Implementation of Data Science for Improved Manufacturing and Production – A review

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Abstract—

Data science and its associated techniques have been a game-changer in any aspect of our life. Data science helps organizations use advanced tools and technologies to solve complex problems that are either expensive or impossible to solve. This work looked at some of the works that have been completed regarding the opportunities for data science in manufacturing. Manufacturing is vital for every country's economy and security. Data science does help manufacturing in many aspects, including the efficiency of manufacturing operations, products with a competitive edge, the rate at which products get to market, etc. The work completed a literature review of some use cases in selected manufacturing industries.

Keywords—data science, artificial intelligence, machine learning, manufacturing, predictive maintenance

I. Introduction (*Heading 1*)

Manufacturing fuels the economies of countries around the world by producing jobs and developing market demands. Manufacturing is a critical component of high-quality economic development, with a more significant productivity growth potential than other industries. It can significantly affect other industries because of its inherent benefits, such as capital accumulation, scale economy, and technological innovation[1]. Manufacturing industry innovation has also contributed to increased economic productivity, eliminating bottlenecks and controlling equipment performance to keep the supply chain flowing. The way we manufacture and consume commodities has evolved since the Industrial Revolution[2]. Innovation has allowed the nation to become increasingly productive in its services [3, 4]. The manufacturing industry is currently undergoing a massive shift, aided by the digital era, which necessitates increased agility for customers, companies, and suppliers. It is widely agreed that innovation will drive manufacturing growth in the twenty-first century; this would necessitate adopting some new technologies, such as data science and artificial intelligence. Manufacturers have challenges as their scale and speed grow[5], where data science comes in.

All manufacturers want to get the right product to market at the right time and for the right price[6, 7]. Data gathering and analysis can help manufacturers improve their processes and provide valuable insights that can aid management in making the best strategic decisions for achieving concrete results. For instance, downtime is when a planned or unplanned machine can be costly to operations in manufacturing contexts and the speed of reaching the market[8, 9]. Data science can make it simple to track equipment health in real-time and predict breakdowns, avoid machine failures and unexpected downtime while increasing productivity and production lines and lowering maintenance costs and energy use[10–12]. Smart Manufacturing applies innovative technologies to traditional manufacturing processes, such as sensing inputs, processing power, always-on connectivity, artificial intelligence, and advanced data analytics[13]. When used together, these technologies should help teams discover new ways to accelerate development, minimize waste, reduce risk, and improve supply chain transparency[14, 15]. The Big Data Analytics in Manufacturing Industry Market was valued at USD 904.65 million in 2019 and is predicted to reach USD 4.55 billion by 2025, at a CAGR of 30.9 percent over the forecast period 2020 – 2025, according to one estimate for the United States. [16]. According to TrendForce magazine[17], the estimated global market for innovative manufacturing solutions will top US$320 billion by 2020.

Data scientists are appropriately recognized as the new manufacturing employees as big data paves the way for businesses worldwide, especially in the manufacturing world. Data is critical for coordinating activities within the manufacturing sector, across manufacturing industries along the production chain, and between manufacturing industries and outside organizations like financial institutions[18]. As a result, data systems can connect the industrial sector with its customers, suppliers, and service providers[19–21].

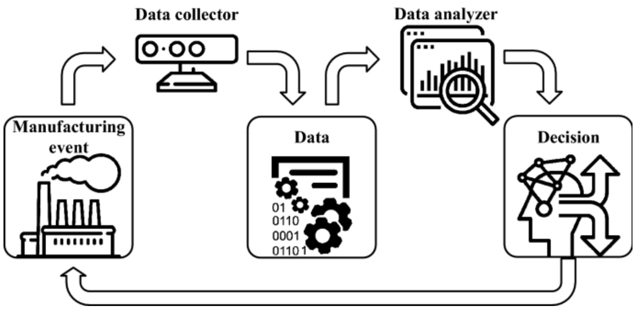

Figure 1. Closing the loop of data-driven manufacturing[22]

Figure 1 illustrates a closed-loop data-driven manufacturing operation depicting how data science impacts decision-making through data collection and analysis[22]. Typical applications in data Science in Manufacturing include improvement of product design and development, manufacturing process optimization, improving quality control on the production line, robotization and computer vision implementation logistics and supply chain management, fault prediction & preventive maintenance, reducing maintenance costs, and improving reliability, equipment & shop floor monitoring, waste and cost reduction, demand forecasting and inventory management, warranty Analysis[23–25].

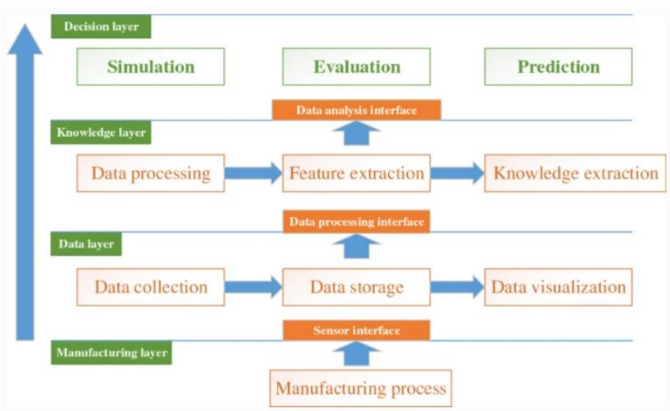

Figure 2. A framework of data-driven manufacturing[22]

II. Data Science and Opportunities in Manufacturing Industry Operation.

Data science is a multidisciplinary field that applies advanced analytics techniques and scientific principles to extract valuable information from data for business decision-making, strategic planning, and other uses[26]. Data science uses knowledge and disciplines such as data engineering, data preparation, data mining, database management, predictive analytics, machine learning, and data visualization, as well as statistics, mathematics, and software programming to extract meaningful information and predict future patterns and behaviors[26, 27]. Data science can be helpful throughout the phases of the supply chain of production and product development. For instance, data science can help provide information about suppliers and customers, which can help companies satisfy their customer requirements across the product's lifecycle, i.e., from the cradle to the grave[28–30]. It can help companies prevent equipment breakdowns in manufacturing plants and other industrial settings[31]. Due to the increase in computational activities, cyber-attack has become a significant challenge for companies; data science can also help [32].

Data Science Lifecycle revolves around using machine learning and other analytical methods to produce insights and predictions from data to achieve a business objective. As shown in Fig. 3, the typical lifecycle data science can be summarized into five stages: Data Capturing, Data preparation and maintenance, Data process, Data analysis, and Data communication or reporting[33]. Fig. 4 illustrates a typical manufacturing data lifecycle that consists of data collection, transmission, storage, processing, visualization, and application[34].

Figure 3. Typical Data Science Lifecycle [33]

Data Science Lifecycle revolves around using different analytical techniques to produce insights and predictions from available data and information for decision making. Data science projects involve a series of data collection and analysis steps. Use cases include predictive modeling, pattern recognition, anomaly detection, classification, categorization, and the development of technologies that can be implemented for more effective processes [34].

A. *Capturing of Manufacturing Data*

Capturing is the processing, extracting, and gathering of information in structured and unstructured data from all relevant sources. The data capturing method transforms it into a computer-readable format for storage and future use[36, 37]. The process involves entering data manually or otherwise by an operator using input devices like a keyboard, touch screens, mouse, etc.[38]. Data collection is a vital component of the modern manufacturing process that helps companies monitor and control costs and ensures the smooth operation of the plant. Different types of data collected in the manufacturing industry can be grouped into the observational, experimental, simulation,

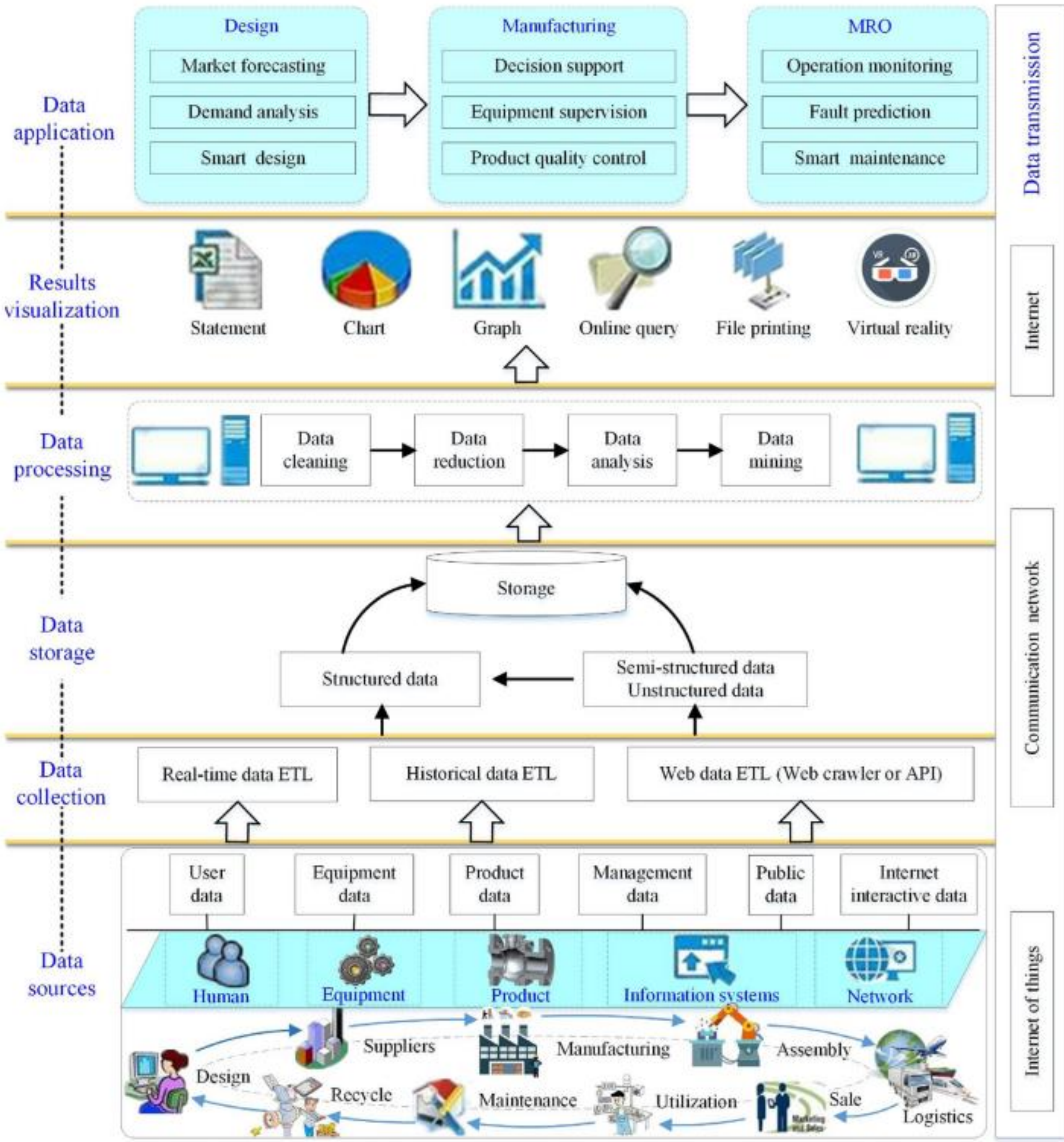

Figure 4. Manufacturing data lifecycle[34]

and derived[39]. Observational data is collected by seeing a behavior or action. When a variable is changed, experimental data is collected by active intervention by the researcher to produce and assess change or create a difference. Simulation data is created by employing computer test models to simulate the operation of a real-world process or system over time. Derived data is created by transforming existing data points, often from disparate data sources, into new data using arithmetic formulas or aggregation. Manufacturing data comes from multiple sources and devices such as coordinate measuring machines[40], sensors[41], and ethernet and serial devices such as databases[42], open platform communications (OPC) servers[43], text files [44], and business systems[45] such as enterprise resource planning software, manufacturing execution systems, and laboratory information management systems. Some techniques used to collect industrial data are sensor

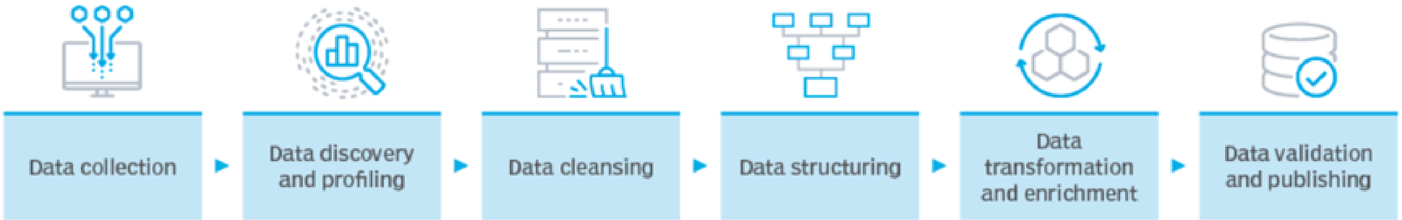

Figure 5. The data preparation process includes these primary steps[35]

integrated system, line human-machine interface system integration, supervisory control, data acquisition system, performance tracking through machine integration, direct interview of suppliers and customers, and product tracking using intelligent tracking devices. Some of the identified challenges for industrial data collection include High costs of the data collection system, the increased error rate in collected data, storage of captured data due to an increase in the amount of data, misinterpretation of data, time consumption, and quality control[46, 47].

B. Preparation and Maintenance of Manufacturing Data

Manufacturing data generated or captured using sensors and other tools generally come with missing values, inaccuracies, or other errors[48]. Sometimes, related data sets from different sources often come with different formats that need to be harmonized for processing. Data preparation is putting raw data into a format that will ensure that the raw data being prepared for processing and analysis is accessible, accurate, and consistent[49, 50]. Data preparation can include gathering, combining, cleansing, deduplicating, structuring, reorganizing, reformatting, and warehousing the data. Figure 5 shows six essential steps for the data preparation process[35, 51, 52].

Data preparation tools used in the manufacturing industry are mainly software products that help consolidate, process, standardize, and enrich captured data. These preparation tools are commonly offered as part of data mining, data integration, Extract-Transform-Load (ETL), or data management tools. Preparation software includes Metabase, Microsoft Power Bi, Tableau Prep, Altair Monarch, etc. Companies can also develop an in-house solution using python or other programming resources. Examples of python programs include Data Prep. Data Prep is an open-source library available for python that lets you prepare your data using a single library with only a few lines of code.

C. Process Data in Manufacturing

Process data is essential for implementing data analytics in the manufacturing industry because many raw data sets are generated. Manufacturing plants can use their insights and predictions to increase plant efficiency, optimize production quality and quantity, and sharpen their competitive edge in a crowded market. Process data involves the examination of data biases, patterns, ranges, and distributions of values within the data to determine its suitability for analysis. Some of the processes include data mining, Clustering, Classification, Data Modeling, and data summary [53]. Data mining predicts outcomes by looking for anomalies, patterns, and correlations in massive data sets. In data science, clustering and classification are pattern recognition algorithms. Clustering divides data into groups, clusters, or hierarchies to determine the structural properties or commonalities of a data collection. The systematic organization of patterns in groups or categories according to specified criteria is called classification. Data modeling represents links and connections between data pieces, kinds, and structures using a visual representation such as text and symbols. The approaches used to find a succinct dataset description are known as data summarization. Oracle data miner, IBM, and others are some of the tools utilized in manufacturing environments to complete data processes[54].

D. Analysis of Data from the Manufacturing Industry

Manufacturing data analytics is the use of machines, operations, events, and system data and technologies in the manufacturing industry for improved decision making that would ensure quality, maintenance, increase performance and yield, reduce costs, and optimize supply chains. Data analytics is a process used to extract meaningful insights, such as hidden patterns, unknown correlations, trends, and preferences in a given data[55, 56]. Types of analytics include explorative, diagnostic, prescriptive, and descriptive analyses[57–59]. Diagnostic Analytics is done to understand what caused a problem in the first place. Prescriptive Analytics prescribes the solution to a particular problem. Descriptive Analytic summarizes past data into a form that people can easily read. Predictive analytics is the use of statistics and modeling techniques to determine future performance based on current and historical data. It encompasses a variety of statistical techniques from data mining, predictive modeling, and machine learning that analyze current and historical facts to make predictions about future or otherwise unknown events.

Data science relies heavily on machine learning algorithms. Machine learning is a form of advanced analytics in which algorithms learn about data sets and then look for patterns, anomalies, or insights. Machine learning is a subfield of artificial intelligence (AI) and computer science that focuses on using data and algorithms to mimic the way people learn, progressively improving its accuracy[60]. Machine Learning is an optimization and regression technique that uses developed algorithms to build models from data[61]. Machine learning can generally be categorized into supervised and unsupervised learning techniques based on the extent to which the training data is labeled. In addition to the two, we can also have reinforced or semi-supervised learning. Supervised learning is the machine learning technique that uses labeled datasets to train

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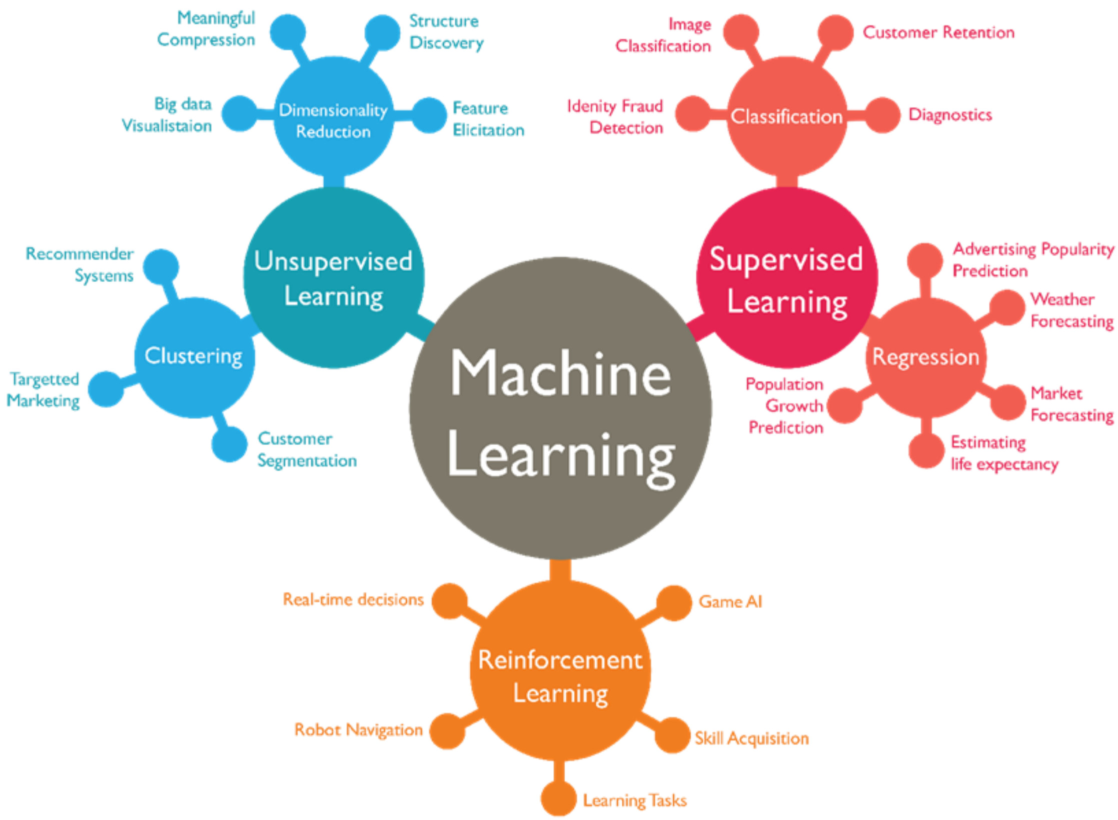

Figure 6. Machine Learning Applications[62]

algorithms to classify data and predict outcomes. Supervised learning is classified into classification and regression algorithms. Unsupervised learning techniques are the training of a machine using information that is neither classified nor labeled and allowing the algorithm to act on that information without guidance. Here the task of the machine is to group unsorted information according to similarities, patterns, and differences without any prior training in data. Unsupervised learning is classified into clustering and association algorithms. The three most used methods for unsupervised clustering include k-means, mixture models, and hierarchical clustering.

Reinforcement learning is the training of machine learning models to make a sequence of decisions based on understanding environmental interaction, perceived consequences, and rewards, i.e., feedback. It is concerned with how intelligent agents ought to take action in an environment. Reinforcement learning uses a trial-and-error search to sense the state of its environment and learns to take appropriate actions to achieve optimal immediate or delayed rewards. Fig. 6 and Fig. 7 show different types of machine learning and where they are applied.

Deep Learning is part of a broader family of machine learning methods based on artificial neural networks with representation learning[63]. Deep Learning is about computers learning to think using structures modeled on the human brain. Deep Learning can be supervised, semi-supervised or unsupervised, though it eliminates some of the data pre-processing typically involved with machine learning. These algorithms can ingest and process unstructured data, like text and images, and it automates feature extraction, removing some of the dependency on human experts.

Physics Informed Learning seamlessly integrates data and mathematical or physics models, even in partially understood, uncertain and high-dimensional contexts.

Physics-informed machine learning allows scientists to use this prior knowledge to help the training of the neural network, making it more efficient. It means it will need fewer samples to train it well or make the training more accurate. It is of growing importance for scientific and engineering problems[64].

E. Some Selected Machine Learning Algorithms

Support Vector Machine (SVM) is a supervised learning algorithm widely used in various classification problems due to its high performance and high level of accuracy. A classification algorithm aims to take an input value and assign it a class/tag or category based on prior knowledge gained from a training dataset. It is very efficient if the classes from the dataset are separated; it is beneficial for a database with many features due to its capacity to separate data in a multidimensional space. It has a downside in situations where much noise populates the data.

The Naive Bayes Classifier is a probabilistic algorithm based on Bayes' theorem used for classification tasks. It involves determining a probability based on other statistical data with strong independence assumptions between features. It is quick and easy to implement. The technique requires that data have independent characteristics, but characteristics of real-life data are generally interdependent; this portrays a letdown for the technique.

The Random Forest algorithm is one of the most advanced machine learning algorithms, especially for large data sets. Combining predictions is specific to extracting knowledge from data and is effective in many situations.

Linear regression is perhaps one of the most well-known and well-understood algorithms in machine learning. It is a linear approach for modeling the relationship between a scalar

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response and one or more explanatory variables. It is represented by a linear equation that combines a specific set of numeric input values. The solution to which is the predicted numeric output for that set of input values.

Regression Artificial Neural networks predict an output variable as a function of the inputs. The input features (independent variables) can be categorical or numeric types; however, for regression ANNs, we require a numeric dependent variable.

K-means clustering is one of the simplest and most popular unsupervised machine learning algorithms. K-means algorithm identifies k number of centroids and then allocates every data point to the nearest cluster while keeping the centroids as small as possible. This algorithm aims to find groups in the data, with the number of groups represented by the variable K.

Agglomerative Hierarchical Clustering (AHC) is an unsupervised method that recursively merges pair of clusters of sample data by comparing pairwise linkage distance. It works from the dissimilarities between the objects to be grouped. A type of dissimilarity can be suited to the subject studied and the nature of the data.

Q-learning is a model-free reinforcement learning algorithm to learn the value of an action in a particular state. It does not require a model of the environment, and it can handle problems with stochastic transitions and rewards without adaptations.

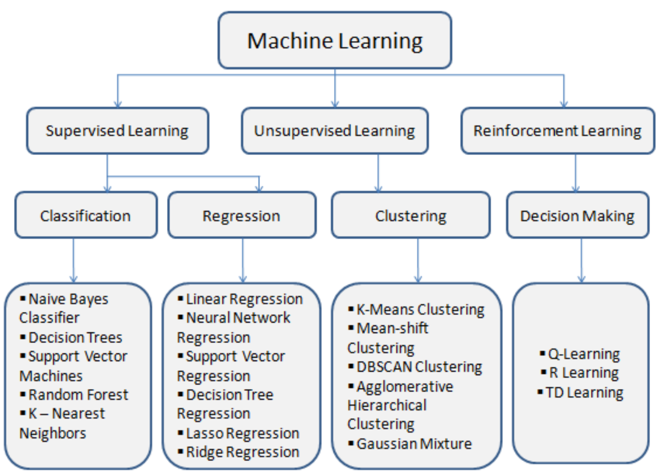

Figure 7. Machine Learning Algorithms[65]

F. Communication and Report of Manufacturing Data

There is a need to communicate the insights, present findings to stakeholders, and complete data evaluation. Insights are presented as reports, charts, and other data visualizations that make the insights and their impact for decision-makers to understand. Components of the communication stage include data reporting, data visualization, business intelligence, and decision-making. Data visualization refers to the process of creating graphical representations of your information, typically using one or more visualization tools. Visualizing data makes it easier to quickly communicate your analysis to a broader audience inside and outside your organization. There are many ways to visualize data; some of the most common data visualization techniques are Pie charts, Bar charts, Histograms, Gantt charts, Heat maps, Box-and-whisker plots, Waterfall charts, and Scatter plots. A data visualization tool is a form of software designed to visualize data. Each tool's capabilities vary, but they allow you to input a dataset and visually manipulate it at its most basic. Some of the tools used for data visualization are Microsoft excel, Google charts, Tableau, Zoho Analytics, Data-wrapper, and Infogram[66]

III. Literature Review of Data Science Use Case in Some Selected Manufacturing Industry

This section will review some work completed about data science's role in some selected manufacturing sectors. Selected industries are the clothing and textile industry, transportation equipment manufacturers, and pharmaceutical industry are some manufacturing companies with intense use of data science.

A. Role of Data Science s in Clothing and Textile Industries

Computational advancements have greatly improved activities in textile manufacturing. Integrating artificial intelligence into the system certainly improves the operations. Artificial Intelligence and machine learning are potentially used in yarn manufacturing, development & inspection of the fabric pattern, defects detection, color management, and fabric grading. Ultimately, artificial intelligence can significantly impact the textile and garment manufacturing supply chain. It can drastically reduce manufacturing costs and improve product quality. It can contribute to sustainability efforts by reducing production waste.[67–71] There have been some use instances that have improved the garment manufacturing process.

Lee et al.. [72] investigated the use of data-driven machine learning to improve the quality and efficiency of the textile manufacturing process. They harness quality inspection and control data such as machine operation parameters from warping, sizing, beaming, weaving process, and management experience data to establish a relationship between key operation parameters. They developed an Operation Parameters Recommender System using regression modeling. The developed method was able to predict up to 91% accuracy. Yildirim et al. [73] investigated data mining and machine learning in the textile industry. They used data mining techniques such as classification and clustering techniques; they explored the effectiveness of tools such as neural networks and support vector machines. They found that they have a high accuracy rate in predicting the textile manufacturing process. Candanedo et al. [74] suggest using predictive machine learning to enhance predictive maintenance in the textile industry. Khan[75] explored the application of artificial intelligence in the textile industry's supply chain. He identified some supply chains that could benefit from artificial intelligence, such as supply constraints, production capacity, and process efficiencies. The work further creates a qualitative model for data collected using a widely subscribed questionnaire to establish significant relationships between artificial intelligence and demand forecast, decision making, and product deliveries. Wang et al. [76] used yarn pattern recognition and robust deep learning to develop a textile coding tag for textile traceability. Their

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traceability coding tag consists of unique features extracted using the deep learning technique for identification, linking the product with traceability information, i.e., traceability signature. Their experimental result shows that these techniques are effective for textile recognition.

Today, Information technology (IT) plays a vital role in the textile industry. Informatics help companies focus on synchronizing all these factors and developing synergies within and outside organizational operations. With the increased competition, companies are taking support of IT to enhance their Supply Chain Management (SCM) and using it as a competitive edge. In short, many textile companies are leveraging technological power to add value to their business.

Supply Chain Management includes sourcing, procuring, converting, and all the logistic activities. It seeks to increase the transaction speed by exchanging data in real-time, reduce inventory, and increase sales volume by fulfilling customer requirements more efficiently and effectively.

In the traditional textile industry, the procurement process takes much longer. So, the retailers need to forecast demand and identify consumption trends at a much earlier stage. Lack of clarity about the future can result in early stock out, delay, or overstock.

Some researchers have investigated the influence of informatics on the textile industry. Zhao and Chao [77] investigated the use of informatics in fashion. They used data mining-based social network analysis by providing dynamic network visualization of social media activities during Paris fashion week. The data were extracted using python and Gephi toolsets. They established the relationship between the contextual clusters and the role of junctions in linking these clusters. Developing a collaboration network is an identified challenge in textile supply chain management. It is believed that effective relationship management is essential for improving customer services, delivering time, promoting information sharing, and shortening product life cycle time in the industry. Hwang and Seruga [78] proposed the use of an intelligent textile supply chain management system using a collaborative network model. Informatics tools such as data warehousing and knowledge management systems, integrated telecommunications networks, multimodal transportation systems, commercial and service support, technical and organizational infrastructure were used to develop this system. Ali and Haseeb[79] explored the benefit of radio frequency identification (RFID) technology to enhance the performance of supply chain operations in the textile and apparel industry of Malaysia. They used survey data collected from participating RFID technology users for their analysis. They found that RFID effectively improves the payment system, traceability of orders, and delivery time, improving communication with customers and suppliers. Nijaguna and Praveen[80] investigated the role of information technology on the supply chain in the textile garment industry. Kumar et al. [81] and Obser [82] implemented a traceability framework for an e-supply chain in the textile industry. Traceability is a data management process that is essentially used for sharing information such as design details, component description, procedures, bill of materials, etc., within and between textile companies; it helps to integrate and bring more transparency to the supply chain. The authors expanded on data storage using a relational database management system and XML information exchange for the textile weaver. Agrawal[83] investigated the use of a secured tag for traceability. Tayyab and Sarker [84] used interactive fuzzy programming for supplier selection. The use of blockchain technology has been explored to improve the supply chain traceability of textile and apparel [85–87].

B. Role of Data Science in Pharmaceutical Industries

Pharmaceutical companies rely on empirical data to test the efficacy of drugs and treatments. Pharmaceutical companies have been leveraging data science to improve the manufacturing process. Data science in pharma has also been used to improve and track sales efforts and provide feedback received during the sales process. The pharmaceutical industry is intense in the rapid turnout of new drugs, and predictive analytics would help companies identify parameters and information that would accelerate drug discovery and development. Zhang et al. [88] studied how data analytics and big data helped confront the COVID 19 epidemic. The techniques helped companies estimate epidemiological parameters, digital contact tracing, diagnosis, policymaking, resource allocation, risk assessment, mental health surveillance, social media analytics, drug repurposing, and drug development during the epidemic. A clinical trial is an important process in drug development; they are usually capital intensive and time-consuming. A clinical trial involves using varieties of participants from a diverse group. This process can be optimized and made more efficient using data analytics through efficient selection, monitoring, and the response of participants. Genomics is an essential part of drug development; Genomics focuses on the collective characterization and quantification of organism genes, their interrelations, and their influence on organisms [89]. Data science would enable pharmaceutical companies to provide targeted treatment for diseases such as cancer-based on understanding a specific class of people through their identified genes through genomic sequencing. Pharmaceutical companies can also develop drugs and treatments based on real-time monitoring of patients using medical sensor data. Data from medical sensors coupled with analytics can also improve drug delivery and effectiveness. Pharmaceutical companies can harness massive data generated from online platforms such as social media, search engines, etc., can be harnessed by using analytics tools to access product safety issues and mitigate risks associated with delivered products and treatment. Artificial intelligence can detect issues with equipment and proactively manage compliance efforts in pharmaceutical companies by analyzing data generated by the equipment within or outside the company. AI-powered predictive maintenance solutions can analyze the performance of pharmaceutical production lines and provide early warning when equipment begins to wear down or require repairs. Summarily we can conclude that data science can play a significant role across the supply chain of the pharmaceutical manufacturing industry[90, 91]. Some research work that shows how it has been deployed across different functions will be reviewed in this section. Sesen [92] proposed an ontological informatics framework for automated regulatory compliance in pharmaceutical manufacturing. Leal [93] developed end-to-end traceability and data integrity in medicine production. A large amount of data is usually produced by computerized production systems in the pharmaceutical environment. Data integrity is a critical issue facing pharmaceutical manufacturers. The developed intelligent system sends an alert before actual deviations are recorded. The intelligence was developed using distributed Artificial Intelligence techniques, which find patterns that may lead to deviations in manufacturing process data. Paul et al.[94] and Yang et al. [95] discussed how different artificial intelligence was used in different drug discovery and development sectors. Including insight on how this resource was used, improving pharmaceutical productivity and clinical trials. They also highlighted some of the challenges and barriers faced by using big data and AI in this industry. Mehta [96] investigated using a systematic mapping approach to transform healthcare with big data analytics and artificial intelligence. The systematic mapping steps include defining research questions, identifying search terms and conducting a search, screening papers based on inclusion and exclusion criteria, determination of prominent keywords and design of classification scheme, and data extraction and mapping. Harrer et al. [97] investigated the use of artificial intelligence for clinical trial design. Clinical trials could take between 10 to 15 years and the cost could be enormous, meanwhile, all of these could come to nothing if a trial a fails. High failure rates of clinical trials contribute substantially to the inefficiency of the drug development cycle. This work identified aspect of the clinical trial process that can be aided with artificial intelligence. Some of the identified aspects include, patient selection, cohort composition, assistance in recruitment, patience monitoring, Patient Adherence Control, Endpoint Detection, and Retention. This work also provide insight into how data from failed clinical trials can still be harnessed for subsequent studies using Ai methodology. David et al. [98] explored the use of deep learning tool for exploiting large scale and heterogenous compound data in industrial pharmaceutical research. The authors described how machine learning can be deployed for the analysis of image-based profiling data. Biological imaging and image analysis are essential parts of the drug discovery process. They also highlighted the impact of deep learning in predicting interactions between chemical compound activities using large chemogenomic models. Chemogenomic generate a matrix that provides all the possible and impossible interaction between compounds. Likewise, deep learning promotes virtual screening and molecule design using a generative model and data augmentation during drug discovery.

C. Role of Data Science in Transportation Equipment Manufacturing Industries

Industries in the Transportation Equipment Manufacturing subsector produce equipment for transporting people and goods. Transportation equipment is machinery used to move people and products from one place to another. The transportation equipment manufacturing subsector consists of automobile and automotive industries, aerospace and part manufacturing, rail system and part manufacturers, and ship and boat building industries. Implementation of data science and analytics in the transportation equipment manufacturing industries has been driven by the availability of vast data, advances in high-performance computation, improvements to sensing technologies, data storage, and transfer; scalable algorithms from statistics and applied mathematics; and considerable investment by industry[99]. Help prevent the company from spending on expensive R&D projects doomed for failure from the onset[100]. Help company rank parts, test data, and suppliers according to performance metrics such as on-time in-full delivery to predict their ability to deliver on time given. With the help of data analytics, companies can have greater control over their logistics and supply chain management.

In the aerospace industry, data on performance parameters such as speed, altitude, and stability of the aircraft during flight, part damage progression, failure incidences, etc., have been collected periodically over the years. A significant challenge has been to account for as much of the data as possible before concluding. The emergence of data science and data analytics techniques has been beneficial. The analysis of this data has enhanced the design accuracy of aircraft and other aerospace accessories. Some other areas in the aerospace supply chain that have been impacted by data science include but are not limited to weather patterns and maintenance schedules, real-time inflight monitoring, and travel pattern optimization for safer and faster flights. Illankoon et al. [31] investigated the use of artificial intelligence collaborated with human expertise in aircraft maintenance. The study proposed a theoretical model coined the collaborative awareness model that integrates augmented reality-based intelligent support system with the technical expertise of the maintenance engineers using the cognitive fit theory and the theory of distributed situation awareness. They identified that the expert requires an understanding of AI principles to interact with the collaborated intelligence system effectively. Zeldam et al. [101]used explainable artificial intelligence XAI to develop an automated failure diagnosis aviation maintenance system. This proposed method is a solution to challenges associated with free-form text repair cards. The authors explore the use of Bayesian teaching, Neural network, and decision tree for their solution. Celikmih et al. [102] used machine learning with a hybrid data preparation method to develop a model that can predict aircraft equipment failure. The model was developed using data sets from the aircraft landing gear system. The feature selection ReliefF algorithm was used to select attributes, and a modified K-means algorithm to eliminate noisy and inconsistent data. The prediction methods used are artificial neural networks, support vector regression, and linear regression. The model's performance was evaluated using evaluation performance measured, including the mean absolute error, root means square error, and the correlation coefficient criteria. They reported significant improvement in the inaccuracy of the predicted failure counts.

Researchers have used Artificial intelligence to optimize aircraft design [103, 104]. Azabi et al. [105] combined stochastic multi-objective optimization and Artificial Neural Network (ANN) to improve an unmanned aerial vehicle's aerodynamic shape design optimization. The method drastically reduces the designer's workload and the time required to complete the design optimization. Bayat et al. [106] investigated the effect of high-impact forces on the aircraft composite structure using machine learning techniques. Impacts caused by hails and debris create localized damage to the aircraft structure, and visual inspection and real-time monitoring of these structures is a big challenge due to the large size of an aircraft. The investigator adopted random forest and deep learning techniques integrated with acoustic emission non-destructive testing to develop a solution that can automatically detect and localize an impact that may occur during flight. The result of the developed solution shows that random forest and deep learning have a better performance when compared to the conventional solution that was based on an artificial neural network.

Automotive and automobile manufacturing has benefitted immensely from data science and data analytics. The automotive industry has always leveraged new technology ranging from sensors to GPS. They have been one of the primary beneficiaries of the computer and information revolution of the last decade. Effort in the industry has been focused on developing the safer and more efficient vehicle. The safety systems in automobiles include driver protection and environmental safety such as the pedestrian safety sensors that have been deployed on some of the new cars. Low emission vehicle development has been enhanced with the use of AI models. In recent times, the development of autonomous vehicles has been possible with the deployment of deep learning models and sensor fusion algorithms. Data science has played roles in car design, wear & tear prediction, fuel-efficient vehicles, travel patterns optimization, effect of environmental factors, etc.

Adopting data science and analytics in the ship and boat building industry might not be as grandeur as the case was in aerospace and automotive. However, there has been some movement in this frontier. The creation of "smart shipyards" is the next big thing that would revolutionize the shipbuilding industry. Data science and analytics are now being applied to some shipbuilding value and supply chain phases. It has been beneficial for the decision-making process, increased efficiency, and company performance. Data science and analytics can help shipbuilders develop ships and boats with reduced fuel consumption and associated harmful emissions into the environment, helping with predictive maintenance of onboard equipment. It can also help with real-time monitoring of vessel performance and situational awareness. Changyun [107] identified some ways the traditional shipbuilding industry can benefit from playing big data analytics, including ship's energy efficiency index, analyzing the impact of waves on ship speed, evaluating the effect of energy-saving technologies, and analyzing the effect of pollution, i.e., ship fouling on the ship's power, application of the sea environmental data such as wind, waves, currents, water depth, water temperature, etc. for ship design and development, analyzes of operational data of ship's major equipment for predictive modeling of equipment maintenance, safety management, and cost management.

ACKNOWLEDGMENT *(Heading 5)*

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks ...". Instead, try "R. B. G. thanks...". Put sponsor acknowledgments in the unnumbered footnote on the first page.

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