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The Application of Artificial Intelligence and Machine Learning in Manufacturing Industry: A Review

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ABSTRACT
The methods used for Artificial Intelligence (AI) in machine learning (ML) focuses on the machines' capacity to receive data series and learn independently. This research aims to analyze, systematically, the body of research on application of AI and ML in manufacturing industry. The examination was conducted utilizing existing published and accessible research studies. Literature review was based on empirical ML and AI studies that have recently been published. Findings show that in order to prevent unexpected damage to equipment, manufacturers use predictive solutions. These AI-powered manufacturing company solutions are able to anticipate equipment failure before it causes damage. AI in manufacturing thereby impacts product quality and ensures revenue. Artificial Intelligence has the potential to be effective in producing, enhancing, and monetizing things. However, human ingenuity remains indispensable when handling unforeseen shifts in preferences and determining whether to produce something at all.

Keywords: *Artificial Intelligence, Manufacturing, machine learning, automation, production systems optimization*

1. INTRODUCTION

John Watson first proposed the idea of artificial intelligence (AI) (McCarthy, 1956) representing the level of machine intelligence. The notion of intelligent machines was initially introduced by British mathematician Alan Turing, computer scientist, and thinker, prior to McCarthy. "Can machines think?" was the basic question that sparked this whole thing (Turing 1950) explained the methodical procedure of dissecting the information piece by piece to create an informed choice using an imitation game. Artificial intelligence can be separated into two categories: traditional or symbolic intelligence, which solves problems with knowledge and thinking problems (Hoehndorf et al 2017) and computational intelligence, which resolves issues and renders judgments using case data (Bhatia 2017) Evolutionary programming, fuzzy systems, and neural networks are examples of computational artificial intelligence (AI) according to the IEEE Computational Intelligence Society IEEE (2021).

There are various ways to acquire symbolic and computational intelligences, such as simulations and experiments used in machine learning (ML) Among the subfields of AI are automated reasoning and (Robinson et al 2001) where machines can reason and act entirely or almost entirely thanks to computer programs. Often, the machine's logic or reasoning must be used in the face of ambiguous conditions (Wu and Shang 2020) Due to the probabilistic nature of decision-making in these circumstances, fuzzy logic (Dubois et al., 1995) and Bayesian statistics are intricate subjects (Blundell et al 2015) can be extremely beneficial in comprehending them. The most prevalent forms of AI are those that can replicate human behavior and continuously enhance their behavior. Though it may seem easy for humans, learning and improvement are extremely complex cognitive processes that have evolved over millions of years in both the brain and the body.

2. LITERATURE REVIEW

2.1 Machine Learning

This is an example of an artificial intelligence application where machines are automatically trained to learn from experience rather than having specific tasks explicitly programmed into them. A branch of machine learning called "Deep Learning" does predictive analysis using artificial neural networks. There are many different algorithms for machine learning available, like Unsupervised Learning, Reinforcement learning and supervised learning. Unsupervised education algorithms do not make decisions on their own using classified data. without supervision. With supervised learning, a function is inferred from the training set, which is made up of an assortment of the intended output and an input object. Machines use rein for cement earning to take appropriate actions to create a set ward and determine which option is the best one to consider.

Machine learning (ML) is the study of patterns and decision-making in order to solve particular tasks using task-related data (Machine 2022) When creating machine learning (ML) software, relevant datasets are sourced (called training data), After selecting a suitable machine learning model, the model is trained to complete the task. Three primary three types of learning paradigms: reinforcement learning, unsupervised learning, and supervised learning can be used to broadly categorize machine learning. For a particular learning task, various One or more of these learning paradigms may be combined in machine learning models or methodologies.

2.2 Machine Learning Techniques and Artificial Intelligence

There is no clear definition for the term "artificial intelligence," and its meanings have evolved over time. Currently, it can be characterized as a technology that combines various computer science disciplines to solve problems collaboratively through what are referred to as "intelligent behaviors" This can be achieved, for instance, by utilizing computer vision, statistical, logical, and natural language analysis techniques.

Machine learning is currently one of the most expansive fields covered by the AI umbrella. This term covers a wide range of methods and strategies, but they all have one distinct and unmistakable characteristic in common: they solve problems using programs that can learn from the input they are given. As a result, knowledge is no longer transferred from humans to machines; rather, machines acquire knowledge on their own through independent means. Man's role now is limited to defining the processes by which machines must learn, using data and examples, so that the machines can independently acquire the "knowledge" necessary to automate tasks or transfer knowledge.

The first category is logical (symbolic) techniques, which comprises the learning set of rules and decision-tree methods. A decision tree is a classification tree that arranges instances according to the values of the characteristics; however, it can be converted into a rule set by generating a rule for every path in the tree that goes from the root to the leaf. Nevertheless, a number of rule-based algorithms can also be used to directly drive rules from training data Kotsiantis et al (2007).

Techniques based on perception make up the second group. One kind of binary classifier is the perception, which converts its inputs, which are real vectors, into an output value, which is a real-type scalar. The most well-known method is the neural network, a mathematical model that is used to explore engineering problems involving various fields (electronics, computer science, simulation, and other areas) as well as to comprehend biological neural networks. Statistical techniques comprise the third group. They are distinguished by their explicit probability model, which offers a likelihood that each class an instance belongs to instead of just a classification. It's a memory-based technique where the computer compares newly encountered problem instances with previously seen training examples that are stored in memory.

The most recent method for supervised machine learning methods are called Support Vector Machines (SVMs). (Cortes & Vapnik, 1995) which employs learning algorithms for classification and regression: The algorithm builds a model that, given a set of training data, allocates the new samples to one of the two classes series, each of which is labeled with the class to which it belongs among the two possible classes. This results in a non-probabilistic binary linear classifier.

2.3 AI Applications in Manufacturing

These days, manufacturing and logistics computing network systems are more capable of handling multiple sets of data as well as handling massive volumes of data. Numerous sensors have also been introduced to track the data processed on a daily basis in logistics application systems and shop floor operations. Many techniques, including automated inspection, faulty inspection, quality check, and others, have been developed by advanced computing systems to detect part dimensions. Artificial intelligence applications have transformed the manufacturing and logistics sectors into environments that facilitate actionable decision-making. AI has brought about changes in material handling systems, pack aging, and semiconductor manufacturing industries. The entire artificial intelligence stool, or tell igencei stool, is used in many functional areas to accomplish many tasks in a faster and more responsive manner without compromising time or cost.

2.3.1 Price Forecasting of Raw Materials

For manufacturers, the extreme price volatility of unprocessed materials has always posed a problem. Businesses need to adapt to the fluctuating cost of raw resources in order to stay competitive in the marketplace. Software with AI capabilities, such as Kantify, can forecast Material can learn from mistakes and has more accurate pricing than human beings.
Quality assurance is the process of keeping a product or service at a targeted level of quality. Systems that are data-driven, networked, and self-governing are assembly lines. These assembly lines are run according to a set of guidelines and equations that specify how to get optimal outcomes. Machine vision technology can be utilized by AI systems to detect deviations from expected outputs, as the majority of faults are apparent. AI programs notify users when the final product is of lower quality than anticipated, giving them time to respond and make necessary adjustments.

2.3.2 Operations

The real use of resources and production facilities is referred to as "operations" (Unnamed 2016) Physically speaking, it involves human labor, facility infrastructure, industrial machinery, sensors, and controls. In a more general sense, it addresses logistics and processes, such as the precise way in which the necessary materials will be relocated and turned into the completed product. Based on the relevant duration, activities can fall into one of two categories real-time actions on the factory floor or long-term plans for facilities and processes. They are essential to guaranteeing that industrial machinery operates as intended and that product quality is upheld. Operational management has historically been limited to human operators. On the other hand, human operators can benefit from the predictive and analytical powers of AI/ML models to help with organizing and providing real-time support decision-making, and enhance production effectiveness and security.

2.3.3 Predictive Maintenance

In order to prevent unnecessary downtime, predictive maintenance involves scheduling maintenance procedures and examining sensor data from apparatus to predict possible malfunctions of the equipment. It is among the most widely used AI/ML applications in production, particularly that of consumer goods goods, electronics, chemicals, and aircraft (R Cioffi et al 2020). The ability to predict Equipment malfunction can halt important material and monetary losses caused by averting unplanned interruptions and idle periods in the production processes, which has enormous value for manufacturers. The average manufacturing facility experiences fifteen hours of unavailability each week; major automakers lose roughly $20,000 for each minute during which their production lines are idle (P Brosset et al 2019) Also, predictive maintenance can reduce the possibility of unscheduled outages that could harm communities, employees, and the environment (Leoni et al., 2021) Predictive maintenance can benefit from the direct application of AI methods such as anomaly detection, models for categorization, computer vision, and regression to the factory floor error detection. The human eye cannot capture the same level of detail as computer vision, and computers are able to monitor factory operations for extended periods of time without experiencing fatigue or interruption. It is possible to train CNNs, computer vision models with machine learning, and different supervised learning methods to forecast the chance of equipment failure. using data from networked sensors.
Y Inoue (2019) Regression models can be used to estimate how long an item of equipment will last before breaking down again or to predict how long it will remain useful. To determine whether a piece of machinery may malfunction down within a specific amount of temporal aspects, categorization schemes can be hired. Anomaly detection is another tool that predictive maintenance may use to identify instances in which equipment deviates from expected behavior (Waring, 2020).
A machine tool's service life may be increased by carrying out regular, timely upkeep. A prearranged timetable is followed when performing preventive maintenance. Consequently, machine learning and artificial intelligence (AI) are utilized to reduce unexpected machine failures, improving machine availability and product quality (Yam et al., 2001) have put forth a system that includes machine condition observation, fault diagnosis, and machine deterioration prediction. It would be easier to estimate the equipment's remaining useful life by using such systems. This will also assist in choosing the machine's proper maintenance schedule (Eckart et.al., 2018) and (Jardine et al,. 2006) have created the procedures required to extract clusters from sensor data. The steps are: data preprocessing; analysis and appraisal based on clusters; and SLM equipment data obtained through the sensor.
In predictive maintenance, equipment sensor data is analyzed to predict probable equipment failures and maintenance schedules are planned to minimize unneeded downtime. It is among the most widely used AI/ML applications in manufacturing, including the production of consumer goods, chemicals, electronics, and aircraft. The ability to predict equipment failure can avert unforeseen disruptions and

downtime in industrial operations, thereby preventing significant material and financial losses. Which has enormous value for manufacturers. The average manufacturing facility experiences fifteen hours of unavailability per week; major automakers lose about twenty thousand dollars every minute when their manufacturing lines are idle (P Brosset et al 2019) Moreover, predictive maintenance can reduce the possibility of unscheduled outages that could harm communities, employees, and the environment.

Leoni, et al (2021) Predictive maintenance can benefit from the direct application of AI/ML techniques like anomaly detection, regression, computer vision, and classification models to factory floor error detection. Computers are able to observe factory operations for longer periods of time without experiencing fatigue or interruption, and they can provide greater visual detail than what the human eye can see. It is possible to train CNNs, computer vision models with machine learning, and different supervised learning methods to forecast the chance of equipment failure. using data from networked sensors.

R. Kaur (2019) The remaining life of an item of equipment can be predicted using regression models useful life or calculate the amount of time until the next failure. To determine whether a piece of machinery may malfunction down within a specific amount of temporal aspects, categorization schemes can be applied. Anomaly detection is another tool used by predictive maintenance to identify instances in which equipment deviates from expected behavior.

2.3.4 Real-Time Build Control

Researchers have demonstrated that the manufactured product's quality can be managed by varying the speed at which molten metals can form and the thickness of those layers. Thus, real-time build control can be used to regulate the quality of AM manufactured goods. For executing three inputs are involved with real-time build control: Free form deposition, training data set, and 3D object geometry. Real-time build control is exercised via machine learning Edward et al (2018).

2.3.5 Process Optimization

Traditionally, supply chain management and facility layout have been two large-scale operations where optimization has been used, in addition to individual manufacturing processes. Because of the increased number of variables and interdependencies growing diversity and intricacy of manufacturing tasks, workflows, and supply chains. It takes a lot of time and resources to manually find the best solution through experimentation, and as the quantity of variables and interdependencies rises, The efficiency of existing mathematical methods like Model-based or heuristic optimization declines (G. Immerman 2022) For manufacturing processes and procedures, AI/ML techniques have become a supplement to, or a comparable alternative to, classical optimization algorithms (G. Goh et al 2021) RL for hydrometallurgical separation process design optimization is one example (S Plathottam 2021) and evolutionary algorithms for multi-objective optimization, as well as hybrid support vector, were used to achieve a 45% energy consumption reduction in the carbon fiber manufacturing process.

Larger-scale processes like logistics, inter- and intra-facility dispatch management, and factory layout design may also be optimized with AI. In order to minimize collisions with pedestrians or other vehicles, autonomous guided vehicles have been using recurrent neural networks to optimize delivery and dispatch services (D. Li et al 2019) RL has been utilized for dispatch as well. optimization inside a building (S Zheng 2019) (like a warehouse or manufacturing floor) and for scheduling jobs in shops where a single product is produced. Calls for multiple jobs that need to be finished on different devices while maintaining the best possible equipment arrangement. Additionally, hybrid applications—which combine machine learning with traditional optimization methods and process simulation—are becoming more prevalent K Ristovski et al (2017).

Another area where AI/ML can have a big impact on manufacturing is with digital twins. A 2020 case study found that using digital twins in large-scale smart manufacturing operations had a lot of advantages (O'Sullivan 2020) Digital twins are computer-generated images of a factory or other facility placed in a virtual setting. The ability to reduce simulation times a number of orders of magnitude greater than traditional methods is a key selling point of AI/ML-based digital twins, making their application in real-time data analysis and process control possible. In addition, they can be employed for experimentation and small-scale system design testing, which enables operators to assess possible process behaviors and responses prior to implementing updated control logic on the manufacturing floor. Intelligent and autonomous manufacturing may be made possible through automation with the help of AI-based digital twins G Zhou et al (2020).

2.3.6 Quality Assurance

Ensuring the health and safety of customers requires quality assurance. In addition to lowering expenses and waste, preventing quality failures can increase customer satisfaction (P Brosset et al 2019) AI/ML models have demonstrated potential to improve quality control in a wide range of manufacturing industry applications. According to recent research, CNNs can detect manufactured product imperfections just as well as, in certain situations, better than, conventional methods (A Kusiak 2020) This is especially essential in the context of additive manufacturing, since attributes such as porosity and density can greatly impact the final product's mechanical attributes. In the semiconductor manufacturing industry, random flaws in wafer maps and electron microscope pictures, which are significant indicators of semi-conductor execution—were found using CNN computer vision models built with the help of Auto ML (Y. Fei 2022) With a 6% increase in detection accuracy, Additionally, similar types have been utilized in assembly lines in the automotive industry to find flaws in fabrics, optical films, and LCD screens.

2.3.7 Material Waste Reduction

A three-dimensional object is created incrementally, from the top layer to the bottom layer, layer by layer in additive manufacturing. Therefore, it is not possible to 3D print objects with overhangs (Leary et al. 2014) To get around this restriction, However, the issue here is that the rough post-processing steps that follow manufacturing must be repeated for the ses up ports. This will raise the manufacturing cost. As a result, numerous researchers have been trying to reduce support and, consequently, waste. An additional factor that needs to be considered by researchers is part orientation. In order to reduce support, proper orientation will result in significant savings. Numerous researchers have noted the connection between support and part orientation Das et al. (2017).

Numerous researchers have experimented with using less expensive materials to offer support. Here, the plan is to dissolve the support material as soon as the component's manufacturing is completed.

Hopkins et al (2009) have employed co-polymers of acrylic as a backing material. The assistance may be removed with ease in this manner. For the third dip, Acryl on Itrilebutadiene Styrene material was utilized, with a polylactic acid-painted support. the component's support will be eliminated upon immersion in potassium hydroxide and isopropyl alcohol (Ni, F et al 2017) has experimented with the 3D printing process by employing the water-soluble polyvinyl alcohol as a support material.

2.3.8 Minimizing Energy Consumption

The amount of energy used by additive manufacturing is greater than that of traditional machining. Even though a lot of researchers are working in little use of additive manufacturing attention is paid to the energy use in the AM procedure. The use of 3D printing is done using FDM or SLS technology. In the SLS procedure, laser light serves as a heat source. Throughout the procedure, a metal platform with evenly distributed vermetal powder is treated with laser light. Throughout the procedure, the laser is incrementally moved in accordance with the CAD model. The metal powder will sinter as a result of this. This creates the 3D object's layer. Following the formation of the first layer, metal powder is evenly spread using a roller, and the process is then repeated. The SL Spruces are transported (Mansour and Hague 2003) by utilizing a variety among polymers, including metals, polyester, ceramic components, etc.

Energy is used in the SLS process not just for handling but moreover for carrying out not adding value tasks. Processing energy is a function of the quantity of material things must be combined to make a combination three-dimensional object. Energy is used for heating, recoater arm movement, and piston movement in addition to processing. Studies have shown that roughly 56% of the energy is used in the sing-con sumesa process. This demonstrates unequivocally how much icantamo unto fen energy is used for a variety of non-value-adding tasks. Therefore, researchers will need to pay close attention in the future to reducing the amount of energy used for non-value-adding tasks. At that point, this would add a substantial amount of value.

The process energy needed to sinter the material powder is determined by the following factors (Lu 2016) found that the laser's average intensity, scanning speed, spot diameter, and absorptivity of the parent material all contributed to the process of single-shot energy consumption. The primary drawback of additive manufacturing is its higher energy consumption compared to conventional machining.

2.3.9 Energy Consumption Forecasting

Predicting how much energy manufacturing processes will require is a proactive approach to lessen environmental impact and increase sustainability. Based on historical energy consumption data, temperature, humidity, lighting usage, facility activity, and lighting profiles, regression models may forecast profiles of the facility's energy consumption and certain process levels. These could be quite beneficial for demand-responsive strategy and energy efficiency, particularly in sectors that require a lot of energy like steel and mining (Chen, et al 2019) additionally within apps involving additive production (J. Qin et al 2020). When training with historical time series information originating from many devices, DNNs perform especially well in forecasting (Duan et al 2019) SVMs can also be used to forecast short-term electricity consumption, particularly when there are few samples and high-dimensional inputs in the forecasting problem.

2.3.10 Security Enhancement and Intruder Detection

Two types of solutions centered on security: techniques that depend on detection or prevention. Encryption and authentication are used in prevention-based methods to guard against potential attacks. When preventative measures don't work, detection-based methods are employed.

The attempt to integrate industrial systems with communications technologies with the introduction of Industry 4.0 has led to a rise in security threats. Several security systems must be integrated in order to provide security for the cyber-physical system. Cyber-physical systems are going to face two different kinds of attacks. a DoS attack, or denial-of-service occurs when an attacker temporarily or permanently disables a device's ability to access the Internet. False data attacks are another name for deception attacks. Here, the target node is injected with fake data by the attacker. Performance degradation or cyber-physical system instability could arise from this. Without human assistance, sensors a cyber-physical system that will compile information and transmit it via a communication network. The aim of this kind of system is to use artificial intelligence to govern a diverse group of cyber-physical systems (Norman 2012) created a distributed system of access control solution utilizing a system of experts. Algorithms for Swarm intelligence refers to now integrated into control systems.

2.3.11 Security And Safety

With the use of sophisticated methods for access control, AI/ML can also enhance employee and critical equipment security in manufacturing settings. It can also be used to lessen the risks to cyber security brought about by a manufacturing plant's growing network of connected devices. Deep learning-based computer vision can visually detect unsafe employee behaviors and the presence of unauthorized personnel in a facility (Sen et al 2019) An examination of the manufacturing processes employed in the chemical industries.

Using deep learning to analyze the connections between process variables in order to forecast possible mishaps (Mao et al 2019) AI/ML the models are used in industrial intrusion detection systems cyber security (Bécue et al 2021) By identifying unusual patterns in user behavior or network traffic, one can, for instance, examine data trends that represent underlying behavior characteristics and simplify datasets before moving on to more intricate, supervised learning-based material selection.

2.3.12 Product Enhancement

Artificial Intelligence is actively involved in the burgeoning field of driverless vehicles (AD). Road detection, lane identification, car identification, pedestrian identification, fatigue identification, and collision prevention are the primary goals of AD Raissi et al (2017).

Within the field of computer science, the set of questions primarily concerns segmentation, localization, and object detection based on images; these are made more complex by utilizing multiple sensors and specifically combining the data that is gathered from them. One of the main elements of autonomous vehicles is sensor fusion. The previous methods of detection may not be accurate or dependable in the event that the sensor signal contains a large mistake. In spite of its.

2.3.13 Automation And Human–Machine Interaction

Modern manufacturing already relies heavily on industrial robots. The integration of artificial intelligence (AI) into current industrial robots holds promise for revolutionizing the level of collaboration between humans and robots. In order to preserve efficiency and safety, it might enable robots to swiftly adjust to changes in human behavior. Because AI/ML allows robots to mimic expert human behavior, it can assist in addressing the shortage of human knowledge. This can carried out by training an ML as a model for mimic the process of making decisions abilities of professionals through the use of supervised learning techniques. Combining supervised learning and reinforcement learning (RL) for increased versatility—enabling the representative to consult a "manual" of data and make judgments based on experience—was suggested in a 2018 study on the use of RL in deep reinforcement learning for automating water purification plants (P. Nguyen 2018) Additional research has demonstrated that AI/ML can empower robots to carry out jobs like metal additive manufacturing support removal (K. Harston 2020) or autonomous vehicle management, which were too complicated for traditional robots and too risky or tiresome for humans. Human-machine interaction is becoming inevitable as AI for industrial robots becomes more widespread, and human flexibility is still required in manufacturing. We need to look at ways to make these exchanges easier and let robots adjust to the subtleties of how people behave. This could take the structure of natural language processing (NLP); for instance, creating a database of languages and using utilizing a recurrent neural network interpret verbal grievances and help with upkeep or repair W Shalaby (2020).

3. DISCUSSION

Manufacturing firms can gain a great deal by using AI and ML technologies. Despite the fact that some progress has been made, it will be a while before ML and AI are used to streamline AM so they can be integrated into other production processes or become a commodity for users. AI can progress manufacturing techniques in the fields of microstructural design, process optimization, design correlation, and improvement. Manufacturing process can greatly profit from the existing strategies created for other operations; the primary obstacle at hand, though, is now the consistency and accessibility of the data required to train the machine learning algorithms. There is a wide range of current experimental data available from manufacturers or the scientific community, some of which are not publicly available. As a result, trustworthy data gathering, storing, and sharing is essential for developing ML algorithms for manufacturing. The kinds of tests that have been carried out or are being carried out differ greatly from the observation. As a result, it is critical that the industrial sector establish a location for data storage. The conditions under which the data were generated must to be given in order for the data to be useful and the machine learning algorithms to function correctly. It is necessary to reveal and communicate the machine type as well as any further information needed for labeling and reproducing the data. Furthermore, the process itself presents difficulties for monitoring and measuring because to factors like high temperatures and velocity. The bulk of current methods rely on thermal or optical imaging of the material's surface, and in most circumstances, it is difficult to obtain information about the depth of the material. It is crucial that producers and scientists create instruments that can quickly and accurately track a wide range of process variables.

4. CONCLUSION

Upon reviewing the conducted research, it became evident that the topic is of great interest to all branches of science and has a particularly broad impact. One immediate effect might be the emergence of new generations of researchers who will add to upcoming comparisons and pose new research questions. AI applications in the manufacturing sector have proven particularly difficult because high-dimensional, highly nonlinear phenomena require nearly perfect modeling. Though AI is still in its infancy, Numerous studies conducted recently have been done on the technology in related industrial sectors, suggesting that it has the potential to revolutionize manufacturing paradigms in the near future.
The structure is dividing the available algorithms and applications into three categories: supervised Robotics, Learning, and unsupervised machine intelligence. Because most It was suggested that since most manufacturing applications can supply labeled data, supervised learning is a suitable fit for them.
With the rapid advancements in algorithmic science, coupled with the growing data accessibility, computing capacity, and machine learning applications, particularly in the manufacturing sector, are expected to grow even faster. Supervised algorithms currently hold the advantage most manufacturing applications. In conclusion, it is confidently claimed that artificial intelligence (ML) is now an effective method for a variety of applications in smart manufacturing and IMS, as well as the fact that its significance will only grow going forward.

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