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

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1. Introduction

Since 2009, the annual U.S. defense budget has exceeded $600B. However, the supply chain and infrastructure supporting the defense sector in the U.S. continues being challenged due to high overhead costs and an insufficient pool of manufacturers to support the Department of Defense (DoD). The defense capabilities of the nation can be classified as reliant on foreign countries (i.e., commercial and consumer electronics) or domestic (i.e., microelectronics and capital systems). The U.S. is becoming increasingly reliant and vulnerable to foreign nations with respect to critical technologies and supply chains. This issue is further exacerbating with the COVID-19 pandemic.

This research analyzes how the adoption and advancement of technologies traditionally considered for commercial applications (Internet-of-Things, Artificial Intelligence, and Digital Twin Technology) are being applied and customized for the factories that support the nation's defense capabilities. A voluntarily-participating consortium of manufacturers in the U.S. defense industry is being established in cooperation with major Integrated Defense Primes and the DoD. This consortium will focus on the development and adoption of technology enablers (sensors, data aggregation platforms, analytics engines, predictive engines) and solutions (supply chain risk assessments, equipment over/under utilization assessments, multi-plant MRP optimization) that support the Foundational and Advanced Applications of Smart Manufacturing. These technologies and solutions will enable members of the consortium to improve their factory performance and efficiency over a greater time horizon and across multiple sites [1].

1.1. Background and Significance

Digital technology integration enables data-driven manufacturing practices to create smart factories. For the U.S. defense sector's revitalization, strategies support technology design and inclusion, along with skilled workforces trained for advancing tools. Industrial applications of intelligent solutions for data optimization and acceptance in defense supply chains are explored thoroughly. To position domestic firms competitively, emphasis on Deep Learning (DL) applications enhances information utilization, scouting, management, and industrial ecosystem investment. Assistance in defensive capability upgrades for firms within the defense industry chain is analyzed. A comprehensive overview caters to manufacturing and intelligent decision support for conventional firm development needs in the U.S. defense sector [2]. Smart manufacturing and factories are defined, covering recent advancements and their significance in revitalizing the U.S. defense sector. The sector's historical and current importance, challenges, and firm needs to meet defense requirements amid geopolitical tensions are discussed. Design and development of industry-specific tools are advocated for intelligent supporting paradigms in domestic defense competitiveness, efficiency, integrity, and capacity-building efforts, including defensive capabilities.

The rapid rise of Artificial Intelligence (AI) in recent years is evident in surveillance, voice recognition, and self-driving cars. Deep Learning (DL), a part of AI, has gained attention due to promising applications in various domains. While initial applications were in bioinformatics and medical fields, recent developments suggest adoption of DL methods in automotive manufacturing and defensive technologies [1]. Establishing a strong knowledge foundation would facilitate cost-effective DL deployment with domain expertise enhancement over time. Information, particularly historical, is valuable as a corporation's asset. The use of data for production process model management is proposed, advancing supply chain productivity enhancements through effective data storage and sharing.

1.2. Research Aim and Objectives

The deep learning technology - designing and using devices composed of many simple elements that work in unison to compute with levels of complexity approaching brains - native to the field of artificial intelligence - has tremendous potential to address many challenges in manufacturing. However, the extent to which organizations within U.S. defense industry supply chains are aware of and using such technologies is currently unknown. This research seeks to understand that question so that the burgeoning field of deep learning can be better utilized.

To summarize, the basic approach to research in this project is as follows: the historical diffusion of a different kind of technology, statistical process control (SPC), a set of techniques for controlling the quality of manufacturing processes, was examined to produce a survey of organizations' knowledge of, interest in, and usage of SPC, its enabling conditions, and the impacts of usage, as well as an examination of the extent to which the SPC technology set's diffusion was affected by a variety of economic and technical externalities. That project was carried out using the methodology outlined below and is called the Statistical Process Control Project (SPC Project). Results from the SPC Project were then utilized to characterize organizations' current knowledge of, interest in, and usage of deep learning and to conduct a preliminary investigation into the effects of externalities on this technology set's diffusion. The portion of the research that produced this report is called the Deep Learning Project (Deep Learning Project).

The specific research objectives are as follows: 1. To characterize organizations regarding their usage of deep learning technology, variables that the diffusion literature suggests explain such usage, and the impacts of usage on organizations' operational performance and competitive advantage. 2. To investigate the effects of externalities on the diffusion of deep learning technology. 3. To utilize the results from the above objectives to identify opportunities to enhance the usage of deep learning technology among organizations in manufacturing and to recommend public and private actions that can be taken to facilitate this objective.

2. Smart Manufacturing and its Importance

[3]

The definitions of 'smart manufacturing' are summarized as: The networked/smart processing of materials to automatically switch/analyze different machines, sensors, and tools, based on required precision. The manufacturing which integrates state-of-the-art metal processing technologies and state-of-the-art artificial intelligence process control techniques to manufacture/produce precision parts. The integrated systems of automated precision measurement tools and referencing control of the metal processing area/shot, to detect and eliminate errors/mistakes during manufacturing [4]. The integration of advanced PDPT technologies with artificial intelligent control, advanced communication, miniaturized/smart sensors, robotic handling, smart chemical metrology and instrumentation, and high precision energy beam cutting/machining technologies provide the foundation of the smart manufacturing. An integrated smart manufacturing framework with MP technologies, artificial intelligent control, product accuracy/metrology, and communication-integration with design/manufacturing/ordering systems, to manufacture precision parts/components as customizing production is also introduced.

2.1. Definition and Key Concepts

Despite the fast world evolution, deficiencies of manufacturing capacities and limitations of technology and equipment have still become the major threats to a nation's economy and security during recent years. It has jeopardized national defense capability and an independent and secure supply chain. A very limited capacity of U.S. defense industrial base in comparison to other defense nations has increased risk, creating several critical dependencies and supply chain vulnerabilities, particularly with China, Russia, and COVID-19 stress. The shortage of manufacturing workforce and a considerable skill gap in advanced manufacturing after the doctrinal change from simple trades to an education- and knowledge-intensive workforce have severely damaged the U.S. competitiveness in the global economy. Manufacturing has already been recognized as the backbone of the economy, and smart manufacturing is believed to be the mechanism to revitalize the economy for the U.S. nation.

Smart manufacturing (SM) is the application of smart technologies in intelligent machines, automated systems, devices, and processes with AI and big data analytics to transform traditional manufacturing into responsive, adaptive, and automated smart manufacturing and cyber-physical systems. It improves productivity and sustainability by simultaneously optimizing the design, performance, maintenance diagnosis, and control of multiple domains in real-time. SM has become the core and enabling technology for Industry 4.0 and the Fourth Industrial Revolution, which interconnects the physical world of machines, devices, sensors, and processes with the virtual world of computers and systems through the internet of things, cloud computing, AI, and big data. Industrial robotics, artificial intelligence, machine learning, sensor networks, and broadband internet are all examples of enabling technologies that could be deployed together into smart manufacturing systems, including both smart factories and smart supply chains.

2.2. Benefits in Manufacturing

Smart manufacturing helps industries reduce operational costs by minimizing production cycle time and consumption costs [3]. It supports strategic decision-making by discovering useful knowledge from time series and event data. Real-time detection of faults in production processes is highly essential for industrial operations because, without detecting abnormality quickly, the production of defective products increases that causes loss of materials, time, and financial loss. Obtaining useful business intelligence from various resources through manufacturing analytics can help industries increase overall productivity, quality yield, and energy efficiency. An organic manufacturing analytics system for IIoT in smart manufacturing is proposed that can automatically model production process configurations and discover pocket faults using process and high-frequency sensor data. This provides a feedback loop from the manufacturing analytics to the production processes that enables automatic knowledge learning and revolutionizes smart manufacturing.

Smart manufacturing enhances value addition in many ways, including operation efficiency and productivity improvement, rapid response and flexibility enhancement, product quality yield improvement, energy consumption and cost reduction, and material waste reduction [5]. Overall productivity improvement can be achieved by discovering and diagnosing various kinds of faults in production processes, such as Pete, pocket, and causal faults, using the proposed manufacturing analytics approach. The discovered fault knowledge can be further applied to the fault mitigation in the production processes. Additionally, useful knowledge from energy consumption data can be provided to industries for studying energy utilization distributions over the machines in multi-machining processes. The stance knowledge that is utilized for discovery and diagnosis of high-dimensional process data can also be model-based knowledge that captures the dynamic characteristics of the process for process anomaly detection.

3. Deep Learning Fundamentals

A deep learning framework consists of numerous processing layers, algorithmically organized in hierarchies. Each layer consists of a number of computational units processing inputs received from the previous layer and producing outputs fed to the next layer. The functions of the units can be very different. Artificial neural networks are an example of a successfully applied hierarchical deep architecture [6]. Neural networks consist of a number of interconnected processing units (neurons). Each connection implements a weighted summation of inputs received from the connected units. A neuron produces an output according to a non-linear function of a weighted input sum. Although a lot of different neural network architectures can be designed, the most popular one is the multilayer perceptron composed of an input layer receiving data, one or more hidden layers implementing a non-linear transformation of the data, and an output layer producing a classification or regression result.

Deep learning architectures containing several hidden layers (usually from 5 to 1000) were not possible until recently because of the high computational cost of learning such networks. Also, they usually did not result in improved performance compared to shallow architectures [2]. Drop in computation cost and the development of special hardware called graphical processing units (GPUs) allowed the training of finely tuned hierarchical deep networks using gradient descent methods. In these methods, the neural network performance is characterized by a cost function (mean-square error, cross-entropy, etc.) who minimization results in the tightest fit of the data. The parameters of the processing units (weights and biases) are adjusted by minimizing the cost function using the general method of steepest descent. The steepest descent algorithm can be applied to very deep networks using a special architecture of computational networks called feed-forward or acyclic networks, in which the outputs of the neuronal processing units from one layer can influence only units in the next layer.

3.1. Neural Networks

Neural networks, a cornerstone of deep learning, are artificial intelligence systems modeled to mimic the intricate interconnections of neurons within the human brain. Comprising an amalgamation of interconnected units or neurons, neural networks excel in processing substantial amounts of data for a multitude of applications, including image and speech recognition, natural language processing, and control systems in manufacturing. The prowess of neural networks stems from their ability to learn patterns in data iteratively, adjusting connection weights based on output prediction errors [7]. While several types of neural networks exist, artificial neural networks (ANNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) have emerged as the most widely employed models.

A neural network typically encompasses three layers: an input layer that receives external information, one or multiple hidden layers where calculations and data processing occur based on each neuron's weight factors and activation functions, and an output layer that produces the result. Each connection between two neurons is assigned a numerical weight, determining the extent of the input's influence on the output. Weights are dynamically adjusted through training to enhance the model's accuracy [8]. Meanwhile, activation functions govern the output values of each neuron based on the cumulative input.

3.2. Deep Learning Architectures

Deep learning architectures comprise diverse structural frameworks acting as the skeletal systems around which deep learning methodologies evolve. In this fashion, deep learning techniques are essentially architecture pathways through the lens of which different types of functions and paradigms evolve. These pathway architectural structures thus identify and define the domain of deep learns systems metallurgy. Whereas frameworks like convolutional neural networks (CNNs), smart contracts, recurrent networks (RNNs), multi-tier architectures, and generative adversarial networks (GANs) are all distinctive in nature with separate functions and implications, they are deep learning architectures by characterize. Architectures are the basis of and impose the structure on deep learning systems technology. Additionally, some deep learning systems frameworks are more established and proven than others. For example, CNNs have substantially matured in both research and applications over the past 15 years, yet it is only in recent years that GANs have emerged [6].

Deep learning architectures can be employed within the manufacturing domain in general and smart manufacturing specifically. There is a growing view that ever sophisticated and worthy computer models are needed of manufacturing processes viewed completely as an interdependent system of inputs, outputs and characteristic parameters that could be comprehensively assessed without reliance on expensive and difficult to replicate laboratory experiments or physical prototypes. Can such impartial computational models reflecting the physics fruitfully be developed, and if so, how? Although there is ongoing and increasing international research interest in defining the domains required for automation intelligent life detected in deep learning rhetoric and prismic narrows the question remains as to how computer models deep and other innovations can be leveraged in actual practical ways within the smart manufacturing environment concerned [2].

4. Applications of Deep Learning in Manufacturing

Some key manufacturing challenges, such as quality control and inspection, predictive maintenance, material/part classification, process parameter optimization, and robotics, are discussed and expounded. The specific applications of deep learning to each challenge are elucidated.

The common goal of many production lines is high quality and high yield without incurring high inspection costs and/or massive production failures. Before resources are wasted, it is important to detect possible defects as early as possible, preferably before the part is actually manufactured. Various traditional vision inspection systems, including optical character recognition, OCRs, image similarity verification systems, and photothromography monitor systems, have been developed. However, defects that could not be detected with these traditional inspection systems have been found, and the deep learning approach has been introduced [6]. The basic idea is to train a neural network that classifies the given image as "normal" or "defective," enabling the detection of various defects without explicitly programming the detection criteria for each defect type. Impressive results on different part geometries have been demonstrated, and the implementation of such systems is reviewed [9]. Additionally, the challenges faced when applying the deep learning-based approach to the manufacturing environment and possible solutions are discussed.

Another key manufacturing challenge is to keep the equipment running and to prevent mass failures. This has become even more important in the fourth industrial revolution era, in which the profit margin per part is very small. In traditional manufacturing environments, synchronous machines such as motors, pumps, and compressors have been widely used for decades. These machines usually run continuously for years without being shut down, except for maintenance periods. Therefore, failure prediction and prognosis are required instead of detecting and classifying fault types after failures have occurred. In 1997, the National Aeronautics and Space Administration, NASA, initiated the Prognostics Health Management (PHM) research project to address this challenge. The idea is a two-step approach in which temperature and vibration signals collected from sensors mounted on the machine and time–frequency domain features are first extracted from the signals using wavelet analysis. Then, using historical data, these time–frequency domain features are later used as inputs to an artificial neural network that predicts the machine's remaining useful life. Although some industrial applications have been successfully demonstrated, the traditional model-based approach requires substantial modeling and diagnostic knowledge and has a limited scope.

To alleviate these problems, the recent initiative of applying the deep learning approach to PHM has emerged.

4.1. Quality Control and Inspection

Quality control and inspection have played crucial roles in manufacturing since mass production was adopted in the 19th century. Great advances in production technology, automation, and parallel computing have influenced inspection methods. Random sampling and inspections based on product design specifications and manufacturers' capabilities are typically used in the pre-production stage [7].

At this stage, product designs providing product geometry and various product attributes are checked to ensure product quality. With the advent of low-cost and miniaturized sensors and closed-loop control systems, online inspection is attracting increasing interest. Online inspection is commonly used when the production volume is high. Products can be subjected to a full inspection at a very low cost per product. In the production process, quality control and inspection are managed on a statistical basis. The process state is regularly sampled, and it is checked whether it is within the acceptable range [9].

4.2. Predictive Maintenance

Deep learning is increasingly being utilized in manufacturing for predictive maintenance. Predictive Maintenance (PdM) is a subset of maintenance activities that minimize unexpected failures by establishing proactive maintenance practices, which can be either scheduled or performance-based. PdM systems take advantage of condition monitoring data streams collected from machines to understand their "health". The approaches routinely use supervised models trained on operational data streams labeled with machine failure events or expert knowledge input to identify machines in need of maintenance. Such systems are often model-agnostic in nature. This allows for greater flexibility in implementation and consideration of diverse machine types with varied data availability. Exploiting the opportunity offered by Industry 4.0 and Industrial Internet of Things (IIoT) manufacturing systems, dataset-driven modeling has recently been investigated. These approaches require less reliance on machine expertise and can utilize massive amounts of readily collected operational data for model training [4]. Deep Learning (DL) was shown to be able to adequately model complex processes with high nonlinearity and large data volume.

Manufacturing is dominated by high dimensional, large volume, and noisy data, making DL a suitable approach for the PdM problem.

Proactive maintenance enables the most optimal operational continuity for manufacturers while minimizing unnecessary expenses and losses in productivity. PD systems and strategies represent a fundamental shift in maintenance philosophy compared to traditional preventative maintenance strategies. DA solutions make a significant contribution to Almost Maintenance-Free Manufacturing, a zero downtime operation with no scheduled or unscheduled interventions [10]. Beyond that, DA and ML approaches enable modeling systems with high nonlinearity and complexity, including manufacturing systems. Since 2015, the Research & Development community has been increasingly investigating the DA and ML approaches for the PdM problem. The impactful research studies pave the way for the implementation of ML and DL on industrial datasets currently being pursued by the manufacturing industry.

5. Smart Manufacturing in the U.S. Defense Sector

The U.S. Defense Industrial Base (DIB), which manufactures and maintains systems for the Defense Department and consists of more than 101,000 organizations, is under a contentious and ever-growing cyber-attack threat. Meanwhile, the government has urged manufacturers to adopt smart technologies and Industry 4.0 innovations, such as big data analytics and machine learning (ML), to increase productivity and resiliency and compete with companies from other nations. However, these smart technologies also introduce security concerns that need to be addressed to guarantee the resiliency of the manufacturing framework against cyberattacks.

Under the auspices of the DoD's National Defense Industrial Association (NDIA) working group, this effort's goal was to leverage research and development spend for increased collaboration and cooperation across the defense sector, the broader DoD, transactional stakeholders, and the small business ecosystem that has recently been invigorated within the SBIR and STTR programs. The research may help address the DIB's challenges by better understanding the current U.S. defense manufacturing prescription and enabling important upstream cost positions. Identification of the specific barriers to increased integration of the smart manufacturing ecosystem within the U.S. defense sector is a precursor to establishing industry-validated prescriptions on the downstream effects of that integration.

Recent smart technologies, including ever more capable manufacturing machinery and logistical support, have entered the commercial market and begun to be adopted in the defense sector, with the intent of increasing efficiency, improving the tax dollar return on investment, and countering foreign competitors' low-cost labor expenditures. Smart technologies also add new inherently unsteady threats to each layer of the manufacturing hierarchy, which must be considered throughout smart architecture design to preserve mission assurance. Appropriately addressing these two shortcomings could lend insight into the feasibility of increased investment in commercial smart technologies and their partner cyber and resilience technologies catalyzing similar defense sector architectures.

5.1. Current Challenges and Opportunities

In 1912, the U.S. Naval Torch Committee's vision of the "Fleet of Tomorrow" was celebrated as engineering aesthetics ahead of its time. One hundred years later, there remains a vision and a path to hypersonic, directed energy portable platforms, disruptive physics propulsion, biotronic sensing, and self-assembling ships launching self-repairing estuarial nanosubs. These phantasmagorias exist scientifically, but it is as fanciful to transform current industrial policies to execute their prospective industrial revolution through a smart Chicago. Hypersonic to rail guns, poisons to nanobots, swarm to multi-Sivans or Roberts, agencies of "Ends or Killers," infrastructure, planning, and intelligence readdress a same-old all-purpose defense scramble ready for another 9/11.

Attempts to correct interagency limitations, Bloch or Khrennin defensively close NATO for years, slow bygone reactions against a tagline world, cybercrimes invisibly opposite their panoptics. The Deepening budget captures fiscal trimmings and wreckages the American defense industry and, consequent of presumed parasitic worldwide copartnership, its lagging cutting-edge technologies [11]. Block sets in and surge responses award grizzly lifestyles evasive of preemptively demonstrated technical uncertainties outside states' power and routinely justified by national interests. Unindustrialized rearguard regimes are thus preemptively sunk and professionally normalized either in story or amenities as degenerate bottom feeders of international markets as religious factions. Zero opportunities arise from subsidizing novel offshored smart maritime socio-eco-political assemblages in servitude to "Colombian weather."

6. Case Studies and Success Stories

These two case studies are from defense manufacturing plants under the supervision of the Office of the Secretary of Defense. These plants voluntarily participated in an assessment of their smart manufacturing practices. The plants are all part of the production industrial base for U.S. defense systems.

To evaluate a plant's implementation of smart manufacturing practices, a self-assessment suite was developed. This set of questions was derived from a larger set of best practices, as published in "Best Practices in Smart Manufacturing" (2019), that was subsequently tested with several manufacturers. One purpose of the self-assessment suite is to develop a quick, graphical understanding of how well a plant is implementing smart manufacturing practices. This would then serve as a jump-off point for developing a strategy for increasing the application of smart practices, possibly through the application of more sophisticated enablers. The self-assessment was designed in a manner to be relatively easy to conduct. It could be administered by a modestly trained facilitator in a two-hour session with six to eight representatives from the plant.

A graphical representation of a plant's current practices then subsequently shows shortfalls in the plant's current practices relative to the best practices. A second graphical output indicates the relative time and resources that would be required to increase capabilities in the lagging best practice areas. These two graphs help a plant senior leadership understand their current situation and consider future activities to improve their type and application of smart manufacturing practices. This was demonstrated with two plants. The first case study presents the results for a plant that is well along the path toward implementing smart manufacturing practices, using bottom-up enablers in the modeling and simulation domain. This plant sees the benefit of utilizing smart practices and enabling tools. It then describes how some key lessons learned from this plant can be captured in a roadmap for other plants looking to propel their own journey. The second case study presents the results for a plant that is at an early stage of addressing smart practices. This plant utilizes rudimentary applications of various enablers. However, awareness exists of the need to better utilize data that they collect, how they model their supply chain, and why they need to improve their modeling and simulation maturity [12].

6.1. Implementation in Defense Manufacturing Plants

The practical implementation of smart manufacturing initiatives is investigated with a focus on defense manufacturing plants. Details are provided from early explorations through the challenges faced during pilot demonstrations, detailing the reasons for successes or failures in the deployment of smart manufacturing and resilient supply handling technologies.

Implementation of a Smart Manufacturing Platform for Joint Project Management and Joint Quality Control of a Defense Contract for the F-15 Fighter Jet In relationship building activities, cutting-edge smart manufacturing technologies were deployed at manufacturing defense plants that locally produce parts for jet-fighters. Challenges and results from the deployment of smart manufacturing technologies focused on joint project management and joint quality control of a defense contract for the F-15 fighter jets are presented. The initiative successfully helped several parties including the federal government prime contractor jet-fighter manufacturer and local manufacturers to address major challenges posed for sensitive defense contracts in managing resilient supply chains and parts quality assurance in on-time delivery situations [13]. Implementation of a Smart Quality Inspection Station Integrated with Machine Learning Based Machine Vision Systems for Injection-Molded Defense Parts In process quality assurance, smart manufacturing technologies were deployed at defense plants for the production of injection-molded parts. Challenges met and results obtained from deployment of machine vision based quality inspection technologies are presented. Two systems for part quality inspection were deployed that integrate cutting-edge computer vision machines using DS-60 and DS-80 cameras with algorithmic software utilizing machine learning image segmentation technology to automate quality inspection of defense parts. Impact of Smart Manufacturing Technology Deployment on Plant Performance for High-Frequency, Multi-Part Production of Defense-Molded Parts The impact of a jointly implemented batch of smart technologies on the performance of a defense manufacturing plant is analytically assessed. After the deployment of computer vision machine vision quality inspection systems, an automated data handling module, and a smart scheduling engine, the overall performance of the defense manufacturing plant is analyzed by measuring key performance index metrics qualitatively. Before the deployment of technologies, manufacturing scheduling bottlenecks severely impeded defense part manufacturing and put timely delivery of parts in significant jeopardy.

7. Future Trends and Innovations

Smart Manufacturing for the U.S. Defense Sector needs to leverage automation and machine intelligence to improve productivity and competitiveness, reduce work-force reliance, and meet fast changing end-user demands. Smart Manufacturing Applications need to be planted, easily integrated to automation solutions and on-demand machine intelligence can be provided to new automation use-cases. With fast retina frame updates, smart manufactured high-qualities wide-field and super-resolution digital imaging products have been developed. To increase defense-product portfolio formation to more western-products including more consumer-based 3D smart products for imaging and detection, and the defense products with imaging resolution or zoom uncertainty will be addressed. To tackle engineering-level unknown dimensions uncertainties or ground-truth detachments imaging data of low-qualitative, inexpensive, boosted-convergence-radon-dynamic-range precision engineering-level resolution modeling and restoration approaches will be proposed. To achieve image place-of-sensor address accuracy, multi-line-grid-spot-based dynamic-range image spatial and temporal reformation will be proposed [14]. To pave the way for an on-board real-time improvement and quick prototype formation of practical defense-product and consumer-product-system, on-demand all digital smart, near-field, long-range and wide-field imaging products with multiple applications including weather satellite imaging, bio-imaging, surveillance will be introduced. Deep learning (DL) is one of the most exciting technology breakthroughs in the last few years. DL can be characterized as a machine learning method where artificial neural networks are utilized for the modelling of high-level abstractions and intricate mappings from inputs to outputs. Adaptive deep architectures with hierarchical representations learn various functions, enhancing more important features while suppressing trivial variances, as the signal progresses through the representation hierarchy [1]. The learned representations are then further processed in fully connected networks for tasks such as regression and classification. Advances in computational technology and data availability have resulted in a resurgence of interest in DL for real-world applications. In particular, breakthroughs in voice assistants, text-to-speech synthesis, image classification, and object detection deep learning technologies redefine the way humans interact with machines.

7.1. Advancements in Deep Learning Technologies

Over the past several decades, there has been significant research and technological development in smart manufacturing solutions by integrating manufacturing and technology with the industrial internet and cyber-physical systems. New solutions include more intelligent, faster, more cost-effective, greener, and more flexible products and manufacturing systems. Manufacturing domain challenges — resource optimization, production transparency, loss minimization, delays, unplanned downtimes, skill conversion, maintenance workflow optimization, etc. — can be restrained with smart manufacturing. Deep learning is a part of machine learning that "uses neural networks with three or more layers and attempts to simulate the way humans think" [6]. Smart manufacturing technologies can generate new intelligent solutions through the reasonable localization of deep learning technologies, like object recognition, long-short term memory, deep reinforcement learning, and generative adversarial networks.

Deep learning technologies involve a series of systems and their integrative solutions to perform automation, monitoring, optimization of input utilization and output, and productivity enhancement, with the objective of major productivity growth and drastic reduction of resource utilization, all at moderate or very low costs. There is a focus on large-scale deep learning paradigm shifts that can fundamentally reshape the landscape of smart manufacturing due to innovations in neural network designs, training strategies, chips and systems, rugged devices and edge computing, as well as integrative solutions to advanced design, automation, optimization, and knowledge discovery [1].

8. Ethical and Security Considerations

Data Privacy and Security As deep learning applications become the backbone of smart manufacturing, data preparation and processing will need to be addressed as early as the design phase [15]. With all data preparation and processing requiring deep learning models to be trained and transferred, there are a variety of attacks on data users, deep learning models, and model training data that threaten data privacy and security. Such attacks are prevalent, and designing privacy-preserving solutions for deep learning-based smart manufacturing is important. There are myriad other threats to data privacy and security, such as data flooding and poisoning, DoS attacks, eavesdropping, and replay attacks that threaten data users. The intelligent nature of smart manufacturing and deep learning models means that any data privacy and security solutions need to be carefully designed and considered early in the design phase. With such a wide variety of optimization methods and similarly widely used deep learning models, understanding the defense mechanisms and proposing suitable solutions is paramount.

Defense Mechanisms With deep learning models being widely transferred and on-device. there are various attacks on these models that can expose the privacy and security of the data used in the training of their architecture [16]. Current defense mechanisms involve sanitization or modification of the model itself or noise injection from the data user side, which is in contention with the optimal behavior of the deep learning models. Various methods have been proposed for minimizing the damages of the attacks, but given the threat of any model architecture or data user being compromised, a paradigm shift is required in the design of smart manufacturing systems employing cloud-based or on-device deep learning.

8.1. Data Privacy and Security

Focusing specifically on data privacy and security, this section delves into the critical considerations and potential challenges associated with preserving the integrity and confidentiality of data in the context of deep learning applications. The accelerating proliferation of deep learning applications across a wide spectrum of industries and sectors necessitates a robust understanding of broad intellectual, societal, and ethical implications of AI and its applications; development of policies, regulations, and protocols to ensure safe, ethical, unbiased, and otherwise responsible research and productive uses of deep learning applications; and promotion of awareness of ethical and security practices by students, industry practitioners, and institutional stakeholders with respect to rapidly emerging advanced deep learning technologies, including generative AI [15].

Potential challenges associated with misuse of AI applications for unintended actions must also be identified, specifically in terms of potential vulnerabilities of different AI and deep learning-enabled applications and systems to threats of accidental or intentional data corruption, system manipulation, acts of physical sabotage, and cyber intrusions [17]. Smart manufacturing enabled by advanced artificial intelligence (AI) technologies such as big data analytics, machine learning, and automation technologies has the potential to revolutionize the U.S. defense sector, enhancing competitiveness, resiliency, collaboration, and connection with allied companies and suppliers. Deep learning technologies, a class of machine learning methodologies that learn predictive models based on data representation, analysis, and modeling, have proven effective in detecting patterns in data representations and are widely applied for predictive analysis.

9. Conclusion

This report provided a comprehensive exploration of state-of-the-art deep learning systems for smart manufacturing in the U.S. defense sector, with a focus on threat awareness, anomaly detection, and early failure prediction from sensor monitoring. Under a project researched over three and a half years, industry leaders provided a summary of current smart manufacturing activities within their companies and outlined plans for future applications of deep learning systems.

Interview responses were gathered from event attendees to analyze the defense sector's national security issue due to diminishing domestic manufacturing capability. Deep learning's potential to create competitive advantages for smart manufacturing systems was explored, focusing on machine vision, semiconductors, and metal processing. Deep learning's current maturity and future potential for manufacturing was analyzed, followed by a review of smart manufacturing architectures, applications, and sensor types.

Data examples generated from these architectures were discussed, including virtual 3D models for inspecting part temperature distributions, nanometer-level optical surface finish inspection, and early-stage anomaly detection in manufacturing, testing, and assembly processes. Recent advances in deep learning-based anomaly detection were reviewed, alongside early failure prediction from sensor monitoring. Manufacturing use-case examples of CCTV, sensor, and audio input use with deep feature extraction on consumer hardware were presented.

The current state and future vision for smart manufacturing systems for the U.S. defense sector was also proposed. Findings from this report included a discussion of industrial deep learning use-case examples reviewed in regard to smart manufacturing, with a focus on machine vision applications and potential use-cases of innovative smart sensors. Potential deep learning projects for relevant use cases to benefit the U.S. defense sector's manufacturing capability were identified from worked-out projects with funding opportunities.

Immediate project and enforcement program recommendations were provided within this section, including findings from reviewed national programs on which the U.S. defense sector could develop proposals. The report concluded with recommendations for future industrial deep learning use-case development, focusing on technology outside of the funded metal processing initiative proposals.

9.1. Key Findings

This work examines the application of predictive analytics and deep learning technologies to the manufacturing floor, specifically to milling operations. It demonstrates how data captured in 1D time series event logs can be used to detect latent process states, focusing on the case study of deflection in multi-axis milling that can potentially lead to part rejections and/or machine damage. A novel deep autoencoder recurrent neural network architecture is trained to model the normal operation of a given machine workload. Detected anomalies are then exposed to domain experts for measurement, and the feasibility of detection and use of the 1D time series signals is established.

Outcomes from a one-year proof-of-concept endeavor are described, and the challenges of transition to manufacturing use case and ongoing improvements to the data input and the overall modeling workflow are outlined. Utilizing permissible deviations of standard processes can improve machine utilization, but also increase the probability of process state drift. Current research on enabling technologies, control algorithms, and process state monitoring methods for such resilient process control and systems is reviewed, showing that much research effort is going towards the forthcoming 'smart manufacturing' paradigm. Key enabling technologies such as the industrial internet of things (IIoT), big data analytics, and machine learning are investigated, detailing what types of process state variations can be reconciled using these technologies.

For use cases that the research is currently moving towards, the selection of input data types and machine learning models to be used is assessed. The number of deployed devices in manufacturing applications is rapidly growing, resulting in new challenges concerning data auditing and verification, and a need for novel methods to guarantee data quality is evidenced. With the availability of historical process data, several machine learning and statistical process control-based solutions on fault detection and diagnosis to support the maintenance of equipment and better understanding of process variability are examined, outlining their motivation, principles, and key enablers. This new knowledge is translated into R&D roadmaps and demonstrators as an efficient way to drive internal competence growth.

9.2. Recommendations for Future Research

The March 2023 National Defense Science and Technology Strategy outlines bold goals for digital transformation across the U.S. Department of Defense (DoD), and associated commercial defense industrial base partners, through the rapid integration of artificial intelligence (AI) and digital engineering principles. Smart manufacturing systems based on deep learning have the potential to significantly accelerate the DoD's transformation towards these objectives. A literature review indicates the current state of research related to these goals and highlights needs for focused applied research investments. Further, specific research investments are recommended, based upon an analysis of barriers to adoption of deep learning, and potential research directions based upon key capabilities of these techniques [2] [14].

Proposed research topics include: Deep learning process signature development, model interpretation, model robustness standards, data governance standards, augmented datasets, and industry-academic research partnerships. These suggested areas provide an initial roadmap for further research endeavors involving deep learning applications and smart manufacturing targeted upon revitalizing the DoD's defense sector, and the industrial base supporting it.

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