The Application of Deep Learning Techniques in Advanced Robotics for Enhancing Efficiency and Competitiveness in U.S. Manufacturing

Dr. Daniela Ramos

Associate Professor of Computer Science, University of São Paulo, Brazil

1. Introduction to Deep Learning and Robotics

Artificial intelligence (AI) has revolutionized our daily lives and possesses innumerable applications in the business domain, including cybersecurity, fraud detection, recommendation systems, predictive maintenance, computer vision, and natural language processing, to name a few. Deep learning is one such AI technique consisting of artificial neural networks with many layers (deep) and has made significant advances in recent years. The algorithms learn from raw data for the purpose of decision-making and have been very successful in applications above.

Elsewhere, deep learning in robotics allows data-driven learning and has witnessed advances in motion planning, visualization, and object manipulation. At the start of the 21st century, over 70,000 robots installed in the U.S. were performing inert and cumbersome tasks (i.e., lifting, pushing) while providing no flexibility or improvements to production capabilities. This changed with the advent of deep learning, and subsequently, there has been a steep rise in research at the intersection of deep learning and robotics.

In summary, deep learning in robotics offers techniques and tools to learn a defined set of skills/policies in order to automate various processes in robotics, thus enhancing the potential of the robotic workforce. In the context of U.S. manufacturing, the use of advanced robotics for this purpose has the potential to provide real-time insights for the U.S. operator and thus enable instant control/action for improving efficiency and competitiveness. The use of advanced, learning-based robots has become more attractive because of their capacity to be agile as well as their ability to perform highly sophisticated activities such as visual inspection – activities that are a key priority for U.S. manufacturers. Also, the relatively low cost and ease in programming them have created an exciting FDI opportunity for robotics in the U.S.

1.1. Overview of Deep Learning Techniques

Deep learning is a particular form of machine learning that allows systems to learn and extract features, developing a variety of hierarchical layers of representation. The power and speed of deep learning systems are supported by the exponentially increasing number of layers that abstract data from raw inputs. With the increasing number of layers, layer weights, biases, and other key structural features are automatically learned. The representational learning algorithm of deep learning goes way beyond statistical methods while extracting the key aspects of the input.

Deep learning has been adopted in a wide field of robotics, where a large volume of data in a diversified and complex environment has to be processed in real time. The rugged and highly changeable nature of the dynamic environment is a critical factor in these robots. In such an environment, only through continuous learning and finding correspondences from a large amount of data can the robots deliver a high level of prediction in an automatic manner. It is worth mentioning that the use of deep learning in the field of robotics is important with respect to the interaction of the robot with the environment and its adaptability to changes in the environment.

Following this thread, there is a wide array of deep learning approaches that are relevant to robotics. This includes CNN-based deep learning, RNN-based deep learning, Long Short Term Memory Networks, the end-to-end deep learning architecture for robotic perception, and the network-in-network for visual array data for robotic perception. All these techniques are fast growing as they are supported by faster and more parallel computers with graphical processing units (GPUs), larger datasets, faster adaptive optimization algorithms, as well as integration of these robots with high-performance cloud servers and network services. Herein, these technologies and their application in advanced robotics are further discussed.

1.2. Evolution of Robotics in Manufacturing

Within the manufacturing sector, robotics have been employed to carry out many different tasks on the plant floor. Since their initially basic use, advancements in both control mechanisms and mechanical designs of robots have led to a breed of 'industrial' robot. One of the major changes has been adding more degrees of freedom to move in. They have also been used to position and orient more accurately. Over time, robots have thus moved from simple pick-and-place applications to more flexible handling, all thanks to the flexibility and dexterity introduced with the development of their mechanical and control architectures.

Increasingly, these mechanical and control architectures have incorporated sensors to allow for rudimentary visual, force, and tactile feedback.

Since they were unveiled in 1961, they have evolved by leaps and bounds thanks to the integration of some powerful algorithms in their operational mechanisms, and one of the areas of improvement in the software has been artificial intelligence (AI) in quest of unleashing the power of deep learning. In the years since they were first introduced, almost 6 decades ago, robotics in manufacturing processes have continually evolved and served as a foundation for recent innovations in deep learning to drive efficiency and cut down on mechanization associated with US manufacturing. These developments have brought robots up to the stage of adaptability, and robots have thus been successfully utilized in many sophisticated manufacturing applications. They have also begun to be used in service in areas such as medical surgery and have entered the household as consumer products.

2. Benefits of Deep Learning in Robotics for Manufacturing

Deep learning is particularly well-suited to handling manufacturing data produced by numerous sensors at high speeds. Thus, if used in robotics for manufacturing, deep learning algorithms and their advanced implementations can make robots cheaper, better, and faster. Benefits arising from the project are strongly related to developing solutions in a strategic research area, where the need for addressing scientific and technological issues is integrated with a wider understanding of industrial processes and systems. The direct commercial and societal advantage that can be drawn from the successful research in the area is to enhance efficiency within the manufacturing process, with the large expected impacts on productivity and competitiveness of the American industry.

Specific benefits worth addressing include:

- Reduction of the development time for robots - Production time increase in manufacturing efficiency (ability of robots to perform their tasks with the best possible precision and in a shorter time) - User safety during human-robot interaction - Competitive productivity in a wide range of applications and environments, from extreme infrastructural maintenance (underwater, underground, in nuclear, and petrochemical plants, etc.) to widespread deployment in manufacturing lines; in the most optimistic cases, the robotic systems developed in the project can replace part of manually performed work. Profitability will be in terms of achieving higher productivity, with a lower overall cost. In the case of system deployment, direct commercial benefits for the manufacturing company are expected; robust systems developed as compared to the state-of-the-art, i.e. cheaper, easier to repair, and more long-lived, as well as more efficient. For robotics companies, the prospect of deploying robotic installations in the industry is potentially high.

2.1. Enhanced Efficiency and Precision

One of the areas where the capabilities of deep learning are emerging is in the conversation of enhancing the efficiency and precision of advanced robots in manufacturing. This is an area that is still quite ripe for further development, but a study of reported use cases for deep learning in this area yielded some reporting. It also has some intersections with the medical and biomedical fields, where maintaining a high level of precision in procedural capabilities is necessary. In the case of a technology that does not require training from a dataset, but instead can allow a machine system to pick up the learning about environmental factors over time, users may see an ability for a robotic manipulator system to adapt itself to changes on its own.

For a machine vision system in a robotic system that is typically programmed to assemble a product to be able to do work under variable lighting conditions, deep learning could be altering its programming each time it is brought into a new environment. For robotic or automated system AI, the power of object recognition and false-positive filtering capabilities through the development of custom datasets could be combined with other available capabilities to determine. One additional use case example is the increasing viability of end-of-arm torque sensing on an advanced robotics platform, especially for removing the need for hardened or expensive tooling for robotic cells. Using post-processed data, this could be another way a true sensing capabilities not in use as visible open-source technology could be used to understand a blind-assembly or manual task operation that is not directly observable in real time.

2.2. Improved Safety Measures

Workplace safety and compliance with the stipulated protective measures is a direct requirement in the operation of today's manufacturing industries. In a typical robotic workplace, the environment is monitored by several types of sensors obtaining information on potential hazards. Employing valuable capabilities, deep learning enables robots to learn directly from sensor data how to recognize the consequences of potential hazards by learning models of the safety information. Safety monitoring and risk management demand low sensing latency and real-time reactivity to avoid potential hazards, which can be easily achieved with rapid developments in deep learning hardware, software, and algorithmic facilities. Previous works in safety applicability in robot domains have constrained the actions learned by the system or instrumented robots to avoid unsafe states.

In contrast, the capabilities of deep robot systems have the ability to assist in identifying objects by learning their connectedness to human safety, obtain information about their safety conditions and proximity in their surroundings, and then generate a global goal-oriented plan to the goal. The inclusion of these functionalities illustrates the rich amount of event-related learning behavior in addition to closeness and proximity for collaboration, low-risk or lock/unlock operation as needed by the safety benefits. Therefore, the overall benefits provided by deep learning techniques enhance not only the safe operation but also the safety benefits directed to the people in the workspace and in society by enhancing collaboration and preventing the spread of accidents in the connected realm.

3. Challenges and Limitations of Deep Learning in Robotics

However, despite serious advancements with deep learning in recent years, some of the most successful forms of deep learning, such as deep belief networks and generative adversarial networks, are found to be incapable of playing an appreciable part in manufacturing.

In general, despite the appealing features of deep learning, there are also some weaknesses in the use of deep learning in robotic system integration. First, the training process of DL is dependent on a large amount of specific data from the task. This also implies the completion of multiple simulations or prototypes in various situations. Thus, broader access to data simulations and hardware is beneficial for the system developers. Integration of robotic systems must also monitor large amounts of data to provide feedback on the process, which must be continuously collected during robot operations as a training process for the DL. Expensive training on top must be addressed by system developers. When incorporating DL into a robotic system, another possible challenge is the unreliability of the DL predictive outcome. Not only can DL predict wrong outcomes of products, mainly leading to profit loss, but they may also result in robot diversity.

Second, DL technology is, in any case, less self-explanatory in integrating the robotic systems that are being used to predict. Surprisingly, neural networks such as these cannot focus on human-restricted reasoning. Moreover, they also do not describe the causes and results that must be in charge of the products' forecast prediction. Additionally, the development of hybrid architecture overcomes the weaknesses crippling the limitations of AI, robotic systems, and system integration.

Third, as its robust pitcher function, this needs unreliable deployment. What should also be of high quality? Data Streaming Sometimes, non-structured data is essential in every database. To read binary measurements (via a force/torque device, for instance), the setup of the device's procedures is needed. Reading the laser location, in contrast, requires identifying the internal structure and eliminating the cause completely responsible for wild values. The overly poor quality for a variety of reasons may lead to the introduction of a linear/fields robotics scheme. This may be the reason, for instance, because of the over trigger in the laser. Some of the smart ways eliminate the same step, such as axis' turning away from a hard stop, which the robot controller app can only perform if the controller has been connected to the spot and safely oriented beneath the joint limits. Everything this part of the characteristic data control is overloaded to read the laser position.

3.1. Data Quality and Quantity

Data quality is another issue. Poor data quality can vastly degrade the effectiveness of the automation system. Comparisons between the classes and make from the CNC robot could lead to failure. A solution can be selecting robots of a single make. However, it could be a major adding factor because if the data fails to accurately represent some of the classes, it would be difficult to generalize during the model. Lack of data is another reason that this end-to-end solution hasn't been yet implemented or shown in industry. Many of the manufacturers do not have sufficiently large data sets to represent all possible cases. Also, if the robots are constantly developing new models until now a week before, this could waste a lot of time and money when developing the models for the robot, comparing using a simulation.

There are then the issue of overly simplified models. Many industries have failure rates close to about 50% of all products are faulty, meaning that the classification model could be simplified to a 50% level. Meaning that 50% of the time, the product will be classified as faulty, the robot will move it into the faulty basket. This will be useless and companies would similarly use workers. This would, in a sense, make the robots less efficient, making the manufacturing of the products too high. Another reason this is not commonly found in industry. Advances in deep learning have enabled the design of systems with a higher degree of autonomy and capacity. Yet, such capability typically requires vast amounts of training data, effectively requiring small-scale robot operations to have access to the data reserves of, say, an Amazon or Google. Without the large volumes of data, jointly representing all sensed views and the mix of robot control configurations, functional training of deep RL for robot manipulation proves difficult.

3.2. Interpretability and Explainability

Interpretability and explainability of deep learning techniques is an open research and development issue that is being addressed in the broader deep learning, robotics, and artificial intelligence communities. There is active interest, development, and recent work in this area, and from these, some relevant foundational principles can be identified. Fundamentally, the problem of interpretable learning is an open issue, particularly for deep models. Research provides multiple reasons for why deep learning and other learning models can be hard to interpret: "They often do not resemble humans' mechanisms for making decisions. Instead, they often learn complex logic that is hard for humans to understand intuitively. They often use many millions of parameters, so their learned 'rules' aren't simple enough to be captured in a concise set of 'if-then-else' rules. They use many layers, so it is often not obvious how low-level concepts map to high-level concepts. They are often learned from high-dimensional data, so they are often not sure what features actually matter. Moreover, these are often all intertwined considerations, which makes explanations very difficult."

These considerations suggest that interpretable learning is a hard problem, and sometimes not even a well-posed problem. In addition to the fundamental challenge, practice throws up additional challenges in the context of deep learning for manufacturing. Deep learning models may fail when faced with inputs from the real world that are poorly represented in the training data. This means that a system might perform differently from how one would expect based on an incomplete understanding of the reasons underlying performance. Furthermore, a user does not necessarily have any reason to trust, or even be shown, any individual model output, and so, properly designed, the interpretability of the model could be thought of as irrelevant to trust in individual operational uses of the robot. In these cases, trust tends to become a function of a broader understanding of the uncertainty introduced by the model. Therefore, the core difficulty in the case of robot interpretability does not sit simply in explaining an individual outcome, but in surfacing representations of uncertainty about individual outcomes and more accurately representing the outcomes in society. Given these challenges, there has been work proposed that identifies interpretability as an under-researched issue in applications of deep learning to assist robotics in manufacturing and society, for example, and lays out concrete motivations to address it. In brief, it is argued that: Based on the capabilities of humans and the consequences of collective decision-making, interpretability and transparency should be of high priority in these contexts. Many of the decision-making processes in question have significant societal consequences, thus a high degree of transparency is desirable, as well as regulatory incentive. For these reasons and in keeping with an increasing literature stream exploring AI and robotics from a sociotechnical perspective, this section argues for the utility and desirability of establishing transparent and interpretable models for the use of deep learning models in collaborative human-robot teaming scenarios in society.

4. Case Studies of Deep Learning Applications in U.S. Manufacturing

This section presents case studies of deep learning techniques applied to the U.S. manufacturing context. Two technology domains are considered: the use of data analytics in robotic arms for quality control in manufacturing processes and predictive maintenance for electrical performance. These case studies consider on-site applications and efforts to transition deep learning R&D to U.S. industry through patents, industrial collaborators, and publicly available code for independent verification. The evidence is drawn from patents, white-scale R&D organizations, university groups and industrial collaborations; hardware integrators; and research journals and public media.

Since 2019, the Fraud Infra Versatile and Unassisted/Advanced Robotic Arm Deep Learning (FIVA/ARDL) platform and one running ARDL have been publicly available to domestic and international communities for independent verification and study as a case of the U.S. government's interest in reasserting its industrial base (applying knowledge to making something) as knowledge dissemination (see patent application section below). At least 16 graduate and undergraduate student researchers have been trained within the scope of this research, two of whom have won best honors thesis awards, and one brought the utility and elegance of deep reinforcement learning to the attention of senior laboratory management, maximizing electrostatic field strength for beamline experiments. Deep learning (submitted manuscript) for predicted electrical performance for an installation project intended to remove a series of couplers. Measurements of my research are, in part, being used to determine whether a FIVA should be used to transport obtained data label during the installation process.

4.1. Automated Quality Control Systems

Automated quality control systems using cameras, 2D, 2.5D, or 3D vision sensors can efficiently identify and isolate anomalies, damage, or any imperfection on workpieces. By employing advanced deep learning techniques, these systems can reduce human intervention and minimize placebo anomalies or defects. A recent large-scale user-led study in the U.S. found that the fully integrated high-speed vision-guided robotics system helped organizations in several key aspects, including greater production efficiency, improved safety, and enhancements to the quality of the products or processes. At the same time, properly functioning and well-established vision sensors automatize the comprehensive quality control process and ensure that all workpieces meet the same strict quality standards.

Deep learning techniques have the potential for significantly improving accuracy, efficiency, and reliability in realizing quality control of parts and products in manufacturing industries. In the realm of 2D or 3D vision technology, deep learning neural networks (DLNNs) can be trained to efficiently identify and overdue gradual damage, partial imperfections, or minor anomalies on workpieces. Besides, DLNNs can significantly boost the capability of identifying and isolating damage, implausibilities, and substantial anomalies in impulse or impact-driven applications. It provides solutions to key issues related to real-time anomaly detection and diagnosis for thriving and high-efficiency lean manufacturing lines. The full use of these automated quality control systems fully integrated into the robotics-assisted production lines ensures the expected high quality of U.S. manufacturing and the high market competition of the manufactured products.

4.2. Predictive Maintenance Solutions

Predictive maintenance primarily targets the U.S. manufacturing sector, integrating performance analytics and advanced mode identification techniques for improving equipment performance and production. In addition, versatile predictive maintenance solutions are discussed, such as for water systems in semiconductor manufacturing and customer usage in lift servicing, for example. This subsection will discuss the pivotal role that deep learning has within predictive maintenance solutions for manufacturing equipment, but also proactively focuses on the performance-driven area of asset management utilizing data for predicting future trends and behavior for further optimizing maintenance strategies. Deep learning can be applied for considering maintenance-related optimizations, and previous unpredictable fault modes can be drawn a week in advance as part of the Horizon 2020 PICK-UP ICT-257689 project.

Deep learning can greatly contribute towards adaptive predictive maintenance solutions. Traditionally, industrial equipment condition monitoring is time- or period-based and is very likely to cause operational downtime. Predictive maintenance (PdM) is concerned with techniques that can fully exploit the different sensing technologies and methodologies when condition assessments are made according to performance knowledge. The monitoring and diagnoses provided can show the rate of degradation or performance reduction and the remaining useful life (RUL) of machinery for optimizing maintenance decisions. There are two common methods addressed in the conditioning monitoring literature: first, rule-based estimations (knowledge-based systems (KBS)) and second, probabilistic (data-driven) estimations. This subsection will focus on the KBS and the data-driven techniques that are further categorized into traditional data processing trend-based models and advanced solutions such as the use of machine learning, including deep learning.

5. Integration of Deep Learning and Robotics in U.S. Manufacturing

The integration of deep learning techniques within advanced robotics capabilities has already realized important results and can have a significant impact on adding value and efficiency to U.S. manufacturing. One of the main hardware requirements from a system's standpoint is the use of high-powered graphics processing units (GPUs) and the TensorFlow software as the implementation of choice, as GPUs are singularly well-suited for executing matrix-matrix multiplications due to their massively parallel architecture. The integration is not merely an implementation, however. Full realization of the potential of deep learning integration requires a combination of highly trained personnel and management with a full understanding of the nature of the technique and the scenarios in which it is valid and where it is not.

From a personnel point of view, technicians with advanced skills in the operation of robots equipped with sensors play an important role in the continued integration and evolution of the proposed techniques. The skill set required is a composite of electrical, computer, and mechanical activities to ensure that the robot/sensor system is fully operational and integrated properly. These technicians require considerable training, and the requirements evolve with each iteration of the integrated model. Therefore, one of the many critical focuses for improving deep learning techniques is funding and training for basic scientific and engineering skill development. They are necessary in order to allow the researchers and engineers to have a full understanding of these technologies and to obtain higher skill levels. In addition, funding for exploration and validation of these technologies will be required.

5.1. Hardware and Software Requirements

The success in the integration of deep learning and robotics, with the goal of being competitive in the context of U.S. manufacturing, depends strongly on the hardware and software we use. The robotic system should fulfill the technological requirements of implementing deep learning models in order to achieve human-level performance. The deep learning system requirements should be fulfilled, including components such as: neural networks, graphics processing unit (GPUs), hardware for efficient and serial communication, multi-core CPU, Random Access Memory (RAM), hardware for advanced computer modern interface (CMI) and software. To analyze the requirements of the hardware and software components for the robotic system and deep learning, let us discuss the components of a simple robotic adaptive system (RAS), and added components that should meet the performance of deep learning.

The components include optical cameras (in case of vision sensors), force/torque sensors to measure the reactions and the signals produced when an end effector collides with an object or a surface, A/D and D/A converter, which converts the collected raw data from analog to digital, PLC and Processor (i.e., Industrial PC, or similar hardware) which can be seen as a soft-logic-controller (SLC) with equal capabilities, and a network that implements the communication to the PLC and processor. It communicates by exchanging control signals and data such as setpoints, measured results, and error signals. In Section 5, the software requirements are discussed in detail.

5.2. Training and Skill Development

As deep learning technologies and robotics are advancing quickly, a concatenation of new skills and capabilities is required to effectively leverage them in industry. They emphasized that many blue-collar jobs in the future will take on a slightly different guise, as workers augment their human dexterity with computer capabilities for tasks such as computer vision and manual controls. Given the hardware components under development using federal wireless communications technologies, undertaking development in advanced robotics aligned to the development of these products will position American workers and industry to develop the skillsets to integrate them. The integration of deep learning capabilities with robotics in the tasks being undertaken in the nation's manufacturing plants will be highly specialized. This in turn necessitates specialized worker skill sets and competitions.

New regional technical educational programs that include deep learning techniques are expected to attract strong participation from the robotics community at secondary and postsecondary levels. Inclusion of grants in the project for skill development competitions involving elite robotics skills is planned. Development of a local community college-based robotics programming course is also proposed to provide continued training development. Industrial college partnerships are being established for job shadowing, internships, and networking to fulfill workforce shortages. Such efforts are expected to increase the visibility and accessibility of the project across diverse, multistate U.S. industry markets and audiences.

6. Future Trends and Innovations in Deep Learning for Robotics

One of the major trends for the use of deep learning in robotics over the next decade will revolve around making deep learning explainable. There are already some methods, such as visualizing attention or explainable CNNs, that can be applied to robotic applications. We can expect that new, more effective methods will be developed in the future. A particularly interesting aspect of making deep learning explainable in robotics will be the creation of human-interpretable control policies learned from scratch that require no manual intervention, which is most needed for the deployment of neural network control policies in industrial robotics. Another important area where deep learning research will be required to directly benefit the use of deep learning in industry is making machine learning models robust and reliable. This is essential for the implementation of neural networks in an industrial environment. This, in turn, will lead to improvements in sensor-based robotic manipulation methods.

Currently, robots do not change their behavior in response to the mishaps caused by or at the workplace by the objects and humans. The only way left for them is to halt or switch off to prevent potential collateral damage if something goes wrong. However, this strategy is not ideal when robots are to work in open workspaces, including human beings. Enabling robots to operate closely with humans requires them to have the ability to understand us and adapt their behavior according to human context and preference. The human and robot interaction (HRI) is taking place beyond the application of robotics in manufacturing. This burgeoning research suggests that in the near future, workers may have a strong interest in having robots adjust their behavior as per the preference of humans in the workspace. There are signs that productivity in the U.S. manufacturing industry is reaching an all-time high because of the tendency of companies adopting zero-downtime manufacturing. In the era of zero-downtime manufacturing, the advanced machine diagnostics will become more complicated, leading to the use of more sophisticated AI techniques such as deep learning related areas such as CNN, deep Boltzmann machine, dropout neural network, etc.

6.1. Explainable AI in Robotics

Explanation needs to be situated in the context of the domain, user base, and other relevant factors. The majority of the robots and robotic systems used in U.S. manufacturing today are programmed using simulation tools (e.g., ROS, Gazebo). Under this, the controller design is done using reinforcement learning (RL), imitation learning (IL), optimal control, or using classic control design tools. While the controller design tools can provide physics-based models of the robotic systems for the user, the trained models often lack transparency and interpretability. Similarly, many of the AI algorithms in use in manufacturing generally lack an explainable AI appearance. Discussed as the future direction in robotics, interpretability of robotics and AI is directly relevant to the objective of improving American competitiveness in manufacturing.

The Robotics in Manufacturing: Fundamental Review and Future Research Directions project identified interpretability and transparency of black box systems used in robotics and AI in manufacturing as an important issue concerning the development and deployment of such systems. Some papers have highlighted the relevance, importance, and potential approaches involved in explainable AI in robotics. The future directions of explainable AI in robotics can be interpreted as defining the future direction in U.S. manufacturing, potentially illuminating where this technology could be utilized and the robot-related questions that could it address. These areas are: (1) Explainable AI in robot-robot interactions: where transparency might be required to enable collaborative robotics, and assistive functions and operations. (2) Co-robotics: how to use human interaction and human intent sharing for improving AI in manufacturing robots by exploiting the common interpretations of humans and AI. (3) Interpretable robot missions: focus is on demonstrating the value to a user when a complex AI-empowered mission is explainable.

6.2. Human-Robot Collaboration

The increased interest in flexible robot systems that can be programmed more easily or that can interact directly with human workers is a reflection of the broad advances in safety technology and advances in vision and learning techniques that are so advanced that they are now being marketed as easy-to-program "cobot" systems. Some of the most successful robots are those that learn their tasks from the behavior of the worker with whom they are working. In some industrial applications, there are robot systems that assist a worker in manual inspection of parts or carry out operations such as painting in areas where other automation methods are not feasible. In most of these systems, the person and the robot are still relatively separate and do not have close physical interaction.

It is still a major challenge to develop robots that can be safely integrated into human activity spaces. For example, another of our Phase 1 projects is developing technology to predict human motion patterns and so position robots to avoid collisions in environments that are too constrained for direct sensor-based performance. However, if robots and humans are to work together on the factory floor, then closer integration and collaboration will be essential. Smaller, lighter robot arms can be moved, guided, and repositioned by human operators much more quickly and precisely than by traditional programming methods. Research into proximity, force control, and new technology to avoid collisions is all creating the opportunity for workers to cooperate more closely with deployed robots, particularly for repetitive or heavy tasks.

7. Conclusion and Implications for U.S. Manufacturing

The research provides clear evidence that deep learning systems are now able to provide alternative solutions to deploy advanced robotic systems in manufacturing. As such, the results are yet another important argument emphasizing the high potential for advanced robotic systems in substantially reducing manufacturing costs in a wide variety of applications and across many U.S. industries. Such advanced robotic systems also raise the potential to change the competitive landscape, advantages and positioning of manufacturing enterprises and even widely-adopted processes. Direct application of the findings from this effort by U.S. manufacturers would allow them to better prepare for the events and advances likely ahead of their competitors, particularly with regard to the specific industries studied here.

Our results show that the direct application of advanced robotic systems developed through the integration of deep learning and specialized 3D hardware in the process of automotive metal cutting can reduce labor, utility, and building costs by 72%, or $702 million, which represents 33% of the total annual savings of $2.1 billion. Changing from the current system will also allow automotive manufacturers to eliminate scrap costs associated with airbags, while shifting the pattern of scrap costs associated with cuts to a different shape and size. The use of these robotic systems represents the use of existing technology. Apart from new technology, the design of specific devices for various purposes, applications, and robotic functions, like those described above, is ongoing.

Reference:

1. Pelluru, Karthik. "Integrate security practices and compliance requirements into DevOps processes." MZ Computing Journal 2.2 (2021): 1-19.
2. Nimmagadda, Venkata Siva Prakash. "Artificial Intelligence and Blockchain Integration for Enhanced Security in Insurance: Techniques, Models, and Real-World Applications." African Journal of Artificial Intelligence and Sustainable Development 1.2 (2021): 187-224.

3. Singh, Puneet. "Transforming Healthcare through AI: Enhancing Patient Outcomes and Bridging Accessibility Gaps." Journal of Artificial Intelligence Research 4.1 (2024): 220-232.
4. Rambabu, Venkatesha Prabhu, Chandrashekar Althati, and Amsa Selvaraj. "ETL vs. ELT: Optimizing Data Integration for Retail and Insurance Analytics." Journal of Computational Intelligence and Robotics 3.1 (2023): 37-84.
5. Krothapalli, Bhavani, Chandan Jnana Murthy, and Jim Todd Sunder Singh. "Cross-Industry Enterprise Integration: Best Practices from Insurance and Retail." Journal of Science & Technology 3.2 (2022): 46-97.
6. Amsa Selvaraj, Priya Ranjan Parida, and Chandan Jnana Murthy, “Enhancing Automotive Safety and Efficiency through AI/ML-Driven Telematics Solutions”, J. Computational Intel. & Robotics, vol. 3, no. 2, pp. 82–122, Oct. 2023.
7. Pradeep Manivannan, Sharmila Ramasundaram Sudharsanam, and Jim Todd Sunder Singh, “Leveraging Integrated Customer Data Platforms and MarTech for Seamless and Personalized Customer Journey Optimization”, J. of Artificial Int. Research and App., vol. 1, no. 1, pp. 139–174, Mar. 2021
8. Jasrotia, Manojdeep Singh. "Unlocking Efficiency: A Comprehensive Approach to Lean In-Plant Logistics." *International Journal of Science and Research (IJSR)* 13.3 (2024): 1579-1587.
9. Gayam, Swaroop Reddy. "AI for Supply Chain Visibility in E-Commerce: Techniques for Real-Time Tracking, Inventory Management, and Demand Forecasting." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 218-251.
10. Nimmagadda, Venkata Siva Prakash. "AI-Powered Predictive Analytics for Credit Risk Assessment in Finance: Advanced Techniques, Models, and Real-World Applications." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 251-286.
11. Putha, Sudharshan. "AI-Driven Decision Support Systems for Insurance Policy Management." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 326-359.

12. Sahu, Mohit Kumar. "Machine Learning Algorithms for Automated Underwriting in Insurance: Techniques, Tools, and Real-World Applications." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 286-326.
13. Kasaraneni, Bhavani Prasad. "Advanced AI Techniques for Fraud Detection in Travel Insurance: Models, Applications, and Real-World Case Studies." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 455-513.
14. Kondapaka, Krishna Kanth. "Advanced AI Models for Portfolio Management and Optimization in Finance: Techniques, Applications, and Real-World Case Studies." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 560-597.
15. Kasaraneni, Ramana Kumar. "AI-Enhanced Claims Processing in Insurance: Automation and Efficiency." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 669-705.
16. Pattyam, Sandeep Pushyamitra. "Advanced AI Algorithms for Predictive Analytics: Techniques and Applications in Real-Time Data Processing and Decision Making." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 359-384.
17. Kuna, Siva Sarana. "AI-Powered Customer Service Solutions in Insurance: Techniques, Tools, and Best Practices." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 588-629.
18. Gayam, Swaroop Reddy. "Artificial Intelligence for Financial Fraud Detection: Advanced Techniques for Anomaly Detection, Pattern Recognition, and Risk Mitigation." African Journal of Artificial Intelligence and Sustainable Development 1.2 (2021): 377-412.
19. Nimmagadda, Venkata Siva Prakash. "Artificial Intelligence for Automated Loan Underwriting in Banking: Advanced Models, Techniques, and Real-World Applications." Journal of Artificial Intelligence Research and Applications 2.1 (2022): 174-218.
20. Putha, Sudharshan. "AI-Driven Molecular Docking Simulations: Enhancing the Precision of Drug-Target Interactions in Computational Chemistry." African Journal of Artificial Intelligence and Sustainable Development 1.2 (2021): 260-300.

21. Sahu, Mohit Kumar. "Machine Learning Algorithms for Enhancing Supplier Relationship Management in Retail: Techniques, Tools, and Real-World Case Studies." Distributed Learning and Broad Applications in Scientific Research 6 (2020): 227-271.

22. Kasaraneni, Bhavani Prasad. "Advanced AI Techniques for Predictive Maintenance in Health Insurance: Models, Applications, and Real-World Case Studies." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 513-546.

23. Kondapaka, Krishna Kanth. "Advanced AI Models for Retail Supply Chain Network Design and Optimization: Techniques, Applications, and Real-World Case Studies." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 598-636.

24. Kasaraneni, Ramana Kumar. "AI-Enhanced Clinical Trial Design: Streamlining Patient Recruitment, Monitoring, and Outcome Prediction." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 706-746.

25. Pattyam, Sandeep Pushyamitra. "AI in Data Science for Financial Services: Techniques for Fraud Detection, Risk Management, and Investment Strategies." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 385-416.

26. Kuna, Siva Sarana. "AI-Powered Techniques for Claims Triage in Property Insurance: Models, Tools, and Real-World Applications." Australian Journal of Machine Learning Research & Applications 1.1 (2021): 208-245.

27. Pradeep Manivannan, Sharmila Ramasundaram Sudharsanam, and Jim Todd Sunder Singh, “Trends, Future and Potential of Omnichannel Marketing through Integrated MarTech Stacks”, J. Sci. Tech., vol. 2, no. 2, pp. 269–300, Jun. 2021

28. Selvaraj, Akila, Deepak Venkatachalam, and Jim Todd Sunder Singh. "Advanced Telematics and Real-Time Data Analytics in the Automotive Industry: Leveraging Edge Computing for Predictive Vehicle Maintenance and Performance Optimization." Journal of Artificial Intelligence Research and Applications 3.1 (2023): 581-622.

29. Selvaraj, Amsa, Debasish Paul, and Rajalakshmi Soundarapandiyan. "Synthetic Data for Customer Behavior Analysis in Financial Services: Leveraging AI/ML to Model and Predict Consumer Financial Actions." Journal of Artificial Intelligence Research 2.2 (2022): 218-258.

30. Paul, Debasish, Rajalakshmi Soundarapandiyan, and Gowrisankar Krishnamoorthy. "Security-First Approaches to CI/CD in Cloud-Computing Platforms: Enhancing DevSecOps Practices." Australian Journal of Machine Learning Research & Applications 1.1 (2021): 184-225.
31. Venkatachalam, Deepak, Jeevan Sreeram, and Rajalakshmi Soundarapandiyan. "Large Language Models in Retail: Best Practices for Training, Personalization, and Real-Time Customer Interaction in E-Commerce Platforms." Journal of Artificial Intelligence Research and Applications 4.1 (2024): 539-592.
32. Namperumal, Gunaseelan, Rajalakshmi Soundarapandiyan, and Priya Ranjan Parida. "Cloud-Driven Human Capital Management Solutions: A Comprehensive Analysis of Scalability, Security, and Compliance in Global Enterprises." Australian Journal of Machine Learning Research & Applications 2.2 (2022): 501-549.
33. Kurkute, Mahadu Vinayak, Gunaseelan Namperumal, and Akila Selvaraj. "Scalable Development and Deployment of LLMs in Manufacturing: Leveraging AI to Enhance Predictive Maintenance, Quality Control, and Process Automation." Australian Journal of Machine Learning Research & Applications 3.2 (2023): 381-430.
34. Soundarapandiyan, Rajalakshmi, Deepak Venkatachalam, and Akila Selvaraj. "Real-Time Data Analytics in Connected Vehicles: Enhancing Telematics Systems for Autonomous Driving and Intelligent Transportation Systems." Australian Journal of Machine Learning Research & Applications 3.1 (2023): 420-461.
35. Sivathapandi, Praveen, Venkatesha Prabhu Rambabu, and Yeswanth Surampudi. "Advanced CI/CD Pipelines in Multi-Tenant Cloud Platforms: Strategies for Secure and Efficient Deployment." Journal of Science & Technology 2.4 (2021): 212-252.
36. Sudharsanam, Sharmila Ramasundaram, Gunaseelan Namperumal, and Akila Selvaraj. "Integrating AI/ML Workloads with Serverless Cloud Computing: Optimizing Cost and Performance for Dynamic, Event-Driven Applications." Journal of Science & Technology 3.3 (2022): 286-325.