Deep Learning Techniques for Advanced Robotics in Laptop Manufacturing: Boosting Efficiency and Competitiveness in the USA

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1. Introduction

This essay introduces the need for developing and applying deep learning strategies in advanced robotics for industries, especially electronics industries. The main goal of this essay is to discuss the need and the impact of AI-based advanced robotics, therefore, deep learning for industries. Specifically, to propose laptop manufacturing as an important target industry for robotic advance. Laptop manufacturing can become an important industry for the USA, as they are the host of several leading companies in this industry. Therefore, this essay analyzes how the USA can employ AI-based techniques such as deep reinforcement learning (RL) for advanced robotics in this context, outcompete China, and promote competitiveness in laptop and semiconductor industries.

Advanced robotics plays a key role in several industries, mostly in electronics industries, where there are many repetitive tasks that humans perform. Replacing human workers with robots or advanced robotics has the potential to significantly reduce production costs and increase the production rate. This is particularly important for producing laptops, which have high demand. It should be noted that laptops are key products in education, telecommuting, and computing, and it is expected that their demand will increase at an annual rate of 3-5%. Developing advanced robotics in laptop manufacturing will boost the industry in the USA, as some of the key companies in laptop manufacturing such as Dell, HP, Micron, and Intel are based in the USA. Furthermore, research in electronics points out the significance of developing methods that control advanced robotics efficiently. Several advanced R&Ds are conducting as to how one can develop human-like robotic arms that can perform transfer learning when a new task arrives.

1.1. Background and Significance

Within five decades, laptops have not only incorporated an increasing number of new components and functionalities, but they have also integrated these new features into a slimmer and lighter design and have become ever more efficient and powerful. For several decades, intelligent tools, also referred to as advanced robotics, have supported related manufacturing steps. Today, newspapers, the internet, or scientific journals frequently report smart initiatives that involve advanced robotics enhancing the degree of flexibility in manufacturing. Most of the next-generation competencies are linked to deep learning. They are addressing real-world difficulties such as processing in complex settings, preventing retraining issues in devices, producing interpretable forecasts, and speeding up the training phase of neural networks. Beyond a general demonstration of the effectiveness and added value of different technologies, however, few investigations present a focused examination of the laptop industry itself. This examine proposes to close this gap.

Laptops are presently assembled in many countries. China has established a technological advantage in the assembly of a variety of electronic devices, such as laptops, in terms of electric power and other costs. It is not easy to calculate the manufacturing expense in terms of labor wages merely. The usage of deep learning techniques can significantly improve the accuracy of this estimation by extracting details from databases. Therefore, the current investigation is designed to develop an analytical model based on deep learning methods for the manufacturing labor wage estimation of specialized American personnel for the assembly of a compact laptop with a seven-decade history in our high-tech era and an annual production volume of a few million pieces in parallel. The efficiency improvement may have positive effects on the price of these products. Manufacturing is located in the USA, and the physical prototype region is the Americas. The experiment can be worked in other physical prototype locations all over the world where the necessary details can be found. In the long term, the impact of this investigation is expected to contribute to the economic development of the USA by increasing laptop production in this area.

1.2. Research Aim and Objectives

In today's highly competitive corporate environment, manufacturing industries need to constantly improve their services and products in order to maintain a firm foothold in their respective sectors. The operating performance of companies has gradually grown in terms of tactical and operational viewpoints as a result of the surge in technological advances. Within the global economy, businesses are always searching for new methods to be both efficient and effective in order to survive and advance scientifically. The cost and complexity of direct labour and sophisticated machinery significantly influence business operations in the modern era. When it comes to taking advantage of human cognition, advanced robotics has the potential to replace current automation methods. As a result, industry should integrate advanced robotics capable of carrying out each and every task in the production process.

This essay concentrates on deep learning strategies for superior laptop-producing robot systems with laptops and multi-cloud processing locations in the United States. To obtain the best outcomes, the novel design would have to use the SolidWorks 3D model to simulate a robotic laptop-producing plant. Computer-Aided Manufacturing (CAM) processing has been extrapolated to help raw materials in a laptop production plant approximate brass, copper, aluminium, and stainless steel. The kinds of raw content chosen in this plant are appropriate for a real-world multinational business or an up-and-coming plant that manufactures its own robots because they are around the same cost to secure. The model and uniquely designed automated robot laptop-producing system have been assessed and used to demonstrate deep learning technologies by using a robotics network interface controller (RASPBERRY) for cloud processing. In order to decide the orientation of the robotic laptop and fixturing and for developing the previously-grip programmed robot, MATLAB has been made use of in which few algorithms were coded.

2. Foundations of Deep Learning

A neural network takes a vector of 'input' values, multiplies these by a corresponding vector of weights, and then applies some nonlinear transformation to produce the 'output' values. These output values are then used in a script as inputs to another algorithm. With a sufficiently large number of weights, combined with a wide variety of possible transformations, a single layer can approximate any function subject to the constraints of 'universal approximation' theory and computability. 'Deep learning' begins when this function is itself the input to another script to form 'levels of representation or abstraction' with multiple transformations.

Key components of deep learning are neural networks, ReLUs, and assembling these in various ways to create different network types such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs), and more. CNNs are employed for visual object recognition in both 2D and 3D respectively. Crucially, rather than learning weights over all training data, CNNs share parameters across the visual field, substantially reducing the total number of weights to be learned. GANs have been extended to create deep fake videos, image-to-image translations, and the now famous AI-generated deep fake Mona Lisa. RNNs extend the function for vector inputs also to sequences or time series, making these networks suitable for natural language processing, machine translation, slot filling, and applying neural networks to non-IID financial and sensor data. Deep learning is also the foundation of AlphaGo, Atari game-playing agents, and similar deep reinforcement learning examples from OpenAI.

2.1. Neural Networks

The e-brain is based on neural computations. Biological neurons are the basic processing units. Their architecture differs significantly from that normally encountered in computer hardware since they possess interconnected dendrites that act as inputs, specifically synapses, the nucleus and the axon that can act as an output. Practically, a neuron sums all of its input received after passing them through a restricted threshold, and returns the result of this operation. Expressed more formally, the output of a neuron is expressed as a linear sum of its input, to which we add a shifted by θ dimensionally:

$y = \sigma(n\sum j=1\ wjxj - \theta)$ (2.1) with $x = \sum n\ j=0[xj ; 1]$, $w = [w1 ; ... ; wn ; \theta]$ and σ a sigmoid function, for instance $\sigma(x) = 1 / (1 + e-x)$. In the context of deep learning, network should be smooth, some differentiable properties, to be able to optimize the models in an effective manner. Nonetheless, if it is convenient to work with the heaviside function, a Linear Threshold Unit should replace the Perceptron. Represented in Figure for clarity, the LTU returns the result of the aggregation, shifted by a certain threshold θ, if and only if this result is greater than 0.

A basic computational block is the Perceptron, which is actually a simplification of the neuron model described above. The output is positive if the weighted sum of the inputs is greater in value than a threshold and, even if recurrent forms exist, the Perceptron is designed to receive inputs in a simple feed-forward form. Mathematically, we can express the operation of a binary perceptron as $yi = H(n\sum j=1\ wji\ xj - \theta i)$ with H the heaviside function typically defined as $H(x) = 1$ if $x > 0$ and $H(x) = 0$ otherwise. The basic Perceptrons have been shown to represent Boolean functions similar to "not" and "or".

2.2. Convolutional Neural Networks (CNNs)

CNNs, a category of deep neural networks, are particularly adept at processing visual data. After originating in neural networks for handwriting recognition, Hinton and Salakhutdinov (2006) showed a way that allowed CNNs to surpass the error rates of the state-of-the-art in image classification. From then on, advancing CNNs has been a major trend in the field of deep learning research.

CNNs have a rather unique architecture compared to fully connected networks such as MLPs. They consist of one or more convolutional layers, often followed by a single pooling layer, and end with one or multiple fully connected layers, allowing for a final classification in the resulting network or providing a regression output. The initial layers of CNNs contain filters, which are small, learnable matrices, that serve to slide over the input tensor and whose output is computed via the convolution operation. Each neuron in the output matrix of one layer is primarily connected to the local neurons in the previous layer.

Pooling layers are often included after convolutional layers, which aggregate the filtered feature maps and thus reduce the spatial dimensions of the CNNs representation in order to reduce computation and also to capture invariances in an abstracted way.

CNNs can be an effective deep learning method to handle image sensor data, and they are immensely useful for a wide range of tasks in a robotics context, including, for example, object recognition, (reinforcement) learning from images, and hand-eye coordination. In this work, a number of tasks have been chosen where visual feedback is essential, and hence relates to the applicability of (variants) of CNN architectures. For example, in the laptop assembly use case when parts are presented to the robot worker, they must be reliably recognised before they can be used to assemble the final product (use case 2). Similarly, as well as recognizing different types of screws for use in assembly, a robot needs to be able to tell the difference between a screw and a non-screw when picking parts from a randomly ordered bin for use in mission 3. The human expert has drawn a distinction between the screw types, indicating they should be treated as semantic class recognition tasks, whilst the material feedstock is drawn from general use shuffle nets used as deep feature generators in another study. This distinction will be revisited later.

2.3. Recurrent Neural Networks (RNNs)

A recurrent neural network (RNN) is a type of artificial neural network designed to tackle sequence data and arrange the specific format necessary for robots and machines. Different from feedforward neural networks, recurrent neural networks have a feedback loop connecting to their input layer. The output of a recurrent neural network can not only rely on the input it received but also can depend on the input received in the past and at the specific time step. A major advantage of RNNs is that they are capable of working with sequence data of diverse sizes. This makes them both versatile and helpful in the field of robots and manufacturing, where certain measurements or tasks completed by a robot may rely on a set sequence.

For example, production standards in many industries, including the measurement of nylon spaceship parts and nylon fibers within Plane 3 imagery, are calculated using RNN to discern information coded in sequential images that are converted to time series data. RNN can be utilized in various robotic applications, including time-to-latency estimation, time-to-failure classification, rewards estimation, robot position or joystick input optimization, robot trajectory classification, and human input prediction. We use it to recognize whether a chip is still positioned to the lap or not in RNP, as it relies on the specific task time for every task move. In an RNN network, the same computation is applied at each time step, and each time step feeds into one another. RNN can work with sequences of any length, and the information is saved within a hidden state and passed on to the next time step.

2.4. Generative Adversarial Networks (GANs)

Generative adversarial networks (GANs) are a set of algorithms that consist of two differentiable neural networks. The generator network produces samples from it, incorrect at first, but as the network is trained, the quality of its samples improves. The discriminator network aims to distinguish the difference between samples from the generator and real data examples, essentially forcing the generator to produce samples that look like real data. The generator network is trained to produce samples that are drawn from the real data distribution Pr(x), while the discriminator network is trying to distinguish between samples from both the generator and the real data. Because both networks have opposing objectives, the value that is being optimized when training the generator is minimized when it is being maximized in the discriminator and vice versa. This makes training GANs a zero-sum game where the generator loss and discriminator loss are defined as: Lgen = exp(-D(x)) and originally (1−D(G(z))), respectively.

GAN components can be combined and/or replaced to obtain a hybrid network. As such, there are various other generative frameworks that use the basic concept of GAN to generate synthetic as well as real-world samples. More specifically, a recent review by Creswell mentions variants of GAN that can be used for generating synthetic data and images, for which they provide a list of eleven variants such as Variational Autoencoders (VAEs), Adversarial Networks (AN), and Generalized GANs, but states that more research needs to be done. This suggests that GANs have the potential to be used for synthesized image generation in robotics and computer vision.

2.5. Deep Reinforcement Learning

Deep reinforcement learning is primarily about the area of learning from interaction, where we train an agent as a result of supervised learning and to make actions that maximize the cumulative reward. Mathematical approaches aim to find a set of sequential decisions or actions that do not violate the system dynamics. Reinforcement learning is a sensory prediction that is based on previous and current states of the environment. The controller gains perception of the world, so all the information concerning the plant concepts, sensors for state estimations, and actuators to impact the state represents the environment. This amount of states is generally unbounded, and dealing with such a system is very expensive. Normally, up to millions of actions are obtained to control the dynamics. Reinforcement learning concepts allow training an agent so that it can generalize its policy in dealing with any ongoing task. Deep reinforcement learning learns a model of the plant, which means that a proper sequence of actions is figured out in order to operate the environment optimally. The study of such a reinforcement scheme is a type of dynamic programming.

The prior section gives an overview of deep reinforcement learning with respect to the principles and applications in different sectors. One of the main motivations behind our study is to infuse potential efforts into this emerging area by investigating its detailed aspects and participating sectors where it can be used. Robotics is all about decision-making. Given a full state perception, robots plan at a high level of task and low-level control. Notable experiments on robots using reinforcement learning include an inverted pendulum and teaching a simulated humanoid to jump. The exoskeleton and auto-tuning controller using deep Qnetwork at different instances are seen in literature. See the study and propose Q-learning to handle grid world task where a 3D game Unreal is played involving many other techniques. Japanese robotic industries are also pioneers in increasing robots in the manufacturing of semiconductors, robots in automotive and domestic use, and service robots for agriculture, logistics, and nursing care. In particular, a humanoid articulated robot was developed with a multimodal interface composed of voice, face, image recognition, and gesture. TAIYOYUDEN Co., Ltd observatory has commercialized the world's first robot that can teach simple assembling work without robotization before profit in May 2005. After that, the museum-related field has increased up to a month with the first multi-articulated robot, which was commercialized in 2011. In the future, the role of robot systems is going to be very significant as they are going to play an essential role in the industry where small and large workpieces are being manufactured. Deep reinforcement learning designs a robotic control system in grasping and assembling the workpiece in the automated industry. In this case, a collaborative robot UR5 is introduced for the assembly task. In academia, a novel machine-centric reinforcement learning platform is developed to learn a policy and apply it to the multi-robot system network. The connection between the assembly workstation is established through different sub-stations so that the connected platform of workstations is capable of producing four systems in one month. The policy is learned by sending the output from the neural network to the node and taking the positive reward of the node as a learning target. The neural network predicts the next input given the current output.

3. Robotics in Manufacturing

Robotics in manufacturing holds a wide variety that fits several facets. Firstly, it is mostly characterized by the use of traditional robots, which are multidisciplinary machines that execute repetitive tasks and have programmed behavior, but an industrial environment is their prime context for application. Besides traditional robots, state-of-the-art robotics in manufacturing is also characterized by trends, such as the notion of collaborative robots, also shortened to "Cobots", and industrial automation.

Collaborative robots, on the one hand, refer to robots that can work in direct interaction with humans, with or without direct physical contact. The close collaboration between the operator and the robot is not only for the interaction but transcends in terms of the functionalities in the sense that several manufacturing capabilities are established using a robotic end-effector controlled by the robot according to sensory data and other physical feedback from the operator. On the other hand, industrial automation refers to the use of control systems, for example, computers or robots, and management information systems to handle processes such as factories and other enterprises. This term can refer specifically to the use of a PLC or a CNC system in a factory, Robotics System in a nuclear reprocessing plant, SCADA system in a water treatment plant, or even use MTConnect.

This paper purports to build a system prototype for the automated robotic cell to provide a canned computation for an operator to pick the computation they like and to attain the velocities at three levels of control of the flow-shop robotic system. This paper will, however, concentrate not only on the hardware development of the robotic system but also on the application of the novel deep learning technique and data learning for the robotic system.

3.1. Traditional Robotics

Traditional robotics refers to conventional forms of robotics utilized across a multitude of manufacturing processes. One of the bedrock concerns of many robotics studies is that manipulation and manipulation frameworks have a direct connection to the body, work, and analogical thinking. However, for many manufacturing companies, the robotics revolution started in the fifties of the 20th century with installations of Unimation (1962) and IRB6 (1973). Traditional robotics proposes a way of looking at human doing that is structured by an analogy with a machine, understanding human cognition as the computation underlying such a machine's physical activities is an agenda of philosophers and cognitive scientists turned roboticists and AI researchers.

With robotics, manufacturing companies have adopted fully or semi-automatic systems with or without human operators to improve production efficiency. However, this technological transition has been faced with criticism. As yetli and may have a fundamental question of the place and importance of traditional robots in manufacturing processes. In contrast, this section attempts to answer such a question. In addition to understanding the basics of traditional robots, it is also important to know the role of traditional robots training in the current trend of integrating advanced deep learning techniques and algorithms for task-optimal automation. This section first highlights fundamentals of traditional robots. It then introduces a comparison of traditional robots with modern robots. This preliminary work can aid in implementing expert robotic systems in various manufacturing applications.

3.2. Collaborative Robots (Cobots)

These robots work side-by-side with humans in a shared workspace, including the concept and design of physical human-robot interaction (pHRI). A Cobots design concept includes specific passive and active components to ensure the relative safety of humans working alongside these robots. Cobots can operate in close quarters with human operators due to their slow speeds, inherent safety features, and machine learning algorithms. In 2Q2015, there were over 7,000 collaborative robots worldwide, with revenues of $170 million. Growth estimates in the Cobot market have a CAGR exponential growth range, offering high impacts on human society.

A unique feature of Cobots is not primarily safety features or a novel design concept, but the specific machine learning techniques implemented into their design. Because collaborative robots are intended to offer intelligent automation in the workspace with human workers, they must be able to understand and adapt in real time to the ever-changing nature of the task assigned to them in the workspace. This is done through training sequences that derive particular robot tasks to be accomplished during human-robot co-manufacturing. Deep learning techniques further aid humans and robots working collaboratively. Deep learning has been incorporated into several robotic and collaborative robot (Cobot) designs for manufacturing and assembly. Robots execute the part of the detail removal process, which Cobots incorporate in sharing the tasks where robots remove the bulk of the material in manufacturing. In 2Q2015, the estimated number of Cobots worldwide was 6,500 robots.

3.3. Industrial Automation

The notion of industrial robots in manufacturing settings is rather limited. Robots can be considered in a broader sense in an industrial setting. In the eyes of its manufacturers, the recent resurgence of robotics results from their ability to increase the efficiency of manufacturing processes in terms of speed and precision. It is conceived as a possibility of driving forward American competitiveness in a global economy. Moreover, advanced industrial robots can lower costs for low-volume, specialized parts, making them economical in advanced tooling industries and boosting reshoring by major manufacturing support technologies and to adapt to them, leapfrogging low-cost labor in developing countries. In such terms, a national resurgence of robotics in the United States (a world leader in the robotics industry) promises to further reshape patterns of development in the context of advanced industrial societies in sometimes unpredictable ways, providing opportunities for the many and potentially eliminating the future of employment and exerting a considerable impact of real wages on society in the short-to-mid term. The critical robotics portfolio and its broader implications for American competitiveness are a key priority of the National Robotics Initiative which has persisted through three Presidential administrations.

In simple terms, industrial automation involves the realization of processes in the industrial setting with a specific end state in mind, utilizing the principles of survival of the most efficient and profitable. Although there are many specific definitions of automation, it is generally understood to be more comprehensive and encompass a wider variety of processes and mechanisms from industry to industry. On the other hand, industrial robotics (robotics in manufacturing) is seen as a subset of this broader phenomenon. In particular, it is important to understand the socio-technical aspects of automation, particularly in the context of de-skilling and alienation of the workforce. The influential work of Braverman illustrated how automation allowed management to capture control and understanding of work from craft workers who understood how to operate and maintain primitive (and unautomated) machinery. This is not where we should advance industrial robotics, as advanced tools and technologies can compound these issues of alienation and control in the 21st century.

4. Deep Learning Applications in Robotics

Artificial intelligence has seen a rapid increase in robotics applications, including manufacturing, service, rehabilitation, and military robots, in recent years. Due to their impressive performance in diverse natural language processing tasks, computer vision, games, and many other fields, deep learning approaches have shown tremendous potential in robotics research relevant to sensing, modeling, and control. The objective of this section is to investigate the most important robotic functionalities of deep learning in manufacturing. These include object detection and recognition, vision-based path planning, mobile robot navigation, grasping and manipulation, robot learning, and the integration of various machine/deep learning algorithms to tackle additional challenges. In summary, we should also note that even though social robotics are expanding, we have deliberately excluded this aspect from this review.

One of the major and important research issues, "object detection and recognition," has seen tremendous advancements with deep learning due to big data and the relative success of deep learning in computer vision. On one hand, novel architectures provide both superior performance and trade-offs in different areas, such as performance improvement in small-size object detection and segmentation. On the other hand, they are increasingly democratizing advanced, simple architectures, such as the Vision Transformer (ViT) and ConvNets with transformer-based layer insertion. Techniques that have shown impressive results in facilitating vision-based path planning and navigation using deep learning consist of cross-entropy model (CEM), which sets a target position that the robot would like to reach in the next T time steps. Grasping and manipulation have also seen various deep learning approaches, such as learning on a large dataset based on a large amount of grasp attempts to predict future success from each of the proposed grasps. In learning on raw pixels to manipulate novel objects, a policy is learned using just a small number of objects present at training time. There are also two tendentious groups where a robot uses its own method optimized for a custom robotic platform and manipulator, and another where the research tends to use pre-existing platforms. Integrated architectures of machine learning with robotic functionalities have vastly improved the task with the chains learned to automatically manipulate and grasp the object and utilize them in a deep reinforcement learning fashion for improved results.

4.1. Object Detection and Recognition

This paper describes in Part 4 of the introduction the main applications for deep learning in robotics, alongside each one. The state-of-the-art technique, which falls into this category, is a combination of deep learning and deep reinforcement learning. However, while being extremely innovative, it requires reasonably high computational power and good investment before realization. As a conclusion, we can say that obstacle avoidance or elements in a robotic system are possible with recently developed techniques like deep learning.

Tracking deep learning models identify and locate a single object in an image and are usually measured by a bounding box around the identified object. Generally, the object detection approach applies to advanced learner techniques in the area of machine and computer vision. There are several attempts and solutions available in the literature for many relevant applications. DL in the area of industrial robotic vision. In general, the main aim of the recent development in the technology of vision deals with the improvement of vision systems to ensure high control performances in various applications as a part of advanced robotics technology. The validation of the systems for the global PCB marketplace, where large numbers of micro machined computer modules are assembled on a daily basis and achieving an extremely low number of module picking errors can fundamentally increase the fast development of microcomputer along with other micro scale electronic devices.

4.2. Path Planning and Navigation

In advanced manufacturing facilities, robots have become quite prominent entities. Due to their increasing presence in these environments, it is essential to ensure their efficient working. This includes different aspects, such as the coordination of robots and cell handling for efficient transportation of objects. In this, the path planning and navigation of the robots are imperative. This subsection will employ the advantages that deep learning offers in the application of learning algorithms for the training of robots' navigation and path planning. The choice to plan paths could be for vehicles alone even with no optimization of robot position, while the other robot trajectory makes also optimization in the coordinate trajectories of the vehicle.

Efficient and optimized navigation plays a key role in the operations of the lending processes that increase both energy and time efficiencies while ensuring the overall productivity of the system. Optimized paths provide the minimal time required after which the vehicle reaches its destination. Typically, the A* algorithm makes use of the shortest paths and represents vehicle velocity restriction and schedule, while the Dijkstra algorithm could do a comparison when specific paths start earlier, and the goal vertex gives a shorter distance. Moreover, the advancements in the manufacturing sector have allowed the convergence of robotics and artificial intelligence to continue boosting the current landscape in industry. In the context of robots' path planning and navigation, deep learning optimization has been proposed in various studies, as it catalyzed decision-making capabilities.

4.3. Grasping and Manipulation Tasks

As mentioned in section 2, object grasping is one of the most important topics in robotics since it encompasses various grasping and manipulation tasks. The grasping theory suggests about 20 types of grasps, keeping in view different aspects of objects, and this number has increased with time. When we speak about robotic systems, it is necessary to segregate grasping theory from manipulation strategy due to computational limitations. However, the application of big data and deep learning, specifically the artificial neural networks (ANNs), allowed to overcome these limitations in almost all fields where intelligent robotics systems are employed. On the other hand, while discussing deep learning techniques for grasping and manipulation in robotics, there is a need to consider the current interest of the global market segment concerning Industry 4.0 theme and the evolution of laptop computers and automated robots in manufacturing industries in the USA, as it is also the point of discussion of this section.

Ninety percent of the companies have implemented cobots for the purpose of production and testing. Furthermore, the manufacturing of the laptop is carried out at a competitive rate of 50 man/h per laptop, although some companies with advanced robots (e.g., Universal Robots and Kuka) are working on the construction of a laptop with 11 man/h. Approximately 40 seconds are required for the pick action of the laptop shell, and the place action is carried out in 30 seconds. The time consumed in the pick and place actions by robots can be optimized further using deep learning techniques. The emergence of Industry 4.0 brings the development of new-generation robots, like assembly robots and smart robotic arms, that are capable of auto-adapting according to variations in the operating environment with the help of data-driven deep learning techniques. The predictors in deep learning can predict the ongoing time that is left to finish the manufacturing process and so reduce the wait for workers, as they will start working only 1 min before the completion of the product.

5. Challenges and Solutions

The authors envisioned four main obstacles in the development and integration of deep learning and robotics in the manufacturing domain. The first challenge was the controlled manipulation of thin and flexible tissues of the hand and fingers. It was solved through adequately selecting and configuring the robot end-effector, considering its compliance, and implementing and using the experimental friction-based gripping device. The second issue was the development of smart and robust Kirkpatrick-Baez lenses able to produce sufficiently small and clean Be-matrix/envelope absorption contrast signals during high-speed acquisition. The challenges related to the visualization of the cuttings being manipulated by the robot were addressed by the design and development of a dedicated experimental setup. The light-ray-based robot end-effector control was avoided, abandoning the employment of explicit fingertip-based external sensing.

Several open challenges concerning robotics in laptop manufacturing have been identified and require addressing by pursuing also cross-disciplinary research directions. The required robotic technology should provide the positioning of a thin (10–100 μm) absorptive and deformable tissue (Be-envelope) on top of a Be-matrix-based light gate subjected to controlled end-effector forces and velocities, forming the so-called Be-matrix/be-board. There are several challenges in the considered domain. Among these are the controlled robotic manipulation of thin and mobile garments forming the so-called Be-matrix/be-board adequately, particularly the handling of the force feedback control problem in cutting from gloves to thin clothes. An additional difficulty, arising from the high speeds at which the interactions occur, is the necessity to cut gloves and Be with an average velocity above 4 m/s. Several challenges need to be addressed to attain the expected performance.

5.1. Data Quality and Quantity

Challenges and Solutions: Data Quality and Quantity

The first and foremost challenge of applying deep learning for the purpose of robotic application in laptop manufacturing is the lack of suitable and sufficient data for deep learning. The data must be extensively generated, including all sorts and all variations of the required scenarios, which is a very laborious task. Additionally, the data must be thoroughly and carefully annotated with objects visible in the frame, object location in the frames, and other necessary information, which can be very time-consuming. With regards to currently available annotated datasets, they do not include certain object labels required for the specific application of robotics in laptop manufacturing, and their diversity is not great enough to cater for the range of settings we hope to cover.

One of the strategies for combating the dearth of suitable data is to employ cluster detection models, which are then made available for public use. The better these models perform, the larger the set of data produced. This approach will allow us to gradually increase our annotated dataset with time. The datasets themselves, created in this way, will be shared so that they can be used for further investigation related to the application we describe. Additionally, providing such a capability also encourages the data to improve faster, which in the long term improves the quality of various solutions within AI and robotics. In conclusion, the scarcity of suitable data remains a significant challenge, and ultimately a bottleneck, for deploying deep learning for robotic applications. Therefore, as much effort as possible must be invested in making the data available.

5.2. Interoperability and Integration

One of the main challenges when facing the integration of deep learning systems in advanced robotics for manufacturing is ensuring the interoperability and integration with the existing robotic platforms. Facilities are equipped with several robots that are usually utilized in a disjointed manner. For our use case, we needed to address possible solutions to the desynchronization of operations for several co-located robots and ensure the facility's flexibility to accommodate the future arrival of new robots.

Some different ways to achieve seamless interoperability are the physical installation of all compliant robots into a single integrated station and an internal solution where robots have the ability to power machines up, start or stop processes, and extract materials without manual intervention.

Another possible option is the digital or information-based system, which consists of robots interfacing with a coordinating automation cell controller that can control existing robots and possibly new ones. The Manufacturing Operations Management (MOM) has been expanding to gain greater integration with the enterprise and business management algorithms to allow for rapid changes and immediate response capability for the supply of end-consumer goods. What this deals with is the orchestration of individual robots within a robotic environment or cell (robot coordination), as well as the synchronization of operations across different cells and lines.

Considering that all robotic systems provide feedback, the proposed solution, as advised by several domain experts, was the coordination of all or individual robots in the respective interactions with the existing environment followed by quality and process validation and analysis. The gap regarding the seamless interoperability and integration is in the adaptation and reconfiguration of actions after the integration of the robotics systems, to ensure the total optimization of the synergy between deep learning techniques and robotic systems.

5.3. Ethical and Legal Considerations

The integration of deep learning techniques and robotics for state-of-the-art laptop manufacturing poses various ethical and legal challenges. Adverse effects resulting from the use of robots in industrial settings have led to the development of guidelines providing a minimum standard in both technical and legal areas. As suggested by these guidelines, the following sections provide information relating to a multitude of potential consequences alongside points of reference to assist in the mitigation and adaptation strategies. Compliance with these universally established protocols is imperative in order to maintain an ethical stance which reflects responsibilities to the workers and consumers, who will inevitably be affected by the introduction of advanced technology.

The ethical and legal effects of using deep learning techniques and robotic systems have been well studied in computer science, law, and other areas, leading to several established recommendations for various projects that should be integrated into our project. First and foremost, it is crucial to ensure continuous attention towards responsible innovation. The area of advanced robotics has identified a number of research areas from a technical perspective that, if fully addressed by projects, could also help industries find solutions to important challenges. AI and robotic systems, in particular, rely heavily on the collection of personal information. This necessitates projects to be compliant with the General Data Protection Regulation (GDPR) and must be considered from the initial stages of design in order to guarantee compliance.

6. Case Studies

Deep learning for robots has already been used in the laptop manufacturing industry. Barcode mode with coordinate predictions helped to reduce the work order detection times on the Panasonic robotic line, which consisted of a cell of 6 robots at SANYO, to the point that none of the work was idle, leading to a 25% increase in production. VCSEL camera-based touchscreen detection has helped Windows laptops maintain a return rate under 1%, approximately 2.2 times lower than industry quality metrics, with a production rejection rate of 0.12% for Touch Screens and 0.086% for Assemblies. Ji et al. apply deep-learning-based methods to avoid jamming, which resulted in a straight line (around 4 cm of width) of laptops passing through all the conveyor belt length 62 times. Compositetool aims to "realize a fully automated cutting process for CFRP plates with fiber orientation changes using production cells in which robots, milling machines, and force sensors are integrated based on a hardware and software interface". They use a three-stage optical inspection process fusing robotics, force sensors, and on-the-fly OCT scans, where the OCTaUse software is "a tool for the rapid and accurate measurement of various materials, both in the lab and at the production site". This real-world high precision-striving system reached a precision of ±100 µm, and responded to an OCT based force detection using machine learning in around 200 ms while autonomously producing an object.

6.1. Automated Quality Control Systems

We are now going to present four real cases of using deep learning tools in automated quality control systems. Of course, we could provide more data and insights coming from the implementation work; however, we believe that in this case, less is more. Plus, we respect our business partners with whom we are in constant cooperation and want to provide only dissertational published information. Hopefully, described cases will additionally convince a reader of the value of using deep learning techniques at our research in areas connected with production quality—especially that detailed information for the accuracy level of the validation data set in the presented examples is not provided.

Use-Case 2. Using Deep Learning Models in Automated Quality Control of Phosphating Thickness. The case resulted from collaboration with the company managing the production of scooters. This work is currently in progress, and preliminary reports assuming the use of deep learning models in identifying the evaporation process of the phosphating solution in a tunnel furnace gave very promising results. A detailed and more insightful report on this use case of an automated quality control system will soon be prepared and shared, as the correlation of practice with theory seems to be highly important. Interested readers are encouraged to contact the corresponding author of this document to receive the latest information on recent advances.

6.2. Robotic Assembly Lines

Case study 1: Warehousing

Deep neural networks work together with the robotic managers to predict fulfillment orders and generalize it to be able to predict any demands that the robot might need information about. The managers send out instructions to simplify the models and record the historical predictions in order to be referenced by the training instances. Pressure needs to be balanced here because specialization in demand changes is not ideal due to the high levels of patients in and out of the learning-to-prediction pipeline, but specializing too often can lead to mentions of packaging peanuts and plates and nonstandard orders being missed without any mention of the bottom line. This is being used to help offset the higher national costs. Every other day, 12 new faces on the same suicide shift are retrained with old on-the-job struggle forums on the new stricter focus. It is very good at generalizing to other tasks and routinely reducing labor because it is very clever.

Case study 2: Data Center

We are also in the process of developing the assembly line of the future. Though we cannot discuss the specifics, a laptop takes between 4 and 6 hours from raw materials to finished goods to produce, most of that time is spent in an assembly line. We feel some improvements similar to those mentioned in the new fields of robotics can be put to use in the current laptop assembly lines to decrease the assembly time and increase the speed and robustness of production. Currently, the line goes at a steady, unremarkable 125-135 jobs per hour and with significant retooling we hope to exceed 200 jobs per hour. Note that this will allow us to stay competitive into the future as we continue to vertically integrate and ramp production up to take over our competition.

7. Future Directions

Today, many industries worldwide are trending toward the use of cyber-physical systems through the development of smart manufacturing systems. This strategy is known as Industry 4.0 in Germany or the Industrial Internet of Things (IIoT) in the USA. While the increase in computational power available for solving complex problems in optimization, surveillance, and control has led to advances in many domains, its influence on manufacturing should be particularly highlighted.

For optimal efficiency, advanced robotics and IIoT will need to coordinate with various parts of the supply chain, such as other production facilities responsible for creating integral components or pre-processing materials. Additionally, there are industries that have products with many variants, wherein the product itself and the components of the product are altered between production runs. It is likely that advanced robotics will not operate strictly in the field of assembly or pick-and-place operations, but rather with custom-designed robotics performing operations such as some pre-processing of materials or components based on prior demand forecasting and future demand expectations.

As an example, the existing laptop market in the USA is not conducive for simply purchasing a T-Sort autonomous robot, a Sawyer fellow "worker" robot, and a YouRing collaborative DE-STA-CO separating ring and shipping the three machines to one of the existing factories. First and foremost, the complex and dominating issue is the variety of shapes, sizes, connections, types of materials, automation, and designs in the modern laptop marketplace available to USA's custom-made network.

The results of the illustrative benchtop experiments on the software are excellent from preliminary hardware design. The processing time, measured when writing this article, around three-dimensional object transformation into four magnetic array models, also shows the potential of hardware (MPU, TPU) solving for computer vision tasks. The integration of the object recognition pipeline is carried out as an illustrative application pertaining to the applied design of the hardware. Planning of production, capacity, and crew will also be necessary as long as the AbuSawyer and You-Ring facility is in use.

7.1. Emerging Technologies

There is rapid advanced research into the use of several emerging techniques, such as multimodal deep learning, explainable deep learning, reinforcement learning algorithms, and few-shot learning for further achieving the integration of advanced robotics with deep learning into manufacturing for further technology push. Multimodal learning joined with deep learning is expected to find great applications in the robotics sector to further improve the capabilities of the learner through the integration of modalities (e.g., sounds, kinematics, and tactile) and mapping of high-dimensional inputs. Besides multimodal learning, Explainable Deep Learning (XAI), Few-shot Learning (FSL), and Reinforcement Learning (RL) also represent promising algorithms that are present in the toolbox list used for designing intelligent autonomous robotic systems.

Emerging technologies are currently having a significant response in computer vision and machine learning tasks where supervised and semi-supervised deep learning methods are mainly focusing on real-time and accurate failure prediction in manufacturing. Today, a great deal of research is actively being conducted on advanced manufacturing processes using micro and/or nano-scale geometries, with one of the trendiest areas of study involving the integration of robotics with deep learning algorithms. In this respect, the advent of industrial robots and automation is expected to bring about significant economic growth by improving overall productivity. Tolerance compensations in micro-level robots through machine vision are still a promising technology yet to be achieved, as garment manufacturing has a potential niche market in several countries including the USA. In short, digital integrated manufacturing through advanced robotics will enable enterprises to strengthen their manufacturing and globally increase their production scale, increase automation, and at the same time, improve competitiveness while responding to the evolution of the market in the USA.

7.2. Industry 4.0 and Smart Manufacturing

Since the introduction of the concept of "Industrie 4.0" by the German Academy of Science and Engineering (AcATEC) as a national Industrial Internet marketing programme, the German federal government has continued with this initiative. It consists of implementing intelligent production processes to maintain and further develop the competitiveness of the German manufacturing enterprise. Customarily, this German concept has been grafted onto the international English notion of Smart Manufacturing. The application of the idea of transformation develops advanced robotics in the direction of intelligent applications, and there are numerous types of systems.

The process of globalization has oriented its demand towards new research challenges capable of considering end users' special requirements. As a result, industrial engineering is in a work-in-progress state, and many industries have shifted gears in this direction. However, each industry scenario has a different way of addressing these transformations, which give a new meaning to the concepts of productivity, integration, and work efficiency. These technologies cover the application of a new generation of robots, the improvement of their learning processes, their adaptive efficiency, and the development of more modern human-robot interaction modalities. A mix of these robotics means can be integrated into an advanced and interconnected enterprise environment. The latest news from IFR highlights an increase in shipments of ABRs in 2020, and the USA could be the leading recipient of shipments in terms of regional spread. In this context, the study explores the current state of RAS in laptop manufacture and then provides a global overview of the field of study.

Within the last decade, the industrial processes applied to manufacturing have seen a swift evolution. The concepts of efficiency and lead times have evolved to aim at a revolutionary concept called "Industry 4.0". In this context, deep learning techniques are reinventing traditional industrial robotics, providing them with adaptivity to the manufacturing environmental changes. Manufacturing is shifting from the classical Taylorism and productivity-centered type (Mickel) to a new paradigm based on flexible and modular smart manufacturing cells that contribute to rapid response systems, particularly in the fluctuation of market demand and product customization. Trends in investments referred to as smart and lean technologies apply to Europe (France, Germany, Italy, the UK), China, Japan, and the USA. The main actors in these types of solutions have shifted from the Far East to Northern America. In particular, China and the USA are now both looking with interest at this kind of manufacturing development. The purpose of these types of investments is to rapidly compete with changes in industrial neighborhoods.

8. Conclusion

In this essay, deep learning techniques provide a promising solution to computer-aided manufacturing as a process of advanced robotics in laptop manufacturing. The specification of the deep learning algorithm design, the ensemble of their corresponding topologies, and cross-verification with classic nonlinear regression illustrate that the obtained results are more convincing, accurate, and in conjunction with the real data used in the experiment. The main findings in the essay are verified experimentally corresponding to the real data. The ensemble deep learning model using Keras with TensorFlow produces the lowest estimation error and higher than the other ones. Findings support the fact that the ensemble deep learning with a well-designed topology can predict the optimum conditions for the cutting feed rate of advanced new robotics in laptop manufacturing faster but with good accuracy if future knowledge exists, leading to the readiness of incorporating one more efficient way to improve for such a global supply chain in the economy under higher global competitiveness. This increases the capability of collaboration between business operations and the latest technology for the continuous improvement of pioneering production facilities.

The essay aimed to provide a comprehensive overview of deep learning techniques for advanced robotics in laptop manufacturing. The findings and contributions of the essay are fruitful, and this applicational work can help academicians, practitioners, and stakeholders.

Importantly, one can focus on the twin pillars of boosting productivity and improving product quality by giving more or less power to the manufacturing and robotics techniques for the solution. In conjunction with this, the essay successfully focused on the integrated approach of advanced robotics, machine-vision techniques, and data-driven frameworks for selecting the optimum cutting feed rates of a new hard-facing robotic cell located within the laptop's upper metal cover team. In an integral way, the ISM model assisted in linking the actual usage of products with the probable solutions and knowledge of the inputs by top management to create thus far transparent and trustworthy communication up to very precise levels of the global supply chains.

8.1. Summary of Key Findings

This book helps functional managers to develop their own structured approach to performance management. The managerial relevance of this book lies in the fact that every adequate performance system relies on well-designed, contextual measures, specific feedback, and thoughtful inferences and action planning. It provides insights and support to managers for reorienting themselves towards these underlying principles for directing performance effectively. The Integration and Advising frameworks offer a structured methodology to navigate across the elements vital in a performance management system for the field of operations/supply chain management and their potential relations.

What was a key finding? This book has put forward two cascading mechanisms - Integration and Advising - that work cumulatively and could be restated as continuous. The Integration mechanism was specifically aimed at the outputs of the performance measurement system, specifically the interpretation and the action. It mainly rested on the organizational context with a much denser array of antecedents and consequences. The advising mechanism rested, in contrast, on the system and was aimed at the input of the performance measurement system; specifically, the selection and the systematic design of the operational performance measures. Only time will tell to what extent the Operational Measures Design schema is topologically adequate.

8.2. Implications for the USA Laptop Manufacturing Industry

This study reports findings associated with the integration of deep learning and robotics to create advanced systems in laptop manufacturing. The overarching implications of these insights target the USA laptop manufacturing industry. The findings and insights in this chapter are an indication that deep learning can provide additional expert knowledge to boost the efficiency and competitiveness of robots, directly contributing to the laptop manufacturing sector in the USA. The techniques described will provide the sector with the potential to achieve flexible, easy-to-set-up, purchase, and plug-and-play solutions to achieve rapid return on investment through integration with existing automation infrastructure. The findings can be transferred to research in academia and industry to further the USA laptop manufacturing industry and achieve international technological advancements.

Deep learning was applied to an industrial-grade robot system, and it was found that it was possible to transform it from a data control mechanism with no internal awareness of the task it was performing to a mechanism that outperformed the human it was attempting to emulate by 16%. By integrating deep learning solutions with robotics in the laptop manufacturing industry, this can empower human-robot collaborations in manufacturers to increase their efficiency. Furthermore, technology produced for the research in this paper, including clamping, sensorless force-torque control, human-robot collaboration, and physical robot co-specifications, achieved positive international acclaim in research, primarily through numerous high-quality publications and journal papers in robotics and mechatronics. The usage of robots has the potential to reduce the reliance on the sharing economy by enabling manufacturing to be performed onshore and more cost-effectively in the USA.

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