Hindawi
Journal of Nanomaterials
Volume 2022, Article ID 6807585, 6 pages
https://doi.org/10.1155/2022/6807585

Research Article

IoT and Machine Learning-Based Smart Automation System for Industry 4.0 Using Robotics and Sensors

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Received 6 August 2022; Revised 23 August 2022; Accepted 2 September 2022; Published 15 September 2022

Academic Editor: Samson Jerold Samuel Chelladurai

The concept of Industry 4.0, the fourth industrial revolution, is not yet widespread, despite the extensive research in this domain. Several aspects of human life will be improved with the implementation of Industry 4.0. Various levels of manufacturing processes, the end-users, cyberphysical system designers, managers, and all employees in the manufacturing process as well as the supply chains, will be influenced by the changes in manufacturing models and business paradigms caused by the implementation of Industry 4.0. Smart automation is enabled in the manufacturing industry with the evolution of Industry 4.0. Smart decision-making, knowledge, problem-solving, self-diagnosis, self-configuration, and self-automation are enabled in industries with this technology. In this work, the decision tree algorithm is used for monitoring energy consumption in machines and appliances, predicting future behaviour, and detecting anomalous behaviour. The efficiency of the proposed system is evaluated, and compared with existing methodologies, it offers an efficiency of 78%. Several standardization issues, security issues, resource planning challenges, legal issues, and issues due to changing business paradigms are faced with the implementation of this technology. The implementation of Industry 4.0 and its success or failure is completely dependent on the entire production chain and all the participants, from manufacturers to end-users.

1. Introduction

Artificial intelligence and its adaptive developments are the prevailing technologies in the modern era [1]. There has been enormous growth and evolution in this field over the decades. Almost every day, the industry designs and develops several new technological products. Recent updates in smart applications, smartwatches, and mobile phones are received at a very fast rate [2]. Regular addition of new features and services is performed. Even before the need for the service is felt by the user, the industry provides the features and conveniences. The tremendous growth in the adaptive processes related to artificial intelligence (AI) is the driving force behind these advancements [3]. This area is tremendously impacted by the collaboration of deep learning (DL) and machine learning (ML) with AI. The machine or computer behaves like a human being and makes decisions in the processes that involve artificial intelligence. Learning is done based on examples in machine learning [4].

ML is a subset of AI. The system is trained based on examples, and then, decision-making is performed based on adaptive learning. The multilayer model principle is used for the operation of deep learning technology, which is a subset of machine learning. When automation is performed in the industrial environment, huge volumes of data is often involved in this process [5]. Voluminous data is generated with the connected appliances, machines, robots, virtual sensor networks (VSNs), wireless sensor networks (WSNs), and wireless sensor actuator/actor networks (WSANs) [6–8]. When the appropriate data analytics technique is applied, a tailored service can be created with this data. Applying extensive data analytics on the data obtained from the sensors would complete the operation of Industrial Internet of Things (IIoT).

Cost-efficiency, failure avoidance, better fault tolerance, diagnostics, and predictive maintenance are ensured through data analytics [9]. Valuable information is generated from the data gathered from the sensors and machines in an IIoT environment. This information is used for controlling devices and performing factory operations. The analysis of industrial big data is performed extensively in the cloud environment. Often, data is generated continuously by the sensors and machines used in these industries [10]. Time-sensitive and performance-sensitive information may exist in the gathered data. For immediate operations and tasks, local processing of this information may be more efficient. Catastrophic situations may occur due to undesired delays. Quick response is required at times for these machines to operate in a smooth manner [11]. Efficient and smart task management can be performed by placing an intermediary node in IIoT systems where standalone machines and sensors cannot operate.

Several kinds of work and tasks are performed by human beings for over a duration of 16 hours each day. However, by involving machines, we can accomplish several tasks in a limited time span. There are certain humanoid robots developed that look and perform certain tasks like human beings [12]. With the development of robotics and industries, repetitive tasks are performed by machines while humans can concentrate on problem-solving and other specific tasks. Strong AI and narrow AI are the two AI technologies available. Specific problems can be solved, and specific tasks can be performed through a computer under narrow AI. Examples include Siri and self-driving cars. Artificial general intelligence (AGI) or strong AI, also called general AI, does not exist yet. The ability of the machine to interact with the physical world is termed artificial intelligence [13]. Smart agents that can analyze the situation, make appropriate decisions, and act accordingly are developed under robotics. Several businesses are transformed with the advancements in AI. The first, second, and third wave classifies the progress in AI. Industries and business are largely transformed during these waves.

2. Literature Survey

Processes are automated by organizations and made more efficient with the collaboration of machines and people in the current era. There is an increase in the business environment and its competitiveness on an everyday basis [14]. Due to the implementation of recent technological advancements in radio frequency identification (RFID), smart sensors, 3D printers, Internet of Things (IoT), robotics, and automation, various aspects of all industries witness significant changes in transportation and delivery, consumption, product system transformation, and business models [15]. More smart systems are required for making smart decisions within the specified time. In manufacturing processes, dedicated tasks are performed by robots and machines over the past few decades. These tasks involve spray painting car doors, assembling parts, and so on. However, when quality assurance, discarding products with defects, and such tasks are involved, human intervention is required.

In the modern industry, robots play a major role and contribute to completing tasks in a smart manner while offering additional collaboration, flexibility, and safety [16]. Society is continuously evolving and will be enhanced over the next few years with the evolution of these technologies. The robotics industry and artificial intelligence technologies are the major contributors to this evolution. The production and manufacturing phases are completely altered by industrial and robotic automation. In order to increase production and economy, automation is implemented in these phases.

Collaborative robots are the derivatives of conventional industrial robotics with advancements in AI and ML software [17]. These robots can sense their surroundings, understand, learn, and act by making appropriate decisions. As several processes are changed to self-adapting processes, the environment where they are implemented has also changed. The demand for customized orders can be addressed easily by the organizations with these changes. The design of robots makes use of cloud, artificial intelligence, big data, and other advanced information technologies. Sales, marketing, and manufacturing fields are impacted by the advancements in these domains [16]. For example, the Autodesk tool is used for faster design and building of drones that enable early delivery of the finished product to the customer. Several skills and engineering domains are brought together with robotics [18].

The journey of the industrial revolution from Industry 1.0 to 4.0 is massive. In the eighteenth century, with the introduction of the steam engine, the first industrial revolution began. In the nineteenth century, the second industrial revolution started with the use of electricity. In the twentieth century, the third industrial revolution began with the use of computers. The fourth industrial revolution currently involves Industry 4.0 with technologies such as big data, IoT, and robotics. When the data and services available on the web are interlaced with the actuators and sensors, they are collectively called the Web of Things (WoT), which is a modification of IoT. Often, multiple services are facilitated over the web in the IIoT scenarios.

Third-party web services may be required for integrating devices, robots, and sensors [19]. Enhanced and flexible services can be created by integrating the devices and sensor data of one company with the data of a recycling company. Hence, IIoT can be driven with WoT as a key element. Digital industrial technology or Industry 4.0 focuses on real-time data, robotics, automation, and machine learning, contributing to a whole new market revolution. Digital assistants, autonomous robots, and expert systems used in smart machines belong to Industry 4.0. With the rise in

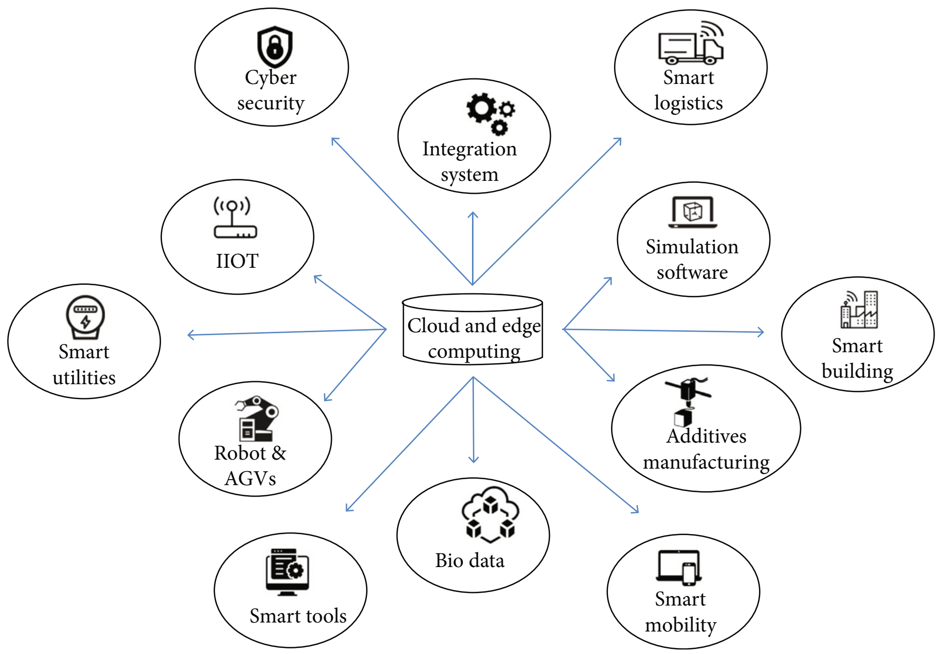

Figure 1: "Industry 4.0" applications in the manufacturing process.

Table 1: Samples of testing and training of datasets.

Current "I "	Change in delta I	Validation	Labelling of validation
8.2	0	Real	—
7.7	-0.5	Real	1
3.6	-4.1	Real	1
3.4	-0.2	Real	1
1.2	-2.2	Real	1
1.2	0	Real	1
-4.2	-5.4	Real	1
3.5	7.7	Real	1
-5.3	-8.8	Fake	2
-6.1	-0.8	Fake	2
8.5	14.6	Fake	2
5	-3.5	Fake	2
-2.5	-7.5	Fake	2

Industry 4.0, robotic technology and manufacturing are also increasing exponentially. Robotics in Industry 4.0 aims in developing a smart industry in which technologies like IoT are used to establish alternatives during disturbances, and products find their own way through the production chain [20]. Wireless control of high-end IoT chips, robotics, and big data are used in an automated smart factory. Each device can communicate with and control the other in this setup.

3. Proposed Methodology

Figure 1 showcases the applications of Industry 4.0 in the industry for manufacturing process and implementation. It shows the most crucial criteria in any manufacturing process includes risk, agility, efficiency, and innovation as far as the production process in industry goes. As far as commercial innovations are concerned, the changes are incorporated in the manufacturing processes of the industry such that mobile communication devices [21–26] which are already enabled within the industrial environment are linked to provide access to information as and when necessary. This can be accessed by supervisors and employees. M2M communication is incorporated in order to extract information and updates on the plant with its equipment and machines regarding repair or replacement at a prior time. The M2M communication is a direct means of communication between two machines with the help of wireless and wired means.

This provides an efficient mechanism to have updated information on the connections and technology in order to prevent blanks from base to control thereby enabling a positive environment of collaborative efforts resulting in optimal solution. In order to arrive at the final product output, it is essential to optimize the available capacities including system manufacturing processes and workers to suit the organization needs [27]. When it comes to agility, it is crucial to ensure external cooperation and connectivity that provides updated information on connections and production along with the capability to develop external cooperation and connectivity with appropriate infrastructure expansion. Moreover, this involves a risk factor which makes it necessary to ensure safety of cyber and physical assets [28].

Using the decision based on insight and data, the introduction of Industry 4.0 brings to the world a range of opportunities in the manufacturing sector. Abnormalities and defects during the manufacturing process are identified with the help of sensors. This in turn paves way to changing parameters and setting adaptation in order to stop production shortfalls in the near future. Thus, it is possible for

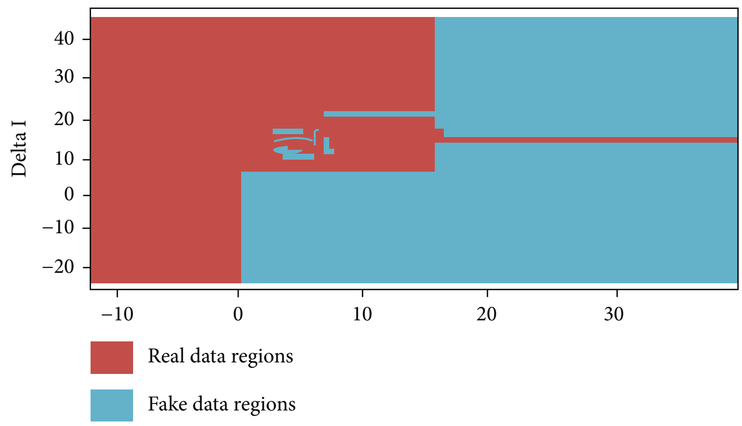

FIGURE 2: Samples of output trained datasets on zooming.

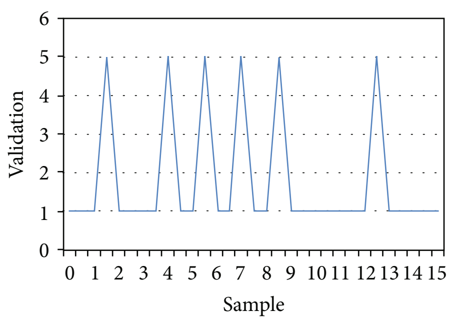

FIGURE 3: Classified regions of fake and real data using decision tree.

companies to prevent failures and breaks and to plan stopping times in an effective manner by incorporating permanent maintenance.

3.1. Machine Learning Decision Tree Algorithm for Training Dataset. To approximate the discrete functions, a decision tree is used such that appropriate rules are generated. The first step involves classification of the input data on analysis. This is followed by determining the output of the new data. The decision tree is built based on the rules between the input data using a learning algorithm. The primary goal of this algorithm is to build the decision tree in a small scale with high accuracy. In case of "if-then" sets, the decision tree algorithm is carried out and classified depending on features space and class. There are three stages in decision algorithm:

(1) Stage 1: choice of features—the best feature or attribute is picked from the set of features

(2) Stage 2: decision generation—relevant questions are asked to follow the answer path

(3) Stage 3: pruning—the process is repeated until the answer is arrived at

Decision algorithms start from the root node using a test case. An example of this is the assignment of a specific feature to the next node based on the previous testing output. At the same time, every node is assigned the tested feature value. This process of feature assignment and testing is executed till the leaf node is reached. The last stage involves dividing the feature values into the leaf node class. To determine uncertainty of the tested set, information entropy is the index used by decision tree. It makes use of the information gain as a measure of purity or uncertainty. The node can be further split according to the feature which holds the most information gain.

x_i is known as the information index and can be formulated using the expression represented in Equation (1) as:

$$A(x_i) = -\log_2 A(x_i). \quad (1)$$

Here, $P(x_i)$ denotes the probability of chosen category. On adding information values, it is possible to determine the entropy using

$$E = -\sum_{i=1}^{m} A(x_i) \log_2 A(x_i). \quad (2)$$

Here, m denotes the variables that need further segregation. The greater uncertainty of the variable is thus represented by the greater entropy. Based on the entropy probability calculation, it is also possible to determine the formation of probability using Equation (3) such that:

$$E(Y) = -\sum_{i=1}^{n} \frac{|c_i|}{|Z|} \log_2 \frac{|c_i|}{|Z|}, \quad (3)$$

where "n" is the total integer limit for "Y" dataset, Z is the summation of c_i and c_i is the size of Y. Hence, the Y value of uncertainty using the variable X can further be denoted using

$$E(Y|X) = -\sum_{i=1}^{q} A_i E(Y|X = x_i). \quad (4)$$

Information gain is formulated using the entropy. This can be expressed using

$$G = E(Y) - E(Y|X). \quad (5)$$

such that Y is the training dataset with empirical entropy $E(Y)$ and the conditional entropy of X is expressed as $E(Y|X)$. Based on the training dataset, the size of information gain also varies.

4. Result and Discussion

The decision tree is specifically used for determining the type of smart meter data. The output thus obtained is further encrypted to ensure online validation by means of IoT. Under several working scenarios and operating conditions for testing and training the decision tree, the real-time dataset is obtained using the smart meter. To measure the efficiency of the system, a fake dataset is included with the real-time dataset. This fake data will be used to train and test the decision tree along with the real data. 30% of the dataset belongs to testing data while the remaining 70% belongs to training data. Table 1 indicates some of the samples that I used to train and test the decision tree. Delta I which is the rate of change and I reach the current is measured and used as inputs. Information on fake data and real data is used as the output of decision tree.

Figure 2 shows the sample output of the training dataset zoomed in for better observation and record. Similarly, Figure 3 shows the output classification region after training process is completed.

5. Conclusions

Several industrial branches have incorporated the industrial revolution 4.0 to produce finished products. In this proposed work, a machine-learning technique known as decision tree is used to check the IoT smart meter. Using the decision based on insight and data, the introduction of Industry 4.0 brings to the world a range of opportunities in the manufacturing sector. Using smart meter reading, the decision tree methodology was able to classify fake and real data types. The efficiency of the proposed system is evaluated and compared with previously existing methodologies, and it has been observed that the proposed work holds an efficiency of 78%. This methodology improves the reliability of smart IoT systems in industries, thereby improving the Industry 4.0 investments. Moreover, it can also be applicable to various types of machines and sensors in the future.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Funding

No funding is received for this research work and publication.

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