An Automation Designed for Industry 4.0 Using Robotics and Sensors that Based on IoT & Machine Learning

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Abstract. Even though there has been significant research conducted on the topic, the idea of the fourth industrial revolution is still not widely acknowledged. The adoption of Industry 4.0 is anticipated to enhance multiple facets of human existence. The integration of Industry 4.0 will influence various stages of production processes, distribution networks, consumers, supervisors, creators of digital systems, and all staff members engaged in the process. This will lead to changes in manufacturing models and business paradigms. This technology enables self-identification, self-configuration, self-diagnosis, and self-optimization in various industries. This study employs the decision tree algorithm to monitor the energy usage of machines and appliances, predict their future behaviour. Upon assessment of the effectiveness of the proposed system and juxtaposing it against current methodologies, it was determined that the system had a 79% efficiency rate. The integration of this technology presents a number of obstacles, such as standardization dilemmas, security risks, difficulties with resource planning, legal considerations, and the necessity of adjusting to evolving business models. The success or failure of Industry 4.0 and its implementation relies entirely on the involvement and cooperation of all participants in the production chain, from manufacturers to end-users.

1 Introduction

The emergence of Artificial Intelligence (AI) has led to a substantial shift in contemporary civilization, offering a valuable contribution to humanity through science and technology. This relatively new technology has been employed in diverse areas and has enhanced the quality of life [1]. Industry 4.0, which is alternatively referred to as the fourth industrial revolution, began at the dawn of the 21st century. It involves the integration of advanced production and operation methods with digital technology [2]. Cutting-edge technologies such as AI, robotics, quantum computing, additive manufacturing, and the Internet of Things (IoT) are utilized to merge smart and connected technologies into businesses, resources, and personal devices [3]. Collectively referred to as the Fourth Industrial Revolution (4IR), the current era of the internet, advanced analytics, automation, and other advanced technologies

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have been modernizing global commerce for several years. Machine learning is an evolving technique that enables computers to automatically learn from available data [4]. By utilizing various methods, it creates mathematical models and generates predictions based on data analysis [5].

This study investigates the utilization of Internet of Things (IoT) and machine learning in the upcoming era. IoT is a concept that entails an assemblage of tangible objects that are embedded with sensors, software, and other technologies. These objects are interconnected to transmit data to other systems and devices through the internet. Robotics is an engineering field that is focused on the development, design, production, and utilization of robots [6]. The primary objective of this field is to create intelligent machines that can assist humans in a variety of ways. Robots are automated industrial machines that are capable of performing multiple functions and can be reprogrammed to perform difficult tasks in place of humans.

When a sensor is referred to as an "input device," it means that it is a constituent part of a larger system that provides input to a central control system [7]. Sensors enable various devices and systems to connect with one another and facilitate interaction among different units in order to monitor systems and equipment at each location. With the advent of the Internet of Things (IoT), conventional sensors have transformed into intelligent sensors, allowing sophisticated calculations to be conducted locally within a sensor module using measured data [8]. This paper seeks to offer a comprehensive understanding of how machine learning techniques interface with Industry 4.0 by utilizing robotics and sensors.

1.1 The Modification of Industry Revolution

Industry 1.0, which commenced in 1784, marked the beginning of the first industrial revolution. This period witnessed the mechanization of industry through the utilization of steam and water power [9]. Manufacturing was transformed from small-scale production facilities to larger ones, representing a significant shift in the industry.

The Second Industrial Revolution began in 1870, which is also referred to as Industry 2.0. This period was marked by the widespread use of electric power, which facilitated the incorporation of large-scale machinery into industrial processes [10]. A hallmark of this period was the deployment of large conveyor systems for simultaneous transportation of goods, including automobiles and energy production.

Industry 3.0, also known as the digital revolution, commenced in 1969. The third phase of the industrial revolution was the most significant as it employed electronics and information technology to automate manufacturing processes [11]. This period was characterized by the transformation of machines that previously relied on electricity to electronic machines.

The present phase of technological progress, recognized as Industry 4.0, is distinguished by the integration of state-of-the-art technologies such as artificial intelligence (AI), the Internet of Things (IoT), robotics, and big data analytics [12]. This era is marked by the emergence of smart factories and the digitization of the production process.

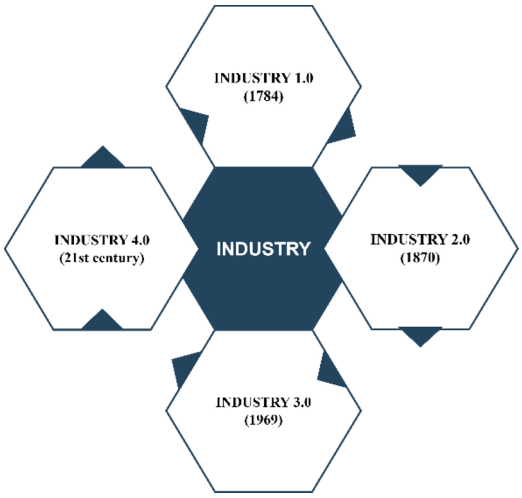

Fig. 1. Industry Revolution From 17th to 21st century

The concept of "Industry 4.0" is established in this paper by utilizing Artificial Intelligence (AI) and the Internet of Things (IoT), which facilitates seamless connectivity between systems, devices, and robots, enabling real-time communication between them [13]. This connectivity empowers manufacturers to gather a wealth of information about their production processes and apply it to optimize production, reduce waste, and enhance product quality.

2 Literature Survey

Organizations strive to increase efficiency by integrating machines and human capabilities. In the present business landscape, the drive for competitiveness is constantly increasing [14]. The recent progress in technologies like radio frequency identification (RFID), smart sensors, 3D printing, the Internet of Things (IoT), robotics, and automation has resulted in noteworthy modifications in multiple areas of all industries. These changes encompass transportation and logistics, consumption, product transformation, and business models [15]. Intelligent systems are becoming increasingly necessary to make timely and informed decisions. In recent times, particular functions in manufacturing processes, such as the painting of car doors and the assembly of parts, have been delegated to robots and machines. The incorporation of robots in the manufacturing sector is noteworthy as they execute tasks intelligently and effectively, while also amplifying cooperation, flexibility, and safety [16]. The field of collaborative robots is a result of progress in AI and ML software, which builds on the foundation of traditional industrial robotics [17]. In addition, the Autodesk tool is employed to expedite the design and production of drones, leading to quicker delivery of the final product to customers.

The field of robotics encompasses various capabilities and technology domains, requiring the integration of devices, robots, and sensors, sometimes with the assistance of third-party web services [18]. The expansion of Industry 4.0, robotics technology, and manufacturing is currently taking place at a swift pace. The objective of Industry 4.0 robotics is to create an intelligent industry that employs technologies such as IoT to generate alternate routes during interruptions and empower products to manoeuvre through the production process autonomously [19]. The purpose of this article is to emphasize the notable changes that have taken place from the first industrial revolution (Industry 1.0) to the present Industry 4.0. The expedition began in the 18th century with the innovation of the steam engine, succeeded by

the second industrial revolution in the 19th century with the implementation of electricity, and the third industrial revolution in the 20th century with the ubiquitous use of computers. The amalgamation of cutting-edge technologies like big data, IoT, and robotics defines Industry 4.0, which is the quintessence of the fourth industrial revolution. The Web of Things (WoT) is an extension of IoT that emerges when internet-connected data and services are linked to sensors and actuators. In IoT settings, a diverse range of services is typically provided by the internet [20].

3 Methodology Approach

The manufacturing process and implementation of Industry 4.0 applications are depicted in Figure 2. It is evident that risk, flexibility, quality, and technology are critical factors in any manufacturing process. Incorporating mobile communication devices into industrial environments through the integration of manufacturing processes is a common practice in commercial innovation. This enables easy access to information at any time and place.

This approach provides an efficient method for keeping up with the latest advancements and interconnectivity in technology, thereby eliminating gaps between the base and control and fostering a collaborative environment to achieve the best solution. To achieve the desired end product, To fulfil an organization's needs, it is crucial to streamline available resources, comprising of manufacturing procedures and personnel.

A method for integrating Industry 4.0 utilizing Artificial Intelligence (AI) and the Internet of Things (IoT), alongside an exemplary graph, is presented below:

- The primary step is to gather data from multiple sources, such as sensors, robots, and manufacturing lines. Temperature, pressure, speed, and other characteristics are examples of such data.
- Once the data has been gathered, it must be evaluated in order to given valuable insights. AI techniques such as machine learning used to do this revolution of industry 4.0.
- The analysed data can be applied to build predictive models that can predict equipment breakdowns, improve production schedules, and detect quality flaws.
- The forecasting can be applied to monitor the manufacturing process in real time, identifying irregularity and informing operators to possible problems. Robots can make decisions automatically using AI, depending on data collected and analysed. This can lead to increased efficiency, decrease downtime, and improve quality.
- Though machines can make autonomous decisions, human operators continue to play an important part in the production process. Collaboration between people and robots can produce improved results. The final phase is to use data analytics and input from the manufacturing process to continuously improve the manufacturing process.

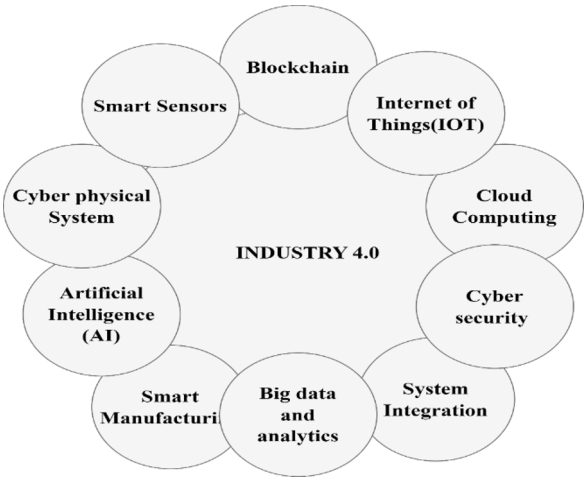

Fig. 2. Pillars of "Industry 4.0"

The convergence of modern technologies, including IoT, AI, and ML, defines Industry 4.0. This integration leads to a highly interconnected and automated system that can enhance processes and improve efficiency.

Following are some equations and algorithms typically used in Industry 4.0:

Training Dataset Machine Learning Algorithm for Decision Trees:

To estimate the various functions, a logistic regression is used to produce effective methods. The first step is to classify the input data for analysis.

The next phase involves recognizing the results of the new data. To construct the decision tree, a machine learning approach is utilized, which depends on the association between the input data and the regulations. The decision tree algorithm focuses on creating a high-precision decision tree on a small scale. It uses the "if-then" sets and categorizes them based on the feature space and class. The decision algorithm consists of three phases.

(1) Phase 1: feature selection— A single feature or characteristic is selected from a set of attributes based on its superiority.

(2) Phase 2: decisions making- Questions that are pertinent to the subject matter are asked to help steer the direction of the response.

(3) Phase 3: The elimination process is iterated until a solution has been identified.

A testing process is utilized to start decision algorithms from the root node. An illustration of this is the allocation of a specific characteristic to the subsequent node depending on the output of the preceding testing. At the same time, the tested feature value is assigned to every node. This process of characteristic assignment and testing persists until the leaf node is

attained. The concluding step is to categorize the feature values into the class of the leaf node. The decision tree uses information entropy to determine the uncertainty of the tested set.

$$A(y_r) = -\log_2 A(y_r\ ) \tag{1}$$

where $\boldsymbol{y_r}$ is the information index and can be expressed using the expression in Equation (1) as.

A ($\boldsymbol{y_r}$) denotes the probability of the selected category. It is possible to calculate the entropy by adding information values as showing in Equation (2)

$$G = -\sum_{f=1}^{n} A(y_r) \log_2 A(y_r) \tag{2}$$

In this case, "n" denotes the variables that require further separation. The more uncertain of the variable, the greater the entropy.

Using Equation (3), it is also possible to determine the formation of probability based on the entropy probability calculation, such that:

$$G(X) = -\sum_{f=1}^{m} \frac{|b_i|}{|Y|} \log_2 \frac{|b_i|}{|Y|} \tag{3}$$

where "m" represents the total integer limit for the "X" dataset, Y represents the sum of bi, and bi represents the size of X. As a result, the Y value of uncertainty using the variable Z can be further denoted by Equation (4)

$$G(X|Z) = -\sum_{f=1}^{p} A_r\, G(X|Z = y_r) \tag{4}$$

Entropy is used to calculate information gain. This can be stated using Equation (5)

$$N = G(X) - G(X|Z) \tag{5}$$

X is the training dataset, with observational entropy G(X), and Z's conditional entropy is expressed as G(X|Z). The size of the information gain varies depending on the training dataset.

4 Result

The type of smart metre data is specifically determined using the decision tree. The output resulting from this is then further encrypted in order to ensure online validation via IoT. Real-time data is collected through a smart meter to create a dataset that is used to test and train a decision tree algorithm under various scenarios and operating conditions. In addition to the real-time data, a simulated dataset is used to evaluate the effectiveness of the system. The dataset is split into 60% training data and 40% testing data. Table 1 provides some examples of the samples used for training and testing the decision tree. The inputs used for the decision tree are the current and the rate of change, also known as delta. The decision tree's output is utilised to determine the difference between bogus and real data.

Table 1. Datasets for training and testing

Current	Change in delta	Validation	Labelling of validation
7.2	0	Real	-
6.7	-1.5	Real	-
2.6	-3.1	Real	1
2.4	-0.2	Real	1
0.2	-2.2	Real	1
0.2	0	Real	1
-3.2	-5.4	Real	1
2.5	6.7	Real	1
-4.3	-8.8	Real	1
5.1	-0.8	Real	1
7.5	13.6	Fake	2
4	-3.4	Fake	2
-1.5	-7.4	Fake	2

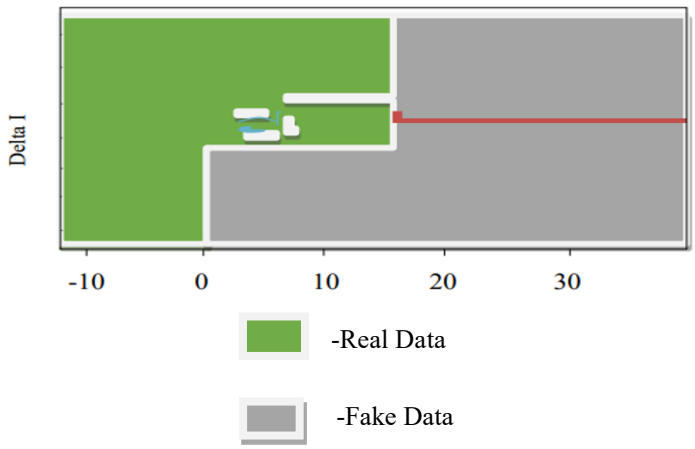

Fig. 3. output of trained datasets

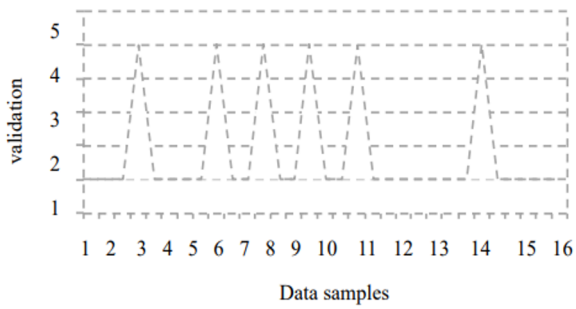

Fig. 4. classification of fake and real dataset using decision tree

5 Conclusion

The proposed approach involves utilizing a machine learning method called decision tree to examine IoT smart meters. By employing this decision-making process that relies on data and insights, the advent of Industry 4.0 has opened up numerous possibilities in the manufacturing industry. The decision tree approach was utilized to distinguish between real and fake data categories by analysing smart meter readings. Upon evaluation and comparison with existing methodologies, it has been concluded that the proposed system operates with an efficiency of 79%. The implementation of this methodology increases the reliability of smart IoT systems in industries, resulting in better investments for Industry 4.0. Additionally, this approach has the potential to be extended to a variety of machines and sensors in the future.

References

1. R. Goel and P. Gupta, *Robotics and industry 4.0. In a Roadmap to Industry 4.0: Smart Production, Sharp Business and Sustainable Development*, Springer, Cham, 1 (2020)
2. M. Elsisi, M. Q. Tran, K. Mahmoud, M. Lehtonen, and M. M.Darwish,, *Deep learning-based industry 4.0 and internet of things towards effective energy management for smart buildings,* Sensors, **21**,1038 (2021)
3. E. Balamurugan, L. R. Flaih, D. Yuvaraj, K. Sangeetha, A. Jayanthiladevi, and T. S. Kumar*, Use case of artificial intelligence in machine learning manufacturing 4.0,* in 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), 656 Dubai, (2019)
4. Z. M. Çınar, A. Abdussalam Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, *Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0,* Sustainability, **12,** 8211, (2020)
5. Z. Gao, T. Wanyama, I. Singh, A. Gadhrri, and R. Schmidt, *From industry 4.0 to robotics 4.0 - a conceptual framework for collaborative and intelligent robotic systems,* Procedia Manufacturing, **46**, 591, (2020)
6. Galbraith and I. Podhorska, *Artificial intelligence datadriven internet of things systems, robotic wireless sensor networks, and sustainable organizational performance in cyberphysical smart manufacturing,* Economics, Management & Financial Markets, **16** (2021)
7. P. W. Khan, Y. C. Byun, and N. Park, *IoT-blockchain enabled optimized provenance system for food industry 4.0 using advanced deep learning,* Sensors, **20**, 2990, (2020)
8. K. Tyagi, T. F. Fernandez, S. Mishra, and S. Kumari, *Intelligent automation systems at the core of industry 4.0,* in International Conference on Intelligent Systems Design and Applications, 1, Springer, Cham, (2021)
9. Novak, D. Bennett, and T. Kliestik, *Product decisionmaking information systems, real-time sensor networks, and artificial intelligence-driven big data analytics in sustainable industry 4.0,* Management and Financial Markets, **16**, 62, (2021)
10. Ahmed, G. Jeon, and F. Piccialli*, From artificial intelligence to explainable artificial intelligence in industry 4.0: a survey on what, how, and where,* IEEE Transactions on Industrial Informatics, **18**, 5031, (2022)
11. D. Preuveneers and E. Ilie-Zudor, *The intelligent industry of the future: a survey on emerging trends, research challenges and opportunities in industry 4.0,* Journal of Ambient Intelligence and Smart Environments, **9**, 287, (2017)
12. Angelopoulos, E. T. Michailidis, N. Nomikos et al., *Tackling faults in the industry 4.0 era—a survey of machinelearning solutions and key aspects,* Sensors, **20**, 109, (2020)

13. M. Khan, X. Wu, X. Xu, and W. Dou, *Big data challenges and opportunities in the hype of industry 4.0,* in 2017 IEEE International Conference on Communications (ICC), 1, Italy, (2017)
14. Lee and C. Lim, *From technological development to social advance: a review of industry 4.0 through machine learning,* Journal of Nanomaterials 5 Technological Forecasting and Social Change, **167**, 120653, (2021)
15. M. Aazam, S. Zeadally, and K. A. Harras, *Deploying fog computing in industrial internet of things and industry 4.0,* IEEE Transactions on Industrial Informatics, **14**, 4674, (2018)
16. T. Kliestik, and A. Novak*, Internet of things smart devices, industrial artificial intelligence, and real-time sensor networks in sustainable cyber-physical production systems,* Journal of Self-Governance and Management Economics, **9**, 20, (2021)
17. K. Coatney and M. Poliak, *Cognitive decision-making algorithms, internet of things smart devices, and sustainable organizational performance in industry 4.0-based manufacturing systems,* Journal of Self-Governance and Management Economics, **8,** 9, (2020)
18. M. Javaid, A. Haleem, R. P. Singh, and R. Suman, *Substantial capabilities of robotics in enhancing industry 4.0 implementation,* Cognitive Robotics, **1**, 58, (2021)
19. L. D. Evjemo, T. Gjerstad, E. I. Grøtli, and G. Sziebig, *Trends in smart manufacturing: role of humans and industrial robots in smart factories,* Current Robotics Reports, **1**, 35, 2020.
20. P. Suler, L. Palmer, and S. Bilan, *Internet of things sensing networks, digitized mass production, and sustainable organizational performance in cyber-physical system-based smart factories,* Journal of Self-Governance and Management Economics, **9**, 42, (2021)