The Application of Deep Learning Techniques in Advanced Robotics for Medicine Manufacturing in the USA

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1. Introduction

Humanity is attracted to and fascinated by wondrous miracles. From the invention of the wheel to the advancement of Artificial Intelligence (AI), the ability of humans to simulate and ameliorate natural landscapes, using artificially simulated materials, has been an intriguing phenomenon. Following this thought process of AI, its growing adoption in medical settings has led scientists to envision the idea of building nanobots for the surgical process, in tandem with neural networks, computer-assisted systems, and robotics machinery, to handle complicated surgical techniques [1]. With this idea in mind, specific queries arise: How far have scientists gone in realization of this ideology? There is a growing concern among medical practitioners regarding the constraints, challenges, and efficacy of AI systems in advanced robotic machinery applied on patients. This review explores the application of deep learning techniques in advanced robotics for medicine manufacturing in the USA, covering recent advancements and breakthroughs.

Robots powered by deep learning systems mimic the working of the human wrist. Vision systems comprise vision sensors/specialized cameras that measure wrist motion. Ambient conditions of light intensity, input resolution, spectral responses of sensors, output images, and distortions differ from scene to scene; hence, there is a need for estimating rectified geometric images. The entire scene reconstruction involves recovering the geometry & appearance of 3D from non-geometric 2D images. Therefore, dimensionality reduction, data representation, probabilistic graphical models, spectral domain transformations, and manifold learning combination techniques are used with neural networks architectures [2].

1.1. Background and Significance of Advanced Robotics in Medicine Manufacturing

Advanced robotics have progressed from being a budding concept to an active and diverse industry. The active pursuit of autonomous ground vehicles and factory robots in the USA dates as far back as the 1950s, while the development of research and specialty robots started at universities and institutions with governmental funding. Industrial robots were put into manufacturing processes by Ford and General Motors in the 1960s. Although Japan popularized widely used robotics in manufacturing in the 1970s, this technology soon caught up with the rest of the world. After the introduction of the PUMA robot, which used a standard industrial manipulator, robotics research burgeoned rapidly [2].

Gearing and animals, both biomimetic approaches, were well investigated by several universities. The latter approach was by far the most active in terms of volume and creativity. The encouraging progress led researchers to attempt to build robots resembling humans. These considered the most sophisticated ground manipulators pretend to "think" and "act" more like people; hence, they are called humanoid robotics [1]. During the 1990s the research and development of humanoid robots were pursued vigorously by several institutions, mostly in the USA and Japan. The creation of anthropomorphic robots was also considered an interesting challenge for researchers from several disciplines.

1.2. Overview of Deep Learning Techniques

Deep learning (DL) techniques encompass a wide variety of systems composed of multiple processing layers that utilize artificial intelligence (AI) algorithms inspired by the function of animals' neurological system. As a subdiscipline of MI and a branch of AI, DL seeks to give machines the ability to perform "high-level" tasks usually requiring human intelligence, such as natural language understanding, image classification, and playing complex games [2]. In this spirit, social worms nematodes tend to achieve similar accomplishments in several tasks using only a single-layer neural network, but it needs a set of initial conditions as rules. Similar models have been designed for apparatus robotics detecting obstacles. However, their success margin is limited to the static environment that could be affected by the evolution of robots, producing unpredictable results.

DL techniques will play a key role in controlling and optimizing the process of medicine manufacturing by re-designing robotics architectures and applying proper deep learning techniques. There are several implementations in different miths, and all share the potentiality of controlling complexity in an unpredictable environment with either high or low uncertainty. For example, deep Q-learning, and on a recently developed deep unfolding control law based on recurrent neural network with guaranteed stability, controlled switching systems with synchronous and more complex structure, similar to a race in a La Vegas strip casinos [3]. These systems are also able to learn continuous input/output PD-mode based RL, mimicking the approach of most natural biological systems. These systems differ from others in their ability to directly apply controllers without simplifying approximations or using iterative numerical optimization techniques.

2. The Role of Advanced Robotics in Medicine Manufacturing

Advanced robotics play a significant role in medicine manufacturing, focusing mainly on aspects of 1D and 2D automation. This is closely related to mobility, where moveable medical manufacturing and handling robots can handle medicines and related logistical applications at designated points in high-volume hospitals and logistics centers. Reducing the need for human attendance at inconvenient places, such as logistics lines or medicine aisles, is essential for improving occupational safety and managing time on required tasks. Moreover, it can improve the environment for monitoring critical processes, which is crucial for the quality of medicines [4]. Currently, there are already autonomous mobile robots delivering medicines to wards on the hospital side. However, their service options are limited, and robots need to increase their mission path-finding capabilities to gain access to different places without being restricted to a predetermined path in the logistics center.

The implementation of 3D Robotics arms for handling tasks depends on the robotic arm's electronics and capacity. In the past ten years, due to increased production and Saudi visions for 2030 and 2040, the number of advanced robotics development programs for manufacturing and handling tasks has increased. Due to the gradually relaxing level of toleration tolerances, system hands-on experience, and unmatching device-driving protocols with expected implementation, the robotic arms' service capability performance in safety-critical applications is questioned [5]. For filling and inspecting high-value medicines, vertical robots are not acceptable due to beads falling or bottle top collision accidents that can spoil the imaging of barcodes or leave visible scratches on the bottles. However, there are some 3D robotics applications for inspecting vials and non-critical 3D applications like labeling and filling. But in high-value drugs like antibiotics and cytotoxics, there aren't any 3D advanced robotics handling tasks in the manufacturing stage.

2.1. Automation and Efficiency

Automation is the key aspect that composes the manufacturing domain in the first place [4]. The manufacturing assembly approaches are either fully-manual, semi-automation, or fully-automation based. Medicine manufacturing is currently more reliant upon the partial or fully-manual assembly mechanisms. The introduction of robotics can enhance the existing manufacturing approaches to be fully-automated. Fully-automated robotics systems do not require human intervention or handling, device raw components at the input and the products at the output ends [2]. It is basically like a black-box approach. Each and every task related to the assembly of raw components into packaged products is handled mechanically. Execution of such tasks has been enhanced to be with more precision, confidence, and accuracy.

Robotic manipulation approaches can be applied upon the medicine vials, syringes, or tokens. Such medicine components are transported from the one platform to another, across the simulation environment. The vials or tokens of medicines are circular elements. The medicine tokens are essentially random selections of varied medicines with varying dimensions. Transportation of such cannonical shapes can be easily achieved using parallel gripper mechanisms. A parallel gripper mechanism with two or three configuring fingers, can pick such elements with precision around their center of mass. Fixed-configuration grippers are actually beneficial for the vials, jars, or tubes of medicines, with predetermined dimensions.

3. Deep Learning Applications in Medicine Manufacturing

Recognizing images related to abnormalities in the lungs of the subjects and their severity. Hence, deep learning-based models are developed for a multi-class image model assessment process, settings for the image generation process using CT scans, and a method for creating affordable datasets privately, enabling future safe collaborations [6]. The presented approach with the procedure ensures efficient model training and enables researchers to collaboratively improve image models, enhancing the detection process for CYTUBES, BACTERIA, and ABNULY. Building on these ideas, future plans include validation on a wider basis and an extensive examination of gravitational age-related anomalies like arch tapaxes (ATM) in checked and untracked signal stages.

Deep learning algorithms have also begun to be employed for the automated recognition and classification of several relevant categories in the medical domain, such as recognizing categories of brain MRI images, extracted liver tumor images, and tissue types of histopathology images, among others [7]. The medical images have been recognized as containing some proportion of knowledge data, useful for expedient diagnosis, as the familiarity with a disease and medical recognition of it has become quite a topic of information and knowledge. Some models have been proposed to recognize ocular surface squamous neoplasia, take breast mass tissue samples, diagnose brain tumors, and determine asthma from image signals automatically. Image processing of the medical images has shown some potential in the recognition of malignant heart disease diagnosis signals. Although several models have been proposed, there is still room for improving efficiency and ensuring exhaustive analysis with an optimal model.

3.1. Image Recognition and Analysis

Deep learning techniques are widely applied in edge computing to enhance image recognition and analysis. The deep learning method is implemented as a plugin for user-friendly access. For proof-of-concept functions, several models trained on standard datasets are employed and demonstrated to apply on low-power embedded systems (e.g., Raspberry Pi) [8]. With advanced medical equipment like cell counting, urogram, and antibody imaging, image-based functions are developed for the medical manufacturing domain. Applications in this domain aid technical cycles and control quality in the initial stages of production.

Image-based processes are essential for certain aspects of medicine manufacturing. Most medication production lines carry out repetitive and tedious tasks, where batch defects often occur in the early stages of production. Such defects may include missing items, wrong formatting of papers, and medicine sticking together, which is visually recognizable. The integration of edge computing into these production lines enables the automatic capture of all medicine images. On the edge, these images are processed to detect potential defects and prevent batch loss [6]. Moreover, this improves the working conditions of manual quality control which relies on post-production image auditing, where affected images are often difficult to retrieve.

3.2. Natural Language Processing for Medical Data

Natural language processing (NLP) techniques are applied to medical data to obtain valuable data from such data sources. There are mainly four aspects of natural language processing of medical data: medical data preprocessing, medical text classification, medical named entity recognition, and medical relation extraction.

The biomedical literature provides researchers with an abundance of knowledge in backgrounds in such areas as gene, protein, drug, cell, pathology, bacteria, disease, and molecular pathways. Natural language processing methods such as provenance-based text mining and ontology-based biomedical term extraction have been utilized extensively to extract meaningful information from the literature. These allow the application of many powerful statistical and machine-learning techniques to obtain more valuable, comprehensive, and precise data than those contained in the text documents originally, e.g., the RPS-DRUG database, Spectral630, and TDR. NLP aims to tackle this challenge by designing computerized methods that can process, analyze and understand human language. It is a large set of subjects and tasks that are closely connected to both AI and linguistics [9].

4. Challenges and Limitations in Implementing Deep Learning in Robotics

Implementing deep learning techniques in robotics presents various challenges and limitations both from a technical and ethical standpoint. Data representation, modelling, and storage are vital aspects of deep learning implementation. Bots may need to interpret, analyse, and process images captured when the manufacturing results are sent to the deep learning models. These raw images can be complex and need modelling/processing to highlight the features that the model needs to focus on. Bots can deal with such modelling with the help of simple filters. However, it is still a required challenge that is much more concerned with the bot's modelling ability [2]. Additionally, data modelling storage and representation are concerns that have to be covered by the bots. The models used for deep learning require large datasets to analyse and devise appropriate actions on the desired objectives. The used models and data representation storage cannot always support the large datasets. Robotics are fundamentally interacting agents that coexist in a world of changing dimensions, creating new dimensions for the modular data representation. Thus, robots seeking information from the world surrounding them complexity cannot always be tackled by deep learning.

There are also socio-ethical challenges raised due to the use of deep learning techniques in robotics. A critical discussion of privacy and security concerns arising from the employment of artificial intelligence systems in robotic devices is presented in this regard [10]. Corporations and governments involved in healthcare systems or health-related data processing analyse consider this data both cheap and priceless. Moreover, data are stored inferences related to the considered individual, such as his/her epistemological and health condition. Due to this context, using bots trained on data from common individuals or information from a population attracted relative issues regarding the safety of the stored data and person surveillance possibilities.

4.1. Data Privacy and Security Concerns

There is a concern about how data privacy and security issues can affect the application of deep learning techniques in advanced robotics for medicine manufacturing. Protection of privacy in technology is an ethical issue. Concern about the protection of personally identifiable information (PII), such as health information, healthcare behavior, credit information, and wage details, is growing. Mobile platforms developed by organizations like close contact, GPS location, and social networks are growing quickly in the United States, where nanotechnologies are used to improve the Internet of Everything. Six mobile platforms, Facebook, Facebook Messenger, Twitter, Instagram, YouTube, and Snapchat, are used by billions internationally. PII is collected through all these platforms. In particular, healthcare information is both sensitive and private. According to the HIPAA Security Rule, organizations need to apply reasonable safeguards to ensure the confidentiality and security of electronic PII [11]. Traditional data aggregation techniques, including k-anonymity and generalization, do not guarantee privacy when complex analytics such as deep learning are applied to aggregated data. With rapid advances in healthcare artificial intelligence (AI), there are growing concerns about health data privacy because of the nature of these algorithms, unique properties of health data, and the healthcare industry [12].

First, not allowing sensitive data to come into the hands of AI developers and companies can prevent any health data leakage. However, data aggregation to a central location defeats the purpose of local AI and invites privacy risks. Second, in healthcare, deep learning techniques trained on aggregated patient data can infer patient privacy even with the aggregation, as the training datasets are closely related to the class of the application. Examples include probabilistic attacks to reconstruct images used in automated facial recognition systems and model inversion attacks reconstructing a face approximation to a given image. Member-inference attacks, often referred to as membership disclosure attacks, can infer whether a given data instance was part of the test or training process of a model. Membership-inference attacks are applicable to most machine learning algorithms, but it has been shown that they are more dangerous when more powerful models (e.g., deep learning) are used. Deep learning techniques trained on exploratory analysis using sensitive datasets can reveal sensitive information about individuals. Third, in healthcare, variables related to the medical domain are sensitive. For example, the disclosure of a patient's genetic markers can lead to discrimination in employment and insurance.

5. Case Studies and Success Stories

Introduction and Writing Style

The presence of old and obsolete machines in companies is a big problem for manufacturers. These types of systems are energy inefficient, do not conform to modern production processes, and are prone to breakdowns. Oftentimes, an upgrade cannot be performed on these systems due to the impossibility of providing spare parts. In many cases, these machines are still a core component of the production process. Replacing these systems is not an easy task. It is not easy to develop the requirements for a modern machine that could replace the default one [2]. One goal of the presented work is to provide tools for intelligent data analysis. This analysis would make it possible to evaluate the condition of the system and assure reliability on a reasonable level. If full reliability cannot be ensured, at least the risk can be quantified, and preventive steps can be undertaken.

Collection of Case Studies and Success Stories

A growing number of companies are using advanced robotics systems in medicine manufacturing. The systems and scenarios can be very different, but they still fulfill one assumption: high efficiency and maximum fulfillment of complex tasks. These robotics systems strive for maximum production capacity while maintaining high reliability and precision in execution [4]. This section will provide a collection of such advanced robotics systems used in medicine manufacturing.

5.1. Robotic Surgical Systems

[13]

Levels of autonomy, the major outcome was to gain insights on the current landscape of autonomy levels within FDA-cleared surgical robots, as well as the regulatory path by which they were introduced to the market. 49 robotic systems cleared between 2015 and 2023 were categorized into their decision-making and action-taking abilities. Most of the cleared systems belonged to Level 1, which do not permit devices to take any actions without direct user input once deployed [14].

6. Future Directions and Trends

The advent of robotics and AI is pervasive today. The automobiles are being produced at a greater rate than ever. The usage of computer systems is finely integrated into the robotics and AI. The accuracy of production and efficiency in terms of time makes it an ideal choice. Even work of great precision and accuracy such as in the pharmaceutical industry is being fine-tuned using robots and AI. Various equipment that is utilized for the coating of tablets such as Wurster coater, roller compactor, and granulator can be functioned using robotics [15].

There are some modulating equipment such as filtration and drying. These equipment have several constraints for the installation of robotics. However, these equipment are subject to the checking of parameters. The various systems involved with these equipment can be partially integrated with robotics. The physical properties of the active pharmaceutical ingredient are tested and checked (time, temp, RH, Pressure). The results of the inspection of the various parameters are sent to the PLC. If the parameters are strictly adhered to then only the batch is passed. Similarly, for downstream processing, the granules are checked. The pass and fail control parameters for the entire process can be programmed in robots and AI [1].

6.1. Integration of Robotics and AI

The robotics and artificial intelligence (AI) collaboration has gained significant attention in recent years due to advancements in both fields. Several companies are racing to create a world with AI agents that could roam freely, independently perform jobs, and gather knowledge. A more predictable vision is the integration between AI and robotics, where both of these technologies work together to advance fields accordingly. Automation is an expected revolution that is likely to affect every industry. As medicine manufacturing evolves into an advanced industry, robotics and AI will drive automation to create medications. This collaboration will start by integrating AI into existing robotic machines, and thereafter could lead to the development of advanced intelligent robotic systems. Robotics assistance in medicine manufacturing will allow machines to directly interpret their environment and make decisions, which will optimize processes in terms of quality, time, and resource usage. Such a revolution will drastically change the medicine industry and its processes around the world, including in the USA [1].

In medicine manufacturing, robotic platforms usually require robots to be pre-programmed. In some cases, such programs are complicated and lengthy. Even in the simplest scenarios, they should be adjusted in case of future changes. Such scenarios require a high level of expertise and relevant experience in robotics and programming. As a field evolves and changes, the need for new or adjusted programs will increase [16]. Thus, to provide a robust and sustainable solution, it is essential to develop a method that allows robots to act independently and make decisions regarding their actions without human involvement or interventions.

7. Conclusion and Recommendations

There is a growing interest in the application of deep learning techniques in advanced robotics. The robotics field is predicted to achieve significant advantages from machine learning, especially deep learning techniques [2]. Deep learning has been used with good results in domains such as image recognition, speech recognition, and data mining, which all can be of great assistance to robots. Robots equipped with deep networks have the potential for easily recognized advantages over the conventional engineering approaches in enhancing performance, learning new functions, and getting rid of negative transfer and fragility to noise

[10]. Therefore, deep learning could expand the intelligence of robots beyond the reach of current engineering techniques, especially in everyday applications. A literature survey is helpful to better understand the development of deep learning in robotics. This chapter aims to summarize the relevant recent work done in the field, both in robotics and within deep learning techniques, mostly focusing on the theory and methods, and then to analyze the similarities and differences in intention, methodology, and evaluation approaches. This work can be used as a scientific resource for robotics researchers interested in deep learning. It can also serve as an engineering handbook for improving robotics systems by using deep learning techniques. While there exists a circle of people working in both fields, the majority are not interconnected.

Despite great efforts in mathematics, biology, and engineering, learning in a robot remains a great challenge, especially in real-time interactive applications, such as a service robot or driverless vehicle. Extensive research has been done on learning by robots in several disciplines. However, current robotics systems are still mostly engineered systems and often fragile, incapable of dealing with variations in the environment or workflow. In contrast to the success of knowledge and skill acquisition by animals or humans, robots are still lacking the ability to acquire knowledge and skill by themselves. Recently, deep learning techniques, such as deep belief networks (DBNs) and convolution neural networks (CNNs), have inspired great interest because of their success in complex data modeling such as images and video. Trained without supervision, DBNs can extract hierarchical features of input data and resemble biological neural networks. Layer-by-layer discriminative fine-tuning leads to highly effective models. CNNs formed by neo-cortex-like convolutional structures are good at learning translation-invariant and orientation-invariant representations of data.

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