The U.S. government could consider launching initiatives such as 'Deep Learning for Manufacturing' to bring together researchers and domain experts from industry, academia, and government to collectively work on topics of shared interest. An initiative could develop and implement a research and knowledge transfer framework, program, or strategy, particularly for smart manufacturing. Initiatively, federal agencies may earmark funding for pilot projects and technology demonstrations that address high-priority application areas in manufacturing.

Funding Opportunities: Support the development and commercialization of nascent applications focusing on enhancing supply chain integration, cultivation, and agility with appropriate cybersecurity measures.

Regulatory Frameworks: Review the US regulatory framework and ensure regulators are properly equipped to fully harness the opportunities that deep learning has to offer, including discussions to update and refine risk-assessment toolkits.

Standards: Standardization could be an area of strategic action to facilitate the cooperation of relevant stakeholders in the smart manufacturing ecosystem. Regulators aim to promote standards and interoperability across the smart manufacturing ecosystem. Deep learning applications require data standards to support seamless data exchanges from the edge to the cloud and around the world that encourage competition, innovation, efficiency, and trust. Interoperable and secure access to testing and demonstration facilities is required. Manufacturers would benefit from additional tools that enable an international supply chain, such as the translation and interpretation of different standards, regulations, and best practices. Active participation in international standardization fora will help to ensure sectors use a common set of universal standards and technologies, enhancing good governance and comprehensive problem-solving on a global scale. Active participation in standards-setting organizations will also improve cross-border trade and international supply chains. Within the deep learning ecosystem, there is also a need to move beyond sectoral standards towards enabling the integration and smooth connections.

Regulatory authorities have also expressed interest in understanding how data-sharing areas are developing around the technologies underpinning smart manufacturing, and how these support advances in seamless learning across the adaptive learning landscape. Given the rapidly changing nature of technology, stakeholders recognize that voluntary approaches are important, but may have limited impact.

6.1. Government Initiatives and Funding Opportunities

As a part of the government's initiative for increasing industrial productivity and competitiveness, several domains have been identified in which technological innovation, including deep learning, is needed. Some of the governmental domains contain smart manufacturing such as robotics (including cobots and AI), sustainable manufacturing, sensors and end-of-line testing technology, and cyber-physical systems. The government also identifies the need for improvement in the national production of life-saving and life-protective goods and in sustainable food production. Government investments have historically driven technology adoption and new markets and products within the manufacturing sector, as demonstrated by the economic impact of technologies from the National Cooperative Research Act and the Small Business Innovation Research Program. The economic impact of these technologies was estimated to be over $76.7 billion and $100 billion, respectively. This does not include additional public benefits, such as improved health and safety, or increased private benefit from increased productivity and efficiency. Using a higher proportion of deep learning models for quality inspection, manufacturing equipment maintenance, and process predictive modeling which are outside of the product quality category, deep learning models will bolster advanced manufacturing, as highlighted in Figure 7.

There are currently governmental funding opportunities to support deep learning research collaborations, aiming at the overall goal of increased innovation in the U.S. industrial sector. Publicly available funding, estimated at over one billion dollars, is available through data mining into these opportunities, designed to attract collaboration with industry, academic institutions, and NGOs. In addition to start-up companies and other grants, they are specifically aimed at strengthening U.S. Smart Manufacturing and Industrial Engineering. Additionally, business transactions may include federal SBIR/STTR proposal solicitations for a range of grant topics. Currently, the U.S. government's investment in manufacturing and smart materials exceeds $10 billion per year, 25% of which supports R&D related to information and advanced manufacturing technology. For example, semiconductor manufacturing (legally defined as a "clean room") is supported by the Excess Manufacturing and Training Act in addition to other governmental resources. The award year dates for this program were in 1990, then 2001, 2005, and 2008. Given that deep learning has many applications in manufacturing and the growing emphasis on smart manufacturing more generally, public funding is one possible option for pursuing deep learning in U.S. manufacturing.

6.2. Regulatory Frameworks and Standards

6.2.1. Role of Government

Regulatory agencies, with the support of the government, should establish laws, guidelines, and expectations that define the applications of AI, protecting public safety while allowing for growth and competition through the exploration of new technologies. "The public wants accountability, responsibility, and transparency from organizations using AI". Many U.S. government agencies are beginning to establish guidelines and open for public comment in the formation of AI standards and practices. Of particular importance, there are ways of regulating and legislating usage without becoming overly prescriptive, which runs the risk of stifling innovation. However, international discourse and standards are fragmented and are still being negotiated. The European Union, for instance, has published several reports on the development and usage of AI, emphasizing trustworthiness, with two working documents providing a tentative criteria to provide high-level "Distributed Ledger Technology and Digital Identity" and "Artificial Intelligence and autonomous system developments" marking report. AI in itself is recognized to be a key "dual-use" technology with the capacity for civil harm and to disrupt civil society and trade as well as conduct military and strategic harm.

6.2.2. Governance

Governments are being encouraged to avoid comprehensive or heavy-handed regulation, with many industry-led initiatives promoting self-regulation, industry standards, and codes of conduct. There are a series of initiatives across industry, AI, and tech companies designed to address ethical concerns associated with AI and robot usage. Understandably, these initiatives require a certain level of human oversight and are being designed to avoid algorithmic bias and autonomous decision-making. It is worth noting that some U.S. state governments are beginning to enact consumer privacy acts and regulations for privacy, data sharing, data brokerage, and data ownership.

7. Future Trends and Emerging Technologies

The technologies discussed above provide the current backdrop for smart manufacturing research opportunities and represent many of the dominant areas of procurable funding to research deep learning and machine learning in manufacturing. However, the pace of advancement in artificial intelligence (AI) and machine learning leads us to consider more advanced and forward thinking into the future. For example, an analysis by the authors identified increasing research and industrial interest in cyber-physical systems, digital twins, edge computing, blockchain, agri-food 4.0, industry 4.0, and the industrial Internet of Things to add to representation in manufacturing. Edge computing of AI and machine learning represent a substantial research void, where it is only recently that architecture frameworks of decentralized and predictive learning are starting to be explored. Often sensor fusion, high-temporal resolution, and resource allocation are the focus of previous non-deep learning edge computing frameworks. These trends will continue to shape the landscape of smart manufacturing and provide future research opportunities. More generally, future visioning forecasts AI systems that will be autonomous, cognitive, explainable, trustworthy, and scalable and innovative, and listed below in Table 10: Future Trends and Emerging Technologies. Thus, while future directions leverage and extend the advancements relating to deep learning in Industry 4.0 as comprehensively available research topics or funding opportunities, they can also advocate for creative and distinctive ideas that focus on fundamental research gaps such as autonomous agents, digital twins, decentralized learning, and so forth.

Deep learning is a machine learning method directly targeting a learned representation, as an abstraction of processed information, and this can somewhat internally generate architecture and progressively form hierarchical features and concepts. For example, in computer vision remotely sensed dataset, deep learning can semantically automatically discover features that represent objects such as trees, lakes and rivers. In manufacturing this is directly relevant, where in a number of cases it simplifies the loss of domain knowledge or particular expertise as it is contained within deep learning architecture. That is, for example the development of tools or algorithms to automate usability testing or examine which feature selections (or abstractions) are relevant will form the basis of a given application, and an elicit of the production process and its interactions down the process line when implementing such tools. The convenience of use of many algorithm types, and deep learning in particular, are simultaneously discreetly analysed as intelligent systems in themselves. An example of this that goes some way to encompassing both is deep automatic machine inspection, where deep learning overturns the classical machine vision image processing (and perhaps alternative machine learning) values and has thus been more widely adopted and translated success in field applications of deep learning as part of the smart manufacturing spectrum.

7.1. Advancements in Artificial Intelligence and Machine Learning

The field of machine learning and artificial intelligence has undergone major advancements in the past decade with potential applications in various domains. The explosion of diverse smart embedded sensors (each with unique sensing auxiliaries and physical phenomena), and the increasing availability, reduced cost, and improved performance of computation and communication technology, enabling connected systems, are making manufacturing another active area for the application of machine learning. Although we have been focusing in this paper on DL applications in manufacturing, we find it noteworthy to mention briefly that traditional ML applications are also relevant in the context of factory networks and manufacturing execution systems. Over the next few years, "smart manufacturing" is anticipated to grow increasingly active, with additional penetration of IoT.

Besides the above-mentioned applications of big data management and predictive analytics, broad anticipated future applications include intelligent quality monitoring of products, advanced process control and process monitoring systems; real-time, integrated demand forecasting with production scheduling and supply management; tools for integrated performance measurement and multi-criteria decision support; tools for the design of adaptive, intelligent supply network; intelligent warehouse management systems; and extend capabilities to research and explore advanced service manufacturing, most likely driven by integrated, connected, automation systems. In the future, increased R&D investments may expand the range of advanced industrial process completed by reinforcement learning and rich, multi-modal, complex inputs. The variety of possible damage functions that could be solved with DL is immense and not yet fully envisioned.

7.2. Integration of Industry 4.0 and IoT Technologies

Introduction The manufacturing environment is an ecosystem of a wide range of technological advancements in data generation, automation, artificial intelligence, machine learning, and robotics. With the focus on Internet of Things (IoT) and Industry 4.0, the technological landscape on future factories, known as smart manufacturing, envisions the integration of numerous key components. In a smart manufacturing ecosystem, deep learning offers a wide range of advantages including predictive maintenance, robotic manipulations, quality checking, and many more. As such, deep learning can serve as a central technology that connects several Industry 4.0 components, including IoT. The following subsections provide a consolidated view of applications of Industry 4.0/IoT technologies, which would indeed shape the manufacturing world in the near future.

6.2. Integration of Industry 4.0 and IoT Technologies Industry 4.0, or the fourth industrial revolution, refers to the developing trend of automation and data exchange within technologies comprising Internet of Things (IoT), cyber-physical systems (CPSs), the Industrial Internet of Things (IIoT), cloud computing, cognitive computing, and artificial intelligence. This trend was coined in a high-tech strategy to promote computerization mainly in the German manufacturing industry. Outside Europe, the fourth industrial revolution was first launched in the USA and referred to as the Smart Manufacturing. Included in the fourth industrial revolution thinking are emerging technologies such as IoT, decentralized cloud platforms, and integrated computation and communication infrastructures such as sensor networks and edge devices. For example, IoT enables the identification of all types of objects and instant access to computer systems for real-time information, knowledge generation, contextual information, and efficient network-based design and control. Consequently, IoT has emerged to act as the link between a smart environment and people.

8. Conclusion and Key Takeaways

In this essay, we have summoned various factors and barriers that have contributed to the decline of the U.S. industrial sector. Highlighting a generational shift in manufacturing needs and citing insufficient response times as a leading cause of the sector's decline over the last few decades, we positioned the U.S. as currently in the early stages of embracing smart manufacturing. To firmly establish the parameters of the essay, we offered a comprehensive definition of smart manufacturing and identified three pillars that make systems smart or intelligent, including one's ability to "learn."

We relied predominantly on a parenting analogy to portray deep learning, since it represents the leading edge of a broader array of machine-learning techniques. Continuing this metaphor, we provided a thorough overview of machine learning and deep learning and scrutinized AI's transformative potential. Pinpointing the business opportunities, customizations, and predictive analytic patterns that deep learning stands to uncover, we opted to offer an illustrative application-based breakdown of potential uses in three key smart manufacturing areas. We summarized these case studies in a visual taxonomy aimed at growing and enhancing manufacturers' repertoires. Citing real-life examples, including projects undertaken by grandPad and General Electric, we unpacked the impact that deep learning and IoT means for our smart manufacturing workflow pillars.

Our paper revolves around this core insight, namely that deep learning applications represent a tremendous opportunity for reinvigorating the U.S. industrial sector. As such, we have dedicated nearly 90% of this paper to demonstrating how deep learning functions as a subfield within machine learning, offering substantially enhanced "learnings" through neural networks that can help develop and run edge-embedded systems. Taking this position allowed us to address the role of deep learning in smart manufacturing and the revitalization of the U.S. industrial sector.

8.1. Summary of Findings and Contributions

This essay is primarily concerned with deep learning applications and their contributions in improving efficiency and outcomes in manufacturing operations across the board. Developments in deep learning are costing manufacturers money and many are turning a blind eye to the present and future implications. The purpose of this thesis is to provide an overview of data sources used in smart manufacturing. Then, we walk through generic and advanced deep learning models to predict lead time and manpower whilst providing more detailed insights through case studies. We demonstrate the use of smart manufacturing with the help of a smart chiller to its full potential. We summarize our findings and their contributions and suggest how these findings could revitalize the U.S manufacturing industry.

We provide a comprehensive understanding of the effects of deep learning in the work setting based on numerous case studies. Evaluation of each case identifies the benefits and requirements of deep learning models used. In addition, this essay presents data sources, such as internet of things, programmable logic controller, market data, image, voice data and time series data, for implementation, before cascading deep learning techniques of prediction and classification into simpler technical models. The case studies present quantitative and qualitative findings, which identify the overall project payback, and in particular, evaluate the decision implemented for one of the case company. Overall, the essay illustrates the significance of and the potential for implementing deep learning applications among manufacturers today. This essay has three original technical case studies, presented as sub-articles. Each offers a deep learning overview in its implementation, supplemented by technical details highlighted to provide a comprehensive explanation of machine learning and deep learning processes.

8.2. Potential Impact on the U.S. Industrial Sector

Potential Impact on the U.S. Industrial Sector

The advancement of deep learning in smart manufacturing stands to establish revolutionary outcomes for this nation's industrial sector. These potential prospects can be summarized as follows:

(a) Enliven the Industry: The application of deep learning algorithms to broaden the features of robotics, sensors, and machine tools can help to revitalize both the industrial equipment and the industrial sector here in the United States.

(b) Help Master the Fourth Industrial Revolution: This intra-device-to-device collaboration approach firmly reflects the notions embedded within the Industry 4.0 framework and mirrors the drive to redefine industrial practices and outcomes. Moreover, this interpretation supports an emphasis upon the need to capitalize upon a thorough understanding of connectivity, automation, and the employment of several intelligent technologies including, but not limited to, AI and big data that must pervade the next generation of digital industrial enterprises.

(c) Stabilize Economic and Workforce Realities: The utilization of machines with deep learning capabilities may serve to temper some of the looming labor ambiguities introduced by the retrospective advancements in AI. Labor opportunities could be developed by an upskilled workforce able to inspect the outward processing of these interconnected devices, perform necessary maintenance, as well as guide the interactions of machines that are designed with features grounded in human experiences (e.g., common sense reasoning, ethical considerations). Such guiding abilities will be particularly critical for the current and emerging domain of deep learning-determined adaptive systems and beyond.

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