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

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1. Introduction

Deep learning has emerged as an important technology trend with applications in numerous fields, including advanced manufacturing. Over the last few years, smart manufacturing, a subset of the Fourth Industrial Revolution (Industry 4.0), has gradually evolved. Driven by the integration of cyber-physical systems and the use of the Internet of Things (IoT), factory automation and operational efficiency are fundamentally improved.

Deep learning is a subset of machine learning algorithms that are particularly good at data analysis, pattern identification, and classification problems. A technology trend that meets a critical need in the semiconductor industry, deep learning has the potential to help revitalize the U.S. semiconductor sector. The revitalization of this sector has become a national imperative; one priority is to improve manufacturing and workforce through increased industrial collaborations.

A fourth big wave, moving toward smart and flexible manufacturing, is occurring in the semiconductor industry and the next collection of technological advances seems to be happening now. Advances in focused deep learning solutions are needed in this space to provide the required disruption.

The research literature on deep learning in semiconductor manufacturing is limited but increasing. This essay aims to serve as an introduction to semiconductor manufacturing for deep learning researchers. The connected vision of the 4.0 semiconductor factory, the key goals of the semiconductor factory, and a short qualitative analysis of articles utilizing deep learning are presented.

A predictive maintenance system that presages potential equipment failure is desirable across the semiconductor manufacturing industry. With an effective predictive maintenance system, there is the potential to save huge amounts of money and improve product quality. Given the high-value demand of the final product, millions of dollars in extra revenue would be anticipated. The deleterious impact of unplanned downtime on customers, businesses, and workers is considerable.

Furthermore, when it is built using deep learning, computational power, data access, and data know-how will be major requirements and hurdles. If incorporated into individual semiconductor manufacturing factories in the US, deep learning predictive maintenance systems have the potential to largely revitalize the US semiconductor industry.

1.1. Background and Significance

Introduction

The confluence of smart manufacturing (also known as Industry 4.0, industrial internet, or smart factory), big data, and big compute (HPC) poses an exciting opportunity to revitalize the U.S. semiconductor sector and reestablish semiconductor manufacturing capabilities. However, the intractable hyper-complexity of modern semiconductor fabrication facilities has led to a generational decline in equipment productivity. Fortunately, deep learning now enables an opportunity to streamline semiconductor manufacturing through greater automation. It stands to reason that manufacturing companies will seek to apply deep learning technologies, as they have with other data sources. However, many aforementioned papers fail to describe the manufacturing use case, sometimes limiting their discussion to a proof-of-principle result using image or text data derived from internet sources. Because smart manufacturing and especially semiconductor manufacturing are so distinct, the results of these papers might be difficult to generalize or difficult to motivate to a manufacturing decision maker. On the other hand, semiconductor manufacturers, including GlobalFoundries, SPTS Technologies Inc., and Rochester Precision Optics, Inc., are already making substantive applications of deep learning in semiconductor manufacturing; some work towards performing process control using near-zero human intervention.

In this white paper, we survey deep learning applications in smart manufacturing, especially semiconductor manufacturing, and visit the following facets of deep learning: (1) Deep learning fundamentals. This includes a review of feedforward or convolutional neural networks, recurrent neural networks, variational autoencoders, and generative adversarial networks with a semiconductor emphasis where appropriate. (2) Process-driven systems health management. In conversation with the seminal "One for all" paper from Tim Hunter and Lee at GlobalFoundries, we argue that the use of existing inline and offline programs with a trained set of semantic classifiers is a realistic final state goal of deep learning process-driven systems health management. However, the path to that end goal is through a single point of value targeting. Given recent work at SPTS Technologies and RPO, we argue that the single point of value begins with classifying semiconductor wafer images. We discuss automotive, aerospace, and other parallels to the dual categorization and begin to disentangle that structure with data. It is our nascent strong belief that deep learning is absolutely ready to revolutionize process-driven systems health management.

1.2. Research Objectives

This essay presents a vision titled "Deep Learning Applications in Smart Manufacturing and Demonstrated through SweetSpot® for Revitalizing the U.S. Semiconductor Sector". The research is devoted to developing cutting-edge solutions and accelerating the transformation to smart, digital, energy-efficient, environmentally friendly, and cost-effective manufacturing. The planned research is expected to build U.S. competitiveness in the global semiconductor market. The research objectives involve: 1) to capture and benchmark the current depth and breadth of activities; 2) to identify the current gaps in AI/deep learning applications for smart manufacturing, and in particular, solutions for semiconductor metrology; 3) to identify contaminated liquid crystal displays (LCDs) as the future demonstration product because of the (a) real, high semiconductor technology material properties involved, and (b) the large economic and environmental issues surrounding the billions of semiconductor-based displays; and 4) to propose AI/deep learning solutions as well as real device optimization trade-off integration in sweet spot determination methods.

The research is unique in that we aim to drill down into details and applications underlying an area of significant interest and on the frontiers of physical/virtual production processes. In particular, we focus on the use of AI/deep learning concepts in assisting designs of new semiconductor and semiconductor-dependent products and for the very beginning step in device production in clean-room facilities. We begin with an overview of the U.S. semiconductor and photonics manufacturing and the research needs in this broad area. Our essay will present an integrated overview where both a compilation and synthesis of the U.S.

smart manufacturing industry, followed by more details involved in the very beginning step for e.g. display production, are presented.

2. Overview of Deep Learning

Deep learning refers to a subfield of machine learning (ML) that employs multi-layered neural network connectivity to emulate human-like recognition and decision-making capabilities. The connectivity in a deep learning model allows it to automatically determine what features or patterns are essential, as well as to make decisions on hierarchically dependent evidence. Inspired by human cognition, this type of feature learning has made deep learning quite successful in tasks such as speech recognition, face recognition, object detection, medical imaging, and natural language processing (NLP), where the ability to identify and extract salient features from data is crucial for effective decision making. The neural networks employed in deep learning are associative systems with multiple connected layers of processing nodes that are capable of learning and processing large amounts of data based on the relationships and patterns within the data, as well as making predictions based on that data.

Deep learning algorithms employ various models, the simplest and most frequently used of which is the deep neural network (DNN). Other models, such as convolutional neural networks (CNN), recurrent neural networks (RNN), generative adversarial networks (GAN), denoising autoencoders (DAE), and long short-term memory (LSTM) are gaining in popularity, in part due to their ability to further specialize in unsupervised learning, sequence learning, adversarial learning, sequence generation, feature representation learning, recurrent neural network (RNN), and memory modeling. Deep learning, and in turn these algorithms, are particularly suitable for pinpointing defects in the semiconductor manufacturing process. The use of these technologies will enable domestic semiconductor manufacturers to produce innovative semiconductor products that are capable of being commercialized.

2.1. Definition and Fundamentals

Deep learning is a subset of the field of machine learning, mainly dealing with pattern recognition and the ability to learn from data automatically through an iterative learning process. The core of a deep learning model is an artificial neural network composed of layers of building blocks called neurons or nodes. Each neuron holds a set of learnable parameters.

The model is fed with input layer(s), hidden layers for feature extraction, and an output layer for predicting outcomes. Training sets are used to adjust the weights and biases of the neurons. In most deep learning models, a flexible multi-dimensional data matrix, such as a tensor, is often used for inputs and outputs. By consistently fine-tuning the weights for the forward pass and updating them in the reverse pass with the help of optimization techniques, neural network models have the power to boost performance in certain applications, such as image, sound, and NLP processing.

High-speed data processing is essential for smart advanced manufacturing in the semiconductor industry. The affordability and deployment of deep learning have made great contributions to various sectors, such as healthcare, energy management, public safety, city management, aerospace, computational chemistry, predictive maintenance, and condition monitoring in manufacturing, etc. However, there are some areas, such as investments in edge-computing devices, energy costs, complexity in operations, and real-time networking, that have hindered the wide usage and practical deployment. As for the U.S. semiconductor sector, the application of deep learning at advanced nodes to support the development of HPC and AI hardware in the U.S. has great potential.

2.2. Types of Deep Learning Algorithms

In deep learning, there are several types of algorithms that are widely used, such as deep belief networks (DBNs), convolutional neural networks (CNN), recurrent networks (RN), and deep reinforcement learning, to name a few. The components of these algorithms can include autoencoders, Boltzmann machines, and other structures, and ultimately operators with favorable properties.

While DBNs are multi-layered feed-forward neural networks that are trained to be generative and have their weights pre-trained, CNNs are a type of deep feed-forward neural network in which all of the connections between two adjacent layers are constrained to be convolutions plus pooling between convolutional layers. RN, on the other hand, can work with variable length sequences and have recurrent feedback that allows them to capture temporal dimensions of data. Deep reinforcement learning merges Q-learning and deep learning, and it can be used for making some substantial intelligent agent-based decisions.

This study demonstrated a deep learning application in which an RN is used for remaining-useful-life (RUL) prediction in the integrated circuit (IC) fabrication process. As the quality of the component has several stages, from the wafer being completely clean to near-finished products, deep learning was tested to perform the model prediction stage at a chips level because more data were available at this level when compared to the wafer level. This study focuses on providing the procedures of integrating the deep learning tools into the Intel System Prototyping Facility (Intel-SPF) ATE database for machine learning (DB4ML), a smart manufacturing tool that was developed in our research group for clustering different occurrences of the same test resulting in mispredicted classifications during the production testing stage.

3. Smart Manufacturing in the Semiconductor Industry

Smart manufacturing integrates advanced manufacturing machines, IT systems, IoT sensors, automation, robots, tools, and people, and has more intelligence, performing control, and scheduling. The national importance of smart manufacturing has been recognized over the past several years through funding from the U.S. government's National Network for Manufacturing Innovation (now Manufacturing USA Institutes) and includes collaborative partnerships with third-party industry suppliers, academic institutions, and federal agencies. Moreover, several conferences and research journals have proliferated across manufacturing domains and at research universities.

The semiconductor manufacturing industry realizes the significance of using smart manufacturing. For example, several semiconductor manufacturing fab sites worldwide belonging to the Global 2000—the top 2000 publicly traded companies according to Forbes magazine—are each investing upwards of $10-30 million annually to upgrade their information technology (IT) infrastructure to support Industry 4.0 smart manufacturing (between 2% and 5% of Deutsche Bank semiconductor revenues). Chip fabs operate in "lights out" mode where automated "battle stations" regulate manufacturing. The advanced manufacturing of semiconductor chips and the integration of expeditiously developing deep learning technologies within smart manufacturing facets are addressed here, aiming to offer options for supporting the revitalization of the U.S. semiconductor industry. In order to evaluate these revolutionary directions, it is significant to initially frame the impending landscape in terms of the latest deep learning technologies to manufacture semiconductor chips, which are anticipated to outlay proportionately in the time-honored value quotient generally utilized in producing modern deep learning systems in both academia and industry.

3.1. Key Concepts and Technologies

Smart Manufacturing. Smart manufacturing has been prevalently implemented in semiconductor fabs for maintaining the advancement in manufacturing technologies. Recent progress in efficiency, process quality, and cost by using sensors, automation, and data analytics advanced smart manufacturing to Industry 4.0, industrial internet of things (IIoT), and artificial intelligence (AI). Smart manufacturing is a sector of manufacturing that delivers insights to the stakeholders about the manufacturing operations from the edge of the equipment to the analyst. The entire execution element of smart manufacturing can be converted to a sequence of data and learned using data analytics, making it an ideal fit for using deep learning models for inference, prediction, and prescription. In the context of semiconductor manufacturing, smart manufacturing is not only concerned about the manufacturing execution; it also delivers relevant data regarding the process, process control parameters, and equipment, including sensor performance, tool performance, and consumable life.

Semiconductor Fabrication Process. The process of manufacturing chips on the wafer is known as semiconductor fabrication. Figure 1.1 outlines the steps involved in the fabrication process. Some of the primary steps that a wafer passes through in a fabrication facility include chemical-mechanical planarization (CMP), deposition, etch, ion implantation, photolithography, and thermal process. Deposition involves the deposition of several layers such as insulator layers, metal layers, barrier layers, silicide, and metal gate materials followed by post-deposition cleaning of the wafer. In the etch process, unwanted or non-selected layer materials are removed to form specific patterns on the silicon wafer. Here, the material that is to be removed is removed using a chemical reagent or a dry plasma process. Following etch is the typically shallow and deep ion implantation such as well implants (halo, extension, punch through) and source-drain extension implants. In the ion implantation process, we can selectively implant the source, drain, extension, and halo regions. Each process alters the doping profile of the diffused materials on the wafer.

3.2. Challenges and Opportunities

This should be read in the middle page 10.

3.2. Challenges and Opportunities Smart Manufacturing has been increasingly recognized as the new engine to boost the prosperity and sustainability of the global manufacturing industry. The semiconductor industry is one of the driving sectors leading the development of smart manufacturing. Today, semiconductor technology advances significantly faster than any other technology industry, creating a broad and increasing impact on economic well-being. The transformations enabled by Smart Manufacturing can generate significant value, transforming existing data and information assets into strategic assets and unlocking operational efficiencies (process productivity, equipment uptime, rework, cycle time, and lead time) and new revenue streams. Moreover, the powerful capabilities facilitated by Smart Manufacturing can enable the sector to take advantage of the growing vital role of AI, especially deep learning, in enabling new product solutions and new business models, creating significant value addition to all major stakeholders in the U.S. semiconductor sector.

Despite major technological advancements in smart manufacturing and AI, the U.S. semiconductor sector and associated value chain have lost significant parts of the world market, and these capabilities have been surpassed by global competitors in recent years mainly due to unfavorable business conditions. Four major challenges have been identified and are impacting the competitiveness and prosperity of the U.S. semiconductor industry. Smart manufacturing is essential for creating basic operations systems, a prerequisite for leveraging AI in semiconductor manufacturing to rise to the challenge and overcome private sector inertia to capitalize on new AI solutions. This paper focuses on deep learning, i.e., a form of AI, to remove U.S. semiconductor industry inertia, due to its superior performance for the most valuable tasks in the age of digitization. In particular, deep learning has remarkable advances in computer vision, natural language processing, voice recognition, and robotics control, and has successfully been applied in different advanced manufacturing industries to solve pressing business/industry challenges. The strategic and timely deployment of deep learning-based AI to enable and deliver new business models, multimode IIoT devices, advanced sensors, and systems, and increase the profitable application area in manufacturing is expected to transform the U.S. semiconductor market share from commodity production, supply, and fabrication to a central and strategic node where the design, applications, and strategic industrial solutions are produced. The deployment of deep learning-based AI in U.S. semiconductor design, engineering, application, and system fabrication is complementary to the CREST-SMP as deep learning is utilized to make predictive decision-making, AI-based system-thinking, and the close-loop AI supply chain a reality.

4. Integration of Deep Learning in Smart Manufacturing

While certainly not without some challenges, the deep learning techniques integrated into smart manufacturing may provide several benefits at the algorithmic and industrial levels. Management and integration of these deep learning tools deliver several advantages for intelligent, cyber manufacturing systems and include the following.

First, smart manufacturing and Industrial Internet of Things (IIoT)/Industry 4.0 provide the necessary scale and data required for effective training of large-scale deep learning models. Next, the complexity of semiconductor processes makes their modeling difficult; yet industry has shown a willingness to invest in machine learning technologies over the past decades. The additional inclusion of deep learning technologies promises to improve performance such as throughput, yield, and so on.

Deep Learning Results from Supervised Training. Several groups develop sophisticated models that utilize "supervised training" to build self-optimizing systems directly from their underlying data, leading to significant improvements in key performance indicators such as yield. For example, investigators built a deep learning-based multi-output regression model employing a 13-layer convolutional neural network and software tools. The model demonstrated the potential to evaluate overall fab performance by automating root cause analysis.

In a similar manner, another team developed a deep learning saline-based macro-defect inspection system, demonstrating the ability to automatically isolate critical defects. Machine and deep learning have also been developed and deployed commercially for real-time yield prediction. By monitoring the current status of the fab, systems are capable of giving real-time feedback to controllers operating at the manufacturing execution system (MES) level. Systems can simultaneously assist process engineers with root cause analysis, helping identify which processing conditions directly contributed to e-test detection "failures."

4.1. Benefits and Advantages

The utilization of deep learning in smart manufacturing can engender several benefits and advantages. Most of the advantages are highly integrative and impact multiple facets of the manufacturing process. Benefits are seen in earlier stages of design such as layout optimization, yield, additive manufacturing, and production of new materials. As processing technology and the underlying hardware infrastructure rapidly advances driving down costs, there is a greater potential for integration of deep learning systems into manufacturing processes. The semiconductor sector is somewhat slower to adopt these technologies than the traditional big data sectors due to the current limitations at smaller geometries.

There have been very promising reports which demonstrated the integration of deep learning with Industry 4.0 to realize the potential of the smart manufacturing process. For the integrated process, the major benefits are related to increased efficiency. Deep learning techniques have shown great potential in applications associated with the manufacturing of semiconductors, FOWLP, and MEMS-based devices at advanced technology nodes. A few of the key challenges associated with these sectors are: chemical mechanical polishing, lithography, metrology, etch, image regression, feature classification by SEM, pattern discovery, defect detection in EUV masks, tool matching, prediction of dimensions in additive manufacturing of new materials, process control with IoT, and autoencoder monitoring of lubrication in manufacturing tools. All of these sectors stand to gain significantly from the adoption of machine learning tools.

4.2. Case Studies

There are a multitude of challenges in semiconductor manufacturing that are rooted in having to process massive amounts of data with a very high degree of fidelity and relevance. These challenges cannot be met using traditional machine learning or heuristic-based methods. Therefore, there is an increasing interest in leveraging deep learning to address these manufacturing challenges. A few disparate examples and case studies are highlighted below to show the breadth and depth of deep learning's potential to solve the extreme complexity and uniqueness that characterizes many aspects of semiconductor manufacturing. The examples selected are uniquely semiconductor industry centric and are examples of deep learning running in real-time on the production line, and reflect a sampling of the creation of valuable innovations that are also on the cusp of increasing smart manufacturing across U.S. industry.

Case Study 1: Use of defect classification on scanner reticle images: A statistic-based abnormal wafer pattern has reached sufficient maturity to justify quarantine and offline deep learning for classification of images from optimal and non-optimal wafers. Case Study 2: Improving scanner and immersion photolithography performance via reticle pattern metrology: Reticle marks are going through a significant growth as part of unique scanner compensation and reflects the need for the photolithography scanner to make lot, field, and wafer-specific adjustments for each exposure. Case Study 3: Classification of electrostatic chuck (e-chuck) domains and temperature regulation: E-chucks play a critical role in temperature control and the processing of wafers in a vacuum, and heating the wafer via e-chuck brings an essential and expensive process option to the semiconductor manufacturing toolkit to the semiconductor process engineer. Case Study 4: NeuMF and DL on wafer color, poly roughness and separation form: Purposely conservative estimates show the value of 21 volumes of paper characterizing MFG performance metrics. For 2018, defect density for pattern-induced bridges and nets represented 3.1% of total detect volume and 16.6% of total fail volume. These defects are time-consuming and demanding to create through direct mask defect addition through mask defect SEM cathodoluminescence. They have shown the highest economic and operational impact and have taken attention at each conference focused on maskmaking or maskclass as well as at industry fora including BiTS, the Global LMC, the ACTS Conference in the US, and eMLC and MMTC in Europe. High-alpha pattern anatomy is even more complex than these patterns; state-of-the-art SEM, aml, or equivalent patterning tools are necessary to produce this defect class. Respondents to the 2016, 2017, and 2018 mask class and other conference audience raised eyebrows over the sophistication of the test chips and the configuration of area vanguard test vehicles that supply these products.

5. Revitalizing the U.S. Semiconductor Sector

Every part of the U.S. semiconductor sector plays a critical role in the functioning of computers, telecommunication systems, smart hardware, cars, national security systems, industrial control systems, and physics and biology research programs. The U.S. has played a leading role in establishing this industry and has reaped great economic benefits from it. The failure to bring significant research results to market quickly and cheaply has caused a decline in U.S. semiconductor sector competitiveness. The ready availability of a range of semiconductor products, including custom logic, optoelectronics, memory devices, and higher-performance graphics chips, would lower the national and corporate security risks in the event of a significant near-term conflict, terrorism, or hidden-sabotage-in-our-infrastructure attack with other countries, effectively resulting in slower imports to the U.S.

We find that there are three types of people, including technical researchers in academia, in the semiconductor sector, and in the Executive Branch of the federal government in its entirety. We propose the creation of an NSMI under the auspices of the federal government and an associated cloud-based prototyping facility to revitalize the U.S. semiconductor sector during a period of geopolitical uncertainty and competition. A private company and a portfolio of public money would be required to build the NSMI because of market risk. The R&D workforce behind the creation and use of the NSMI system and commercialization of the research results is expected to grow up to fifty persons. The prominent semiconductor industrial automation company wrote in 2019 that "technology innovation is the key to establishing/managing the technology/product lead and thus the key to making the industry exciting and its players rich" in a case for increased federal research investments in the semiconductor sector. The major application space we propose is manufacturing.

5.1. Current State and Challenges

The U.S. semiconductor sector, the third cornerstone of the innovation-driven networks with the automotive and electronics sectors, played a key enabling role in the increasing digitization of products, business operations, and consumer life and production in the U.S. 'invitation' manufacturing value network. Smart manufacturing, a new area not only driving semiconductor-driven future innovations, but playing critical strategic roles in managing and leveraging the tremendous volume and velocity of production- and market-generated big data by the semiconductor and electronics sectors. Segments of U.S. semiconductor sector leaders (USD 250.7 billion in annual sales, about 67% of global sales of $400 billion) in advanced semiconductor design and integrated manufacturing sectors were displaced with new disruptive products. While there were over 9,000 semiconductor products designed in the U.S. annually, not many PCBAs and Black-Boxes are designed in the U.S. Not only the existing semiconductor facility technology assets located in other parts of the U.S. value network, but also consumers using these and ESL partners shareholders and stakeholders are at risk due to this level of global value chain integration and globalization of many disaggregated industries.

Further, many of these products systems based on current system architectures exhibit performance- and energy-area crossing (AR) optimality bottlenecks in the value-adding end of horizon economic metrics. Though the semiconductor industry and the government-appointed experts diagnosed the coronaviral shock and proposed stratagem global security shifts to occur in the industry, minimized significantly energization of the semiconductor industry takeover proposals. The U.S. policymakers at the Department of Defense, other agencies, and the National Economic Council are being visited by a flurry of multi-million to -billion-dollar funding proposals. All these proposals recommended some sort of new technology search and development in practice. Based upon a hard-hitting innovation HVE, demand, and supply multi-country regional economic effect studies, a larger part of the U.S. semiconductor industry history has been articulated HVE contention. This research rests on the Taiwan experience oral history conducted under conditions of constraint in the birth of the IDS, oral history from the Vice President at TI and then the CEO at Sematech where a new technology and HVE for national revitalization flank the semiconductor industry death, and leaves the anti-industrial policy sadomasochism to venture capitalists and their UBLP or over-hyped breaker blurbers who claim a clean negative side, content with write-ups of spousal interviews. Policymakers and other stakeholders may be helped by findings from semiconductor industry history on defensible evolution- and operation-relevant frameworks for the U.S. semiconductor industry agnostically based on innovation HVE trajectories and contingencies.

5.2. Role of Innovation and Technology

In the past, the U.S. semiconductor industry was leading the world in terms of chip production. However, over the decades, the growth and competitive edge of the U.S. semiconductor sector have diminished due to increased international competition and loss of government interest. Today, one of the key factors for revitalizing the U.S. semiconductor sector is technology, which is advancing at a very fast pace. Moore's Law, a driving force for technological advancement, is slowing down as there are increased abstraction layers and miniaturization of transistors. Researchers are also finding it difficult to develop profound architecture, hardware, and scaling principles to get more computational power.

Most of the AI/ML and big data applications are impeded due to the complexity and size of smart manufacturing data. In the U.S., it is anticipated that deep learning may be used to create advanced AI solutions for the semiconductor sector due to the lack of advanced capabilities, and they are true in truth. The rapid advancements and potential capabilities of deep learning in smart manufacturing and semiconductor technology may potentially increase the growth of the U.S. semiconductor industry. Typically, there are multi-level industry requirements starting from the microelectronic industry, semiconductor industry, chip manufacturing, and application-specific integrated circuit (ASIC)/chip solution. Apart from the microelectronic industry, the remainder of the requirements are likely interrelated with the advancement, standards, and market requirements. Consequently, the possibilities of these applications are significantly high.

6. Future Trends and Prospects

Demonstrated in our paper, many of the latest developments in the field of deep learning have been successfully applied in semiconductor manufacturing to provide innovative solutions to overcome various existing industry problems, set new targets to be achieved in order to push the limits further, and increase industry yields ultimately. Due to the exceptionally increasing research and development funding available in semiconductor research, the continuing trend towards the production of even larger datasets, and the emergence of new and diverse features of deep learning models in parallel, new opportunities from multiple perspectives have opened the doors of such different applications. All these advantages of recent trends and prospects related to increased interest by various researchers have created a driving force in the industry that can motivate strong competition and boost the economy even further by producing state-of-the-art and more efficient solutions in production.

In view of the decade's staying power of the present industry where AI products are applied extensively, it can be asserted that the power of deep learning applications is one of the factors that influence the direction of future trends. This fact is expected to revitalize the U.S. economies, which have started investing heavily in the semiconductor sector in the past and then become one of the strongest countries in this field, primarily because of the significant energy efficiency they provide in production lines, which can make an unprecedented source of value added.

6.1. Emerging Technologies

6.1.1. Scope Advancements made in emerging technologies, collectively referred to as the frontier of technology, are expected to drive revolutions, transform industries, and globally disrupt marketplaces. Consequently, semiconductor industry players aiming for sustained growth will need to embrace and leverage these innovations.

In this section, authors provide the relevant background information of the chosen emerging technologies: van der Waals constituents; Epitaxial lift-off process; Photonic-CMOS Hybrids; Growing directly on Silicon ("2D OS") as well as creating heterogeneously-integrated modules with light-absorbers, light-emitters, and light-routing elements (including transistors) epitaxially on silicon; Atomic Precision Materials; near- and in-body Internet-of-Things. Together, these technologies inform the emerging, evolving landscape of the chip market with potential dedicated applications. Jointly, the objective is to establish a point of reference where deep learning applications in smart manufacturing will assist in an overall market evolution and at the same time contribute to a healthy development of a key part of the U.S. economy.

6.1.2. Analysis Advances in AI, particularly in the field of deep learning, and the hardware accelerators to support their implementation have been expanding at an increasing speed over the last 10 years. Their capabilities are now, or expected to be, at a point where "mankind begins to depend on such machines and devices." Deep learning is the driving force behind most of these applications, challenging existing paradigms across a multitude of predictive fields from speech and language recognition to traffic predictions, drug discovery, and personalized medicine. A commonly employed model for prediction is the artificial neural network designed into sets of layers where data is passed to and processed.

6.2. Potential Impact on the Semiconductor Industry

As deep learning becomes more widely utilized, new opportunities will emerge for those with access to the necessary bandwidth and hardware. According to experts, the emerging addition of machine learning workflows on data at rest places the semiconductor industry at the cusp of an impending revolution. There is general consensus that continued deep learning advancements may boost the semiconductor industry. At the same time, the potential for deep learning to surpass the human brain makes it difficult to predict its eventual impact. However, the added layers inform new algorithms and promise to surpass current state-of-the-art capabilities, leading semiconductor industry experts to believe deep learning and machine learning could not only revitalize the China-U.S. tech cold war but revolutionize the smartphone and semiconductor industry as a whole.

It is not yet clear whether continued deep learning advancements will remain focused on the computational or whether the algorithms will eventually infiltrate chip design. In the longer-term, applications of automated chip design may decrease semiconductor development timescales and promote symbiotic relationships that may seem outlandish from today. As widespread digitalization reduces the barriers to entry for silicon development, the market will grow. So while table stakes in the semiconductor sector are determined by fast advances we are currently seeing, the emergence of cornerstone capabilities takes time to bear fruit. With smart manufacturing as described, the United States can ensure that the tariffs and export restrictions leveled by the Trump administration undermine Chinese tech dominance and arm American commerce with some resilience.

7. Conclusion

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The semiconductor industry's significant and increasing role in the economy has motivated growing interest in strengthening its U.S. manufacturing capacity, especially during the COVID-19 pandemic. Since the first U.S. semiconductor production, deep learning technologies have been implemented in various semiconductor manufacturing applications to enhance their performance, such as improving equipment productivity in wafer fabrication, prediction of die quality in packaging, and reducing maintenance cost and increasing on-time delivery in the facilities area. Therefore, this study explores emerging deep-learning applications in the smart-manufacturing domain of the U.S. semiconductor industry. This approach not only adds value to semiconductor firms as end users by providing them insights and understanding of how to implement DL effectively within their manufacturing domain but also has the potential to impact the AI and smart-manufacturing literature by conducting empirical research using a value-added practical AI application in the semiconductor industry.

Within the semiconductor industry, specifically in the smart-manufacturing domain, the purpose of this essay is threefold. First, we offer a precise and practical description of a set of the most recent detailed DL-driven smart technologies in the U.S. semiconductor industry—

specifically in wafer fabrication, packaging, and the facilities domain. We then discuss the practical implications as related to the way in which firms can utilize this knowledge to bolster the U.S. semiconductor sector as a whole. Lastly, to extend this essay, we suggest potential research directions that can be pursued by other scholars as related to DL-based smart-manufacturing, in particular, for the U.S. semiconductor industry.

7.1. Summary of Key Findings

In this essay, we provided an overview of relevant literature on digital twins, zero defect manufacturing, and the application of deep learning in manufacturing. We proposed a deep learning-based zero defect manufacturing model as a component of a smart manufacturing system that can be embedded into an Industry 4.0 framework. Different stakeholders can potentially benefit from such a model, including manufacturers, end-users, suppliers, regulators, and competition regulators. In an Industry 4.0 environment, it is possible to protect system parameters and operation from external access. Data sufficiency and identification of external disturbances, including malicious intent, become central to the smooth operation of such systems. However, data sufficiency is likely to be an issue for small to medium-sized manufacturers and end-users. Even for use with relatively simple surgeries, the installation of a new cyber-physical system requires large pools of historical data.

This essay offers an overview of the revitalization of the U.S. semiconductor industry and the relevant literature on manufacturing economies of scale, Industry 4.0 and smart manufacturing, and the U.S. semiconductor industry workforce. We then present a conceptual framework to increase the economies of scale in semiconductor manufacturing with an Industry 4.0 embedded smart manufacturing system. Furthermore, we describe the deep learning revolution and the application of deep learning in the industry and in the semiconductor industry. In IoT, big data is created as the data is collected from the sensors in the devices. The high-dimensional big data can potentially be used as input into deep learning tools to generate a deep learning-based smart manufacturing process for the U.S. semiconductor manufacturer. The model can be converted into a zero defect operational strategy as a competitive advantage for a U.S.-based semiconductor industry that must operate at a smaller economies of scale.

7.2. Implications for Industry and Research

In practice, the essay shows that the U.S. semiconductor industry may also benefit from employing deep learning applications in the production of high-quality semiconductor devices. This essay introduces six step-by-step procedures for applying deep learning methods in the development of smart production schemes in the U.S. semiconductor sector. This report serves as a guide for engineers, managers, and researchers in the U.S. semiconductor sector in order to facilitate the utilization of deep learning technologies for rapid, accurate, and reliable high-quality semiconductor production processes, which lead to lowering the defective product costs of semiconductors developed by the U.S. semiconductor industry.

In addition, as an academic essay, the downloadable findings of this paper would serve to facilitate research topics for future work in semiconductor manufacturing research since the paper provides insights to those who are interested in the latest and fastest research and development associated with deep learning applications in the field of semiconductor research.

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