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Internet of Things, Big Data, and Artificial Intelligence in The Food and Agriculture Sector

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ABSTRACT

Big data often referred to as streaming data produced by the internet of things creates new options for monitoring food and agricultural processes. Along with sensors, social media big data is also playing a bigger role in the food business. The IoT, big data, and artificial intelligence are discussed in this review along with how they will impact the agri-food industry in the future. We begin with an introduction to the fields of IoT, big data, and AI before talking about how IoT and big data analysis are used in agriculture, including smart farm equipment, crop imaging using drones, and monitoring of greenhouses, food quality assessment using spectral techniques and sensor fusion, and eventually, food safety using gene sequencing and blockchain-based digital traceability. The commercial viability of applications and the outcomes of translational research are given significant consideration.

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1. INTRODUCTION

The terms "internet of things," "big data," and "artificial intelligence" may be outdated buzzwords in the tech sector that have just recently begun to have an impact [1]. IoT and big data have actually attracted a lot of interest from general internet users in the previous five to six years, according to statistics from Google Trends search history, while AI has been a subject of interest for well over a decade in figure 1. Indeed, as the number of communication devices increases, so does the volume of data created, and AI is continuing to be well-integrated into the lives of a large portion of the world's population in one form or another. In contrast to AI, IoT, which is essentially an industrial technology, continues to be of little interest to the general population. Maximizing the effects of these cutting-edge information technologies for global food security would be a logical area of study for agri-food scientists and engineers [2]. This review's initial objective is to provide a quick introduction to these subjects for readers with backgrounds in agricultural and food sciences.

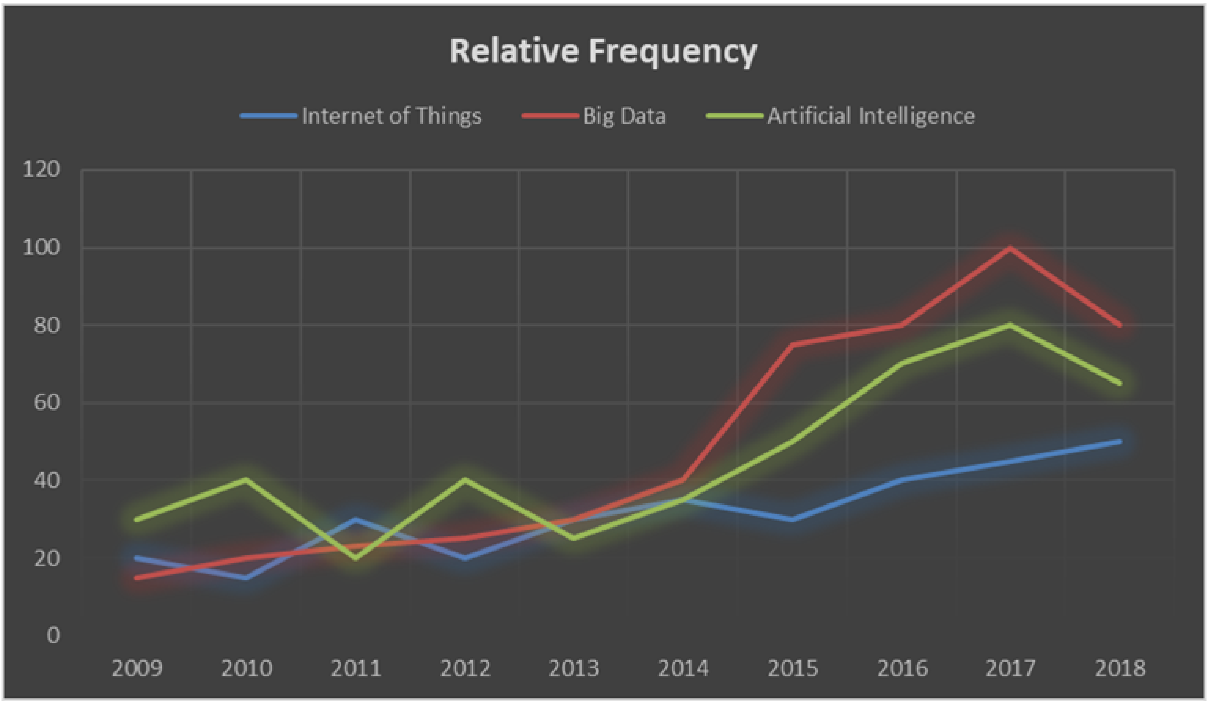


Figure 1. Internet of Things (IoT), big data, and artificial intelligence search volume relative to the rest of the world over the previous ten years. on October 11, 2019, data was accessed from Google Trends

The term "Internet of Things," first used by Kevin Ashton, refers to a huge network of equipment and objects that are digitally connected. The machines or objects in this situation link digitally over the internet. Other names for IoT include the Industrial Internet and the Internet of Everything [3]. The fourth industrial revolution is a term used to describe the idea that the Internet of Things (IoT) can enable robust connection across the physical and digital worlds. In fact, there are several names for the application of IoT in industry. Industrial Internet of Things (IIoT), no matter the industry or size of the business, remote sensors collect data from machines to boost efficiency, encourage improved decision-making, and create competitive advantages [4]. IoT platforms act as a link between the sensors on devices and the data networks, allowing linked IoT devices to communicate with each other utilizing internet transfer protocols [5]. Large amounts of data are produced by the sensors of the IoT network's devices, and these data streams are continuously sent to a data lake, which could be a local server or cloud storage. This data lake enables the necessary data processing using the right algorithms or machine learning techniques to produce useful insights [6]. So, it is important to remember that the Internet of Things is simply a method for producing and sending vast volumes of data that contain information that is useful in real-world situations.

In truth, there is no official definition of what big data is or what it entails. Big data in the IoT environment comprises components of analytics, insights, and automated choices, all of which often take place in real-time, in addition to organized or unstructured data. In addition to the huge amounts of data generated by devices/sensors, social media is a significant source of user-generated big data that demands specific attention. Although social media data is becoming increasingly important, it should be noted that it does not precisely come under the IoT framework [7]. Recent advancements in artificial intelligence, machine learning, and the data science industry, along with increases in computing power, have made it possible to use supervised learning models more effectively and to automate decision support. Later in this article, there is a discussion of the pertinent machine learning technologies for artificial intelligence [8].

2. FROM ANALYSIS TO IMPLEMENTATION

All IoT data originates from sensing. With the usage of various IoT devices, the agricultural industry generates a vast number of heterogeneous datasets in terms of content, structure, and storage type [9]. Heterogeneity, variety, unstructuredness, noise, and excessive redundancy are some of the traits that define large data. To extract useful information from such massive amounts of data, complex data curation and storage techniques, as well as time-consuming statistical methodologies, are all required [10]. The pre-processing and conditioning of primary data yields the information needed to comprehend the agri-food system's current state [11]. A system can be made capable of independent localized decision-making and appropriate action-taking by using advanced algorithms and monitoring the system's performance in relation to the desired outcome. An intelligent Internet of Things system is one that has this amount of independence, which enables autonomy in sensing, decision-making, and actuation [12].

Artificial intelligence is the study of how to make computer systems and theories that can carry out tasks that would typically need human intelligence, like sensory perception and judgment [13]. According to Kaplan and Haenlein, artificial intelligence refers to a system's capacity to accurately read external input, to learn from that data, and to use that learning to accomplish certain goals and tasks through flexible adaptation [14]. Consequently, AI directs systems toward predetermined goals by acting on external data via IoT and other big data sources, utilizing knowledge-based rules provided by developers, or by identifying the underlying rules and patterns using machine learning. A system with true intelligence is able to learn, generalize, amass knowledge, determine goals and priorities, and reduce risks associated with decision-making [15].

Rule-based AI is a method for integrating AI into the business world that uses "expert systems" that are founded on rules. All of the laws that control how the system behaves are either derived from physical laws or from the experience-based knowledge of human experts. This strategy involves employing IoT devices or sensors to continuously monitor the system or process [16]. The rules are used to analyze the data that the IoT sensors provide regarding specific system attributes. On rare occasions, the uncurated raw data is also collected, saved, and used to create trend visualizations [17]. Due to the inclusion of numerous unknown variables in agriculture, it should be recognized that agri-food systems are extremely complex, the variety of ingredients used in cuisine and consumer eating habits. Due of this, it is incredibly difficult to convert the knowledge of farmers, industry professionals, and consumers into computer programs with clearly specified, well-defined rules that can be used to create expert systems based on AI. But when real-time judgments and control are required and frequent training of the AI system is not feasible, rule-based based AI is appropriate [18].

Since the ability to learn from its surroundings is typically associated with intelligence, machine learning is one of the main subjects of AI [19]. The capacity for a computer to learn without being explicitly programmed is provided by the ML technique used to create AI. Simply defined, ML algorithms extract knowledge from disorganized data and combine it in such a way that the results are computer programs that can carry out beneficial activities like alerting a user or triggering crucial actions. It investigates the research and design of algorithms that can infer knowledge from data and make predictions based on it [20]. By generating predictions and judgments based on data, these algorithms outperform simply static programming instructions. The following four major categories can be used to categorize machine learning algorithms: Supervised learning: These algorithms produce predictions for unobserved points using training sets of labeled data. Unsupervised learning: These algorithms use training sets of unlabeled data to create predictions about points that have not yet been observed. The goal of reinforcement learning is to maximize the reward across a series of actions and iterations with the environment [21]. Reinforcement learning algorithms continuously interact with the environment, sometimes affecting it, and receive rewards for each action. Representation learning, commonly referred to as feature learning, is a class of techniques that enable a machine to automatically find the representations required for detection or classification after being presented with raw data. The most effective illustration of representation learning is the well praised deep learning approach based on neural networks [22].

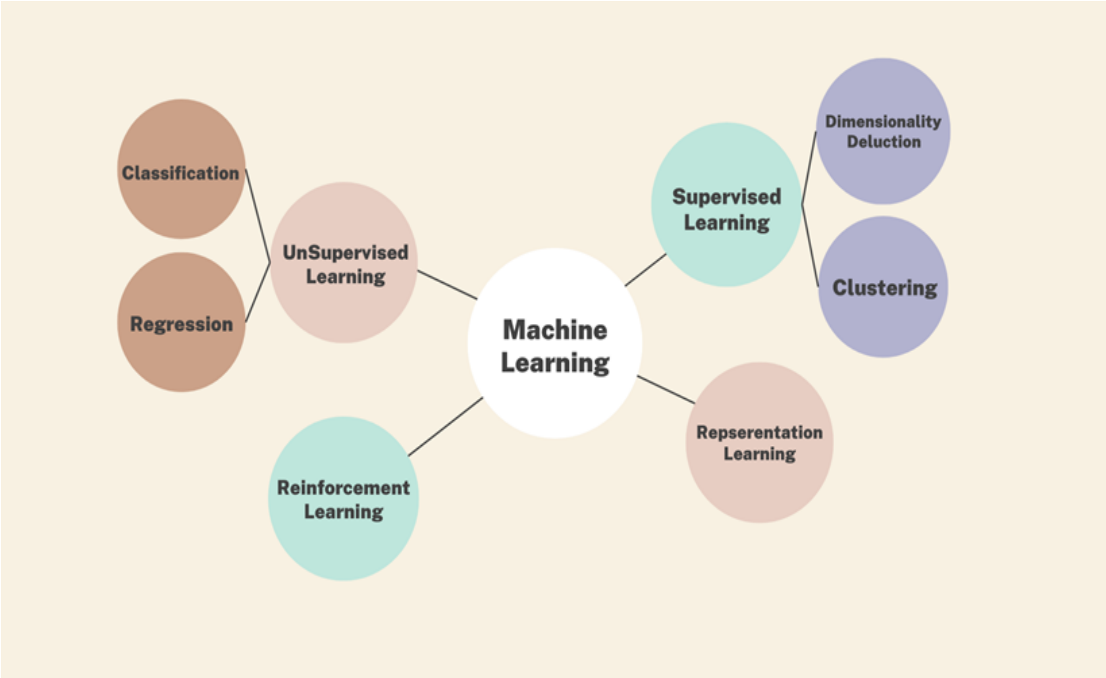


Figure 2 shows various models under these mentioned categories and their technological applications. There are other places where ML techniques and their applicability to the agri-food industry are covered in greater detail. The field of deep learning with neural networks merits particular attention because of its unparalleled effects. High levels of information can be extracted using deep learning techniques from very huge data volumes. Deep learning algorithms are structured hierarchically according to increasing complexity, in contrast to typical machine learning techniques. In order to learn representations of data with various levels of abstraction, deep learning computational models need numerous processing layers.

In Figure 3, the entire data flow is depicted from the data source via the AI platform or data processing to the end action, which is typically some sort of control. Despite the rapid advancement of AI approaches, the majority of new applications will probably combine rule-based analysis with new AI techniques. When daisy-chaining datasets along a supply chain, this is particularly true. In order for people to comprehend and have faith in the methodology used by computer programs to get their results, data and novel algorithms are also anticipated to be combined with skilled human domain expertise. In an industrial setting, some form of process automation or control is typically the end goal of AI or big data workflow. However, the final use of all IoT, big data analytics, and AI systems depends on the context and may include automation as well as data gathering, prediction making, alerting, and fault detection.

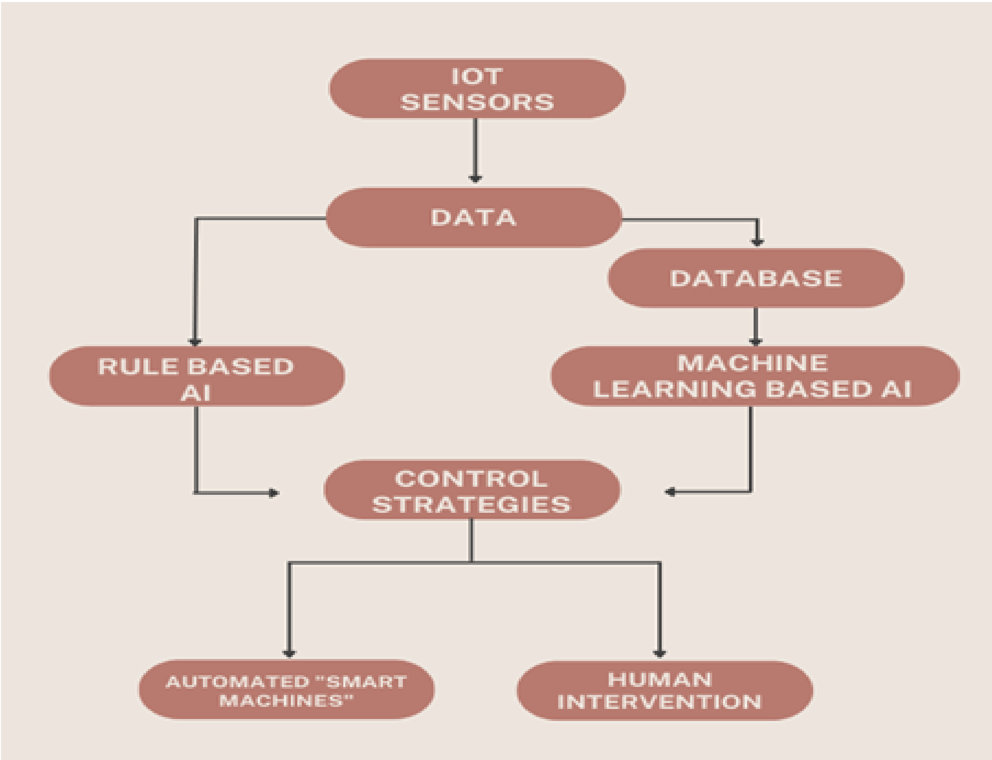


Figure 3. Streamlining the data-to-action process and incorporating artificial intelligence into the Internet of Things ecosystem

3. SMART FARMING WITH BIG DATA AND IOT

By 2050, it is predicted that there will be about 10 billion people on the earth, necessitating the use of novel methods for producing food [23]. The rate of agricultural productivity growth, however, is significantly lower than that which is expected to be required to feed the globe in the future. Consequently, the world needs to witness a change in agricultural techniques, much like we did in the 1970s when we had the first agricultural revolution. For global food security, food safety, sustainable food consumption, and the health and well-being of society, it is critical that new and clever solutions be created. Global agricultural sustainability will be greatly aided by technologies that could enable reduced use of resources for agriculture, such as water, fertilizers, and agrochemicals, as well as help to drastically reduce the carbon footprint of farming. Similarly, environmentally friendly intervention strategies that guard food crops or food products from pests or decay are crucial tools for addressing the challenges of global food security. These strategies reduce losses and/or permit shelf-life extension while also reducing losses and/or pest damage [24]. Smart farming is the general term used to describe the use of contemporary technologies in agriculture [25]. We believe it is worthwhile to address low altitude airborne hyperspectral imaging and the usage of sensors placed to monitor farm conditions among the various breakthroughs in this assessment. Our goal is to present an exposition of the advancements where several agri-food-automation enterprises are actively participating or benefiting from them. A full analysis of the role of big data in smart farming is currently accessible.

a. Field Sensors and Equipment that are Networked

In order to maximize agricultural productivity while reducing environmental effect in a particular place, precision agriculture is a management concept that detects variability in the soil environment. The 4R concept, which underpins PA, is the idea that the proper material should be used in the proper amount at the proper time and location. Since its inception in the 1990s, PA has been met with great expectations for improving agricultural operations' efficiency, particularly in commercial production, where excessive chemical use as a management strategy has resulted from management practices driven by the fear of yield loss. Despite the fact that agricultural yield monitoring has been practiced for almost 20 years, current advancements in smarter farm equipment, crop sensors, and data analysis software have changed the way crops are yielded.

The positioning of PA as a new management paradigm has improved with the growth of technology over the past few decades. Real world characteristics are being monitored using digital sensors, which are still available on the market for reasonable rates. For instance, digital temperature sensors can be placed everywhere in an agricultural field to collect reliable temperature data for a few dollars and a few cents, providing they are properly insulated and operated. The use of electronic components has also changed machine-to-machine communication protocols, and the internet stands out as one such protocol that can transmit data and information between a number of remote computers located anywhere in the world. The term "IoT" is used to describe the connecting of mobile devices and sensors to the internet as standalone items due to the constant reduction in size and price of electronic components including processing units, modems, and antennas. IoT-based solutions for precision agriculture are already available from technology companies, and they include sensors that can detect the environmental conditions, for instance, information extraction methods for artificial intelligence can be used at many localized locations within a farm using cloud-based platforms to collect and combine data as well as to inform the farm management of circumstances, directions, or necessary activities, predict patterns communication mechanism through the internet.

Global engineering giant Bosch Corporation has embraced Industry 4.0 in its operations and entered the agricultural sector by offering a variety of solutions. Smart manufacturing is currently at the vanguard of Industry 4.0, which is the digital revolution of industrial markets. It stands for the discrete and process manufacturing, logistics, and supply chain aspects of the so-called fourth industrial revolution. Despite being developed in the manufacturing sector, Industry 4.0, Agriculture is a sector that benefits greatly from the technologies used and converged in Industry 4.0. The agricultural fields may be monitored for many factors using Bosch's Deepfield Connect technology. Each solution consists of a collection of sensors that are directly connected to the internet via a communication box. The communication box delivers the data to the cloud, which then notifies the farmer on his or her computer or smartphone of information and alarms. The sensors will begin communicating with the farmer on a regular basis once they are installed in one place, so that unnecessary trips to the field to check on frost, heat, or dryness can be avoided. These communications will include information on the environment's temperature and humidity as well as the soil's moisture level. Using an asparagus crop as an example, in-field temperature sensors allow farmers to monitor the temperature at various subsoil layers, which is crucial for producing a good yield. The benefits of such a connected solution extend to the maintenance services that businesses offer since they can track the decline in performance of a piece of equipment or a component (like a battery) and deliver replacements in a timely manner.

Yield Technology Solution is a distinct company that deploys sensor nodes (a collection of environmental and soil sensors) across a field of crops, connecting them to a single gateway via a local communication network. For the purpose of storing and processing data in the Microsoft Azure cloud, the gateway connects to the internet. In order to provide information that aids in decision-making, such as when to plant, harvest, water, feed, and protect crops, their system collects microclimate data from all across the farm. It then employs artificial intelligence and data science to analyze the data. As a result of a variety of situations, the system creates a thorough picture of the microclimate on the farm and provides the farmers with this information in the form of present-day forecasts. A farmer can link a group of sensors located in several greenhouses that are close enough to each other to be connected locally to a single gateway that is connected to the internet using Bosch's Plantect solution, which was just introduced in Japan and is aimed at greenhouses. Bosch uses cloud computing and artificial intelligence to detect disease outbreaks and provide guidance on pest control management for specific greenhouses based on the information it receives about changes in environmental conditions in the greenhouses. Such a method contributes to the PA management's goal of optimizing spraying by, among other things, spraying fungicide and finally aiming to maximize the use of plant protection goods. It should be simple to expand this system to other crops by developing appropriate prediction models for each disease while utilizing the same hardware to gather and show data, even though the solution for tomato greenhouses is currently available.

Similar to this, Softbank's 2015 launch of E-Kakashi as a sensor box to track greenhouses was transformed into a platform after the company partnered with CKD Corporation and Ericsson. The platform manages the greenhouse's atmosphere in addition to keeping constant watch over fields and greenhouses. The machinery in the greenhouse are linked to the cloud through Softbank's NB-IoT cellular network and the sensors that measure characteristics like temperature, humidity, and CO_2 do the monitoring. Equipment may be adjusted depending on environmental data using the AI-powered e-kakashi platform from PS Solutions, and the device onboarding and data administration are handled by the Ericsson IoT Accelerator. The electro-pneumatic equipment made by CKD Corporation also enables remote control of machinery. As a result, E-kakashi is able to make the necessary adjustments to machinery like irrigation, fertilizer, and ventilation systems for greenhouses. The e-kakashi user can connect to the system and engage with it via a smartphone, tablet, or computer whenever and wherever he or she pleases. The farmer has the ability to alter the AI-based default settings in order to incorporate their unique expertise.

Lastly, it is believed that since 2012, John Deere, the largest producer of agricultural machinery in the world, has placed several hundred thousand connected units in use. According to firm estimations, IoT automation and data collecting have increased yield and decreased costs for farmers by more than 10%. A 20% compound annual growth rate is expected to see an increase in IoT device installs in the agricultural sector from 30 million in 2015 to 75 million in 2020. Examining the advantages of IoT and big data applications in agriculture, dairy, poultry, and meat production is being done by several sizable public-private EU partnerships. In order to comprehend the advantages of big data technologies in the raw material production from agriculture, forestry, and fishery/aquaculture for the bioeconomy industry to produce food, energy, and biomaterials, responsibly and sustainably, a project sponsored by the EU called DataBio (Data-Driven Bioeconomy) is being carried out. Similar to that, the EU Horizon 2020-funded IoF 2020 (Internet of Food and Farm 2020) project, which was overseen by Wageningen University, focused on the "Farm of the Future" and sought to translate and modify "internet of things" technology for the unique circumstances of farms.

b. **Agricultural Technology Advancements**

The manufacturers of conventional farming equipment are working on developing smarter machinery that can connect to the Internet of Things, integrate with computer environments, and create smart tractors and pumps that can sense their surroundings and react to abnormalities in real-time. There have been a lot of attempts in recent years to develop agricultural autonomous systems for applying PA approaches, and several start-ups are now using these systems in farms. The development of smaller, less expensive environmental sensors has been mirrored in the development of cameras. Although one of the primary early issues for its deployment in real-time settings was the requirement for high spec processing units in comparison to other sensors, their capacity to collect spatial and spectral data made them the topic of research. The availability of powerful processing units has, however, led to a change in this in recent years.

In order to detect weeds in agricultural fields, cameras are being used as sensors due to the expensive expense of applying herbicides and growing awareness of the negative effects of chemical overuse on the environment and human health. Both chemical and mechanical methods have historically been used to control weeds. In general, chemical control has the opposite characteristics of mechanical control, which has the advantage of being labor-intensive but environmentally favorable. A few startups have recently made a name for themselves as manufacturers of clever, autonomous weeding equipment that use cameras to detect weeds in fields. We'll give a few instances of recent business growth in this region.

A tractor-driven weeding device equipped with a machine vision, control system, and weeding mechanism has been created by Garford Farm Machinery and is marketed as the Robocrop in-row weeder. The primary benefit of this equipment is that it mechanically removes weeds that are present between the rows. A weeding device that spirals around each plant is used to do this. Utilizing RGB color cameras, the machine detects the plant, and the crop's center of rotation is identified using the crop's data, which is processed inside the machine. The majority of crops with standard plant and row spacing can utilize it as long as the plant foliage is kept apart from the following plan. It was first designed for use on transplanted crops like lettuce, cabbage, celery, etc. It can be applied to the majority of crops that are sown with regular plant and row spacing, with the leaf of one plant readily distinguishable from that of the following plant.

The autonomous mechanical weed controller was created and tested by Bosch's Deepfield Robotics. It employs a GPS antenna to self-navigate throughout the field and cameras to discern between crops like sugar beet and weed. The robot can function at night in settings of artificial lighting, with its weeding mechanism located underneath the machine. In order to target weeds in the production of sugar beets, a commodity with a high economic value in Germany, this autonomous vehicle was created. Another weed-control device that utilizes cameras, computers, and artificial intelligence to discriminate between crops and weeds has been created by Blue River Technology, a startup that John Deere recently bought. Herbicides are particularly sprayed on weedy areas by the tractor-propelled machine, which is now used on a limited basis to weed cotton. This method uses chemicals to attack weeds. This technology's primary benefit is lowering the amount of chemicals needed in agriculture, which has positive effects on the economy and ecology.

Along with weeding, vision technology is being tested for use in time-sensitive and labor-intensive orchard harvesting operations. The picking of apples and kiwis serves as typical instances of these trials. The fact that fruits often grow in an unstructured setting presents the biggest obstacle to automated orchard harvesting. The location of fruits on trees cannot be predicted, in contrast to weed, whose distance from the machine is determined by the roughly constant distance between the machine and ground. Furthermore, compared to weeds, which only have other plants and earth as their background, the scenery around fruits has more commotion. Despite the necessity for such devices for labor-saving and yield-optimization purposes, this makes the development of commercial harvesters a significant issue.

Since the beginning of the twenty-first century, when Bulanon created a machine vision program to locate apples on trees, research on apple recognition and picking has been available in academic literature. The development of a gripper that can pick apples without damaging the skin coincided roughly with the beginning of research on robotic arms and effectors. As real-time detection systems were developed by Bulanon et al., stereo vision was created by Mao et al. to determine the distance between the machine and the apple to be harvested, and Kong et al. used least square support vector machines to increase the accuracy and speed of stereo vision in detecting apples, the recognition of apples on trees continued to advance. Research on robotic arms and end effectors has helped grabbing and removing apples from trees with greater accuracy and speed. The design, integration, and field testing of a robotic apple harvester with an average picking time of 6 seconds per fruit was reported by Silwal et al. The robot was capable of detecting and picking 84% of the apples.

Advancements in academic research have been made in the imaging-based kiwifruit recognition system for a future robotic harvester. Fu, et al. proposed harvesting at night with artificial lighting to lessen the possibility of misclassifying kiwifruit in order to deal with the issue of noise brought on by variations in ambient light. The problem of "visual individualizing" was addressed by Fu et al. since, unlike apples, kiwifruits have a tendency to cluster in groups, making it a crucial component of any kiwifruit picking robot. But before a commercial product may be built, problems like a low detection success rate and a delayed identification time still need to be resolved. Investment in this technology is anticipated to continue despite the sluggish development of a vision system for robotic orchard fruit picking, since the need to replace hand harvesting is growing more and more critical in nations like the United States, Japan, and China.

c. **Spectral Imaging From a Low Altitude**

Normal infrared absorption by healthy plants in agriculture is largely blocked. Plants, on the other hand, have a tendency to absorb more infrared light when they are in distress (ill/stressed). A plant infestation, nutrient shortage, or moisture deficiency can all be identified using this information. In a similar vein, the amount of nitrogen present typically corresponds with how green an agricultural field is in relation to the crops' chlorophyll content. Utilizing low-resolution satellite-based remote sensing techniques, which detected the vegetation cover on a scale of counties or states, monitoring of field and agricultural conditions, such as crop health, and coverage, was traditionally done. Farmers saw little value in these techniques that allowed for the gathering of yield data on a national scale. Low-altitude manned vehicle based spectrum imaging was chosen as a method to address the problems brought on by low spatial resolution and make spectral imaging techniques available at the level of individual farms. Given that the infrared-operating spectrum cameras were large and cumbersome with a large footprint, this strategy was only marginally beneficial. The size and weight of spectral cameras have significantly lowered because to improvements in spectral imaging technology, making it possible to place them on drones or quadcopters with ease. The development of portable, palm-sized hyperspectral imagers is the most significant development in spectral cameras to date. Compared to push-broom or line scanning hyperspectral imagers, these are both lighter and cheaper, and they also have a smaller footprint.

By mounting hyperspectral and multispectral cameras on manned or unmanned aerial vehicles (MAV or UAV), such as quadcopters and drones, data firms are now collecting aerial photos of standing crops in farms. Informally, up to 10 bands are referred to as "multispectral" and more than 10 bands as "hyperspectral" in the context of spectral cameras, which take image stacks at various wavelengths. Some image service providers combine high resolution R-G-B (visible) cameras with multi-spectral cameras operating in portions of the spectrum that are not visible. In order to give results that are realistically relevant, spectral imaging systems' images are typically down-sampled (smoothed) from suitably high resolution (from meter scale to even centimeter scale).

Due to the heterogeneity of the fields' natural circumstances, such as hydrothermal, soil, geomorphological, and the agricultural systems, such as tillage methods, irrigation, application of fertilizers, herbicides, pesticides, etc., spectral images of vegetation exhibit a great deal of variance. Data analysis platforms can produce insights regarding a variety of indices crucial to crop development and quality using machine learning algorithms applied to imaging datasets and incorporating environmental variables. Vegetation index, weed cover, pest infestation, water logging, yield monitoring, nutrient shortages, and maps for variable rate application are a few examples of these insights. Typically, two to three times throughout a cropping season, drones are flown to image the fields in order to collect this information. In the future, time series imaging data analysis to evaluate the efficacy of farming operations and self-learning strategies for advancement may also be incorporated into the data analysis in some systems. The Swiss start-up Gamaya is an outstanding illustration of the "data analytics as a service" business model for drone-based hyperspectral photography of sugarcane and soybean fields (www.gamaya.com). Gamaya uses crop models and artificial intelligence to create extensive information on crop phenology and physiological features using 40-band hyperspectral imaging data that is specific to a crop, variety, and geographic region.

4. MODERNIZATION OF THE FOOD SUPPLY CHAIN

According to the United Nations, one third of the food produced worldwide is wasted every year, totaling $750 billion. This indicates that around 28% of the world's agricultural land is used to grow food that is ultimately wasted. Due to the requirement for sophisticated control systems to manage perishables, unpredictable supply-demand differences, and specific goals for food safety and sustainability, supply chain management in the food industry is highly difficult. In order to reschedule, recall, or take other relevant actions, the food business can benefit from the adoption of IoT networks that incorporate humidity, temperature, light, microbiological, and product quality sensors for real-time monitoring of products in transit. The market for artificial intelligence applications in supply chains was valued at $491 million US dollars in 2017 and is anticipated to grow to $6,548 million US dollars by 2024, with a CAGR of roughly 44.76% between 2018 and 2024, according to a report by Zion Market Research. Lezoche, et al. give a review that is specifically focused on the agri-food business, while Ben-Daya, et al. have performed a thorough analysis of the function of IoT in supply chain management in general.

IoT might aid in reducing hazards given that food supply networks span large geographic areas and are exposed to a variety of global dangers. A fish export company from Norway to the Netherlands recently demonstrated effectively how the food supply chain can be virtualized using IoT and an information systems architecture. In their paper, the team made a strong case for supply-chain virtualization, demonstrating how it can provide detailed representations of the objects and their surroundings by integrating real-time product observations made possible by IoT devices with business operations. When deviations are noticed, such as temperature changes that affect product quality, this virtualization will enable stakeholders to take prompt action. The free interchange of logistical data as well as the ability to analyze and report on shared data intelligently to enable early warning and enhanced forecasting are key components of the virtual IoT-based supply chain.

An Italian team that created an IoT-based solution in LabViewTM to integrate the parties involved, the product flows, and the limits of the food ecosystem has proven a more generalized method to virtualize the supply chain phases. The authors came to the conclusion that the food supply chain's inefficiencies, costs, emissions, and social consequences might all be significantly reduced by IoT-based virtualization. Consider a food truck fitted with temperature, humidity, and location (GPS) sensors that is transporting soft berries as an illustration of the power of virtual or cyber-physical supply-chain systems (say, strawberries). Logistics companies are able to precisely trace the location of the food truck at any moment by using virtual supply-chain technologies. Now, a truck can be diverted to a new location in the unlikely case that there is a food shortage at the old one. Alternately, the truck can be redirected to the nearest market for an immediate sale at a reduced price if a temperature change is noted that could impact the shelf-life of the berries. Thus, IoT technology has the potential to not only assist farmers in meeting consumer demand for their products but also to reduce food waste.

In our hypothetical case, the location of the food truck can potentially be chosen based on the preferences of users of social media or mobile phone applications. For instance, Food Cowboy (www.foodcowboy.com) uses a mobile app to let truckers and food businesses divert damaged produce to nonprofits, rotting fruit to composting facilities, and extra food from nearby restaurants to food banks and soup kitchens. There have also developed a variety of different online interactive maps, applications, and websites that connect locations with extra food to charity and people in need. In these peer-to-peer food sharing networks, the legal ramifications and food safety are yet unknown. The use of machine (or computer) vision to quickly and effectively carry out repetitive operations in the supply chain, such as quality control inspection, has increased significantly during the past ten years. For automated material handling in manufacturing, the supply chain sector increasingly relies on automated guided vehicles (AGVs) built on AI, machine learning, and navigation technologies (such simultaneous localization and mapping, or SLAM). End-to-end automation has been made possible by machine vision, and now research is being done on how AI may be used to supply chains to track specific products. Grocers now assess the rates of inventory consumption using inventory barcodes and sensor data, allowing them to set stocking levels that will meet demand but not go above it. To create traceability systems, farmers, food processors, the agri-food supply chain business, and retailers have adopted radiofrequency identification (RFID), another sensor technology, at an exponentially increasing rate.

In a same vein, food and pharmaceutical firms face a significant problem when imitation goods enter the market. The transportation of a product consignment to a site other than where it was intended to go, or "product diversion," also happens occasionally, despite being rare. Despite the fact that holograms and barcodes have been around for years, Systech International has used the little variations in barcode printing as a unique fingerprint (www.systechone.com). The distinctive fingerprint created by their approach is based on the minute variations in identical barcodes seen on various products. As a result, it is possible to trace specific products throughout the supply chain and avoid product theft using the fingerprint data that a computer vision system was able to obtain in the manufacturing plant. Additionally, using brand owners' applications, retail stores and customers can validate the product using this data, assisting in the fight against counterfeiting.

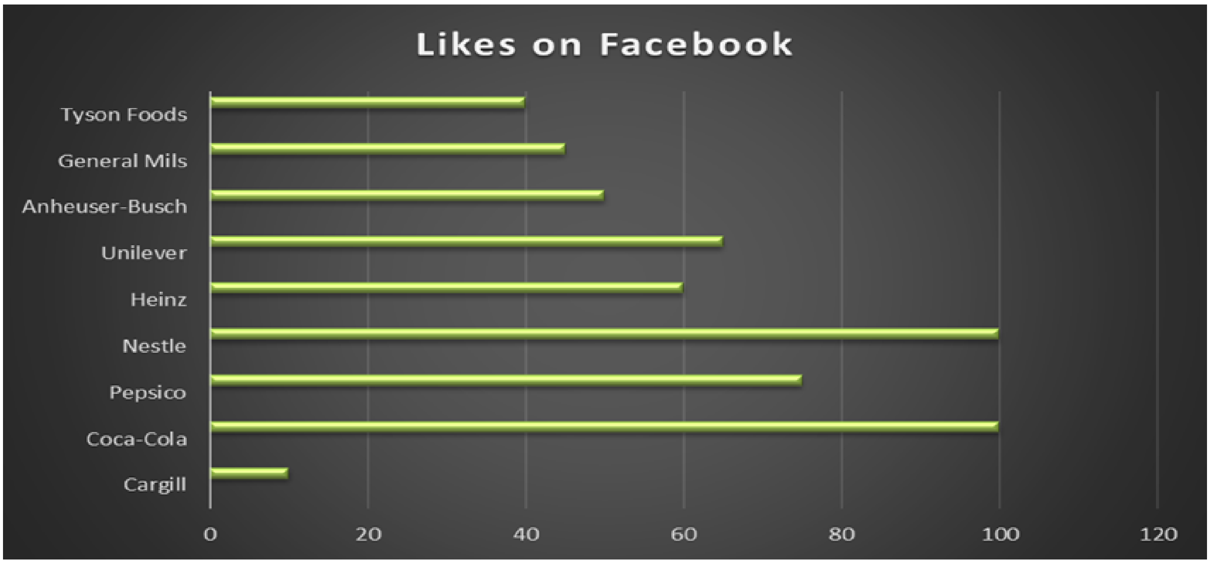
The process of documenting and maintaining regulatory compliance will become much more straightforward and effective if IoT linked with cloud computing takes over the role of connecting the movement of raw materials and final goods to the automated databases. It will also be interesting to note that consumers are becoming more picky about the kind of food they choose, including the size, shape, flavor, and color of the servings as well as the pricing and degree of service. End-of-line and "last-minute" customization solutions for the food sector may be made possible by IoT and AI. Thus, in the future, a customer's internet-based meal order that includes a number of odd requirements may be instantly forwarded to the robots on the assembly line for "last-minute" modification. In fact, it won't be overstating things if I say that one of the major accomplishments of the food business 4.0 will be customization-oriented production facilitated by IoT and AI.

Despite the anticipated advantages, the IoT's integration with business operations in the food supply chain and the food industry in general are still in their very early stages of development. When constructing an end-to-end digital thread from farm to consumer, there are several issues with regard to granular data alignment. The fact that supply-chain systems entail data sharing between organizations and commercial entities and are very cross-functional should be recognized. In the agri-food industry, where data from farms is currently quite scarce, cross-entity data sharing consequently becomes considerably more difficult. Even huge food producers and businesses use contract processors or co-packers, which means a third party has access to all the production facility data and does so under various naming conventions. Furthermore, the developed world's industries frequently import a large amount of raw agricultural supplies from developing or underdeveloped nations, where there is frequently a dearth of data knowledge. To avoid algorithms performing poorly due to missing data and preventing the loss of optimization chances, it is essential to include the majority of partners in the AI system. The majority of agricultural products then experience dynamic variations in quality and price. In comparison to other supply chains, this extra layer of significant uncertainty makes it more challenging to track such data in real time. For IoT, big data, and AI to be successful, it is critical to act quickly on the development of suitable frameworks.

5. ANALYSIS OF SOCIAL MEDIA AND THE WEB

An exponential increase in data quantities across the Internet has been caused by the tremendous increase in computing and mobile device usage. 3.3 million Facebook posts, 448,800 tweets, 65,972 images, and 3.8 million google searches are thought to have been made every minute of online activity in 2016. The platforms through which social media data can be gathered include blogs, conversations or comments on websites (like news pages), microblogs (like Twitter), collaborative projects (like Wikipedia), social networking sites (like Facebook and LinkedIn), and content communities (e.g. YouTube and Instagram). Followings, shares (or retweets), likes, comments, mentions, and metadata related to clicks are a few examples of metrics that can be derived from user-generated material on social media. Depending on what the user wanted to reveal, the metadata linked to their actions may contain data on their age, country, education, occupation, geolocation, and more.

In a nutshell, social media data is information that is acquired from social networks that shows how users interact with material or profiles that have been generated by a person or organization. The most typical illustration is when customers "like" a company's Facebook page, which causes them to receive updates and content from the page in their news feed. The interaction between brands and those who like or follow them on their pages is facilitated in this way. Many people follow the Facebook pages of almost all food firms, making them quite active on social media and contributing to the process of data production and social interaction (see Fig. 6). A typical social big data analysis's goal is to extract useful knowledge from the vast volume of complicated user-generated content, which is frequently conveyed verbally or visually, in order to support stakeholders, industry, or agencies in making informed decisions.



a. **Crowdsourced open innovation and remodeling**

Innovation is the act of bringing anything original, whether it be a new service, market, product, or business model. To enhance product lines and reduce the time needed to bring items to market, the idea of open innovation promotes businesses to acquire outside sources of invention. Additionally, it places a strong emphasis on selling or releasing internally generated technologies that do not align with the company's business model but may be used successfully elsewhere. Various facets of open innovation in the food business have been the subject of several reviews. By analyzing hundreds of customer comments on websites like Amazon, eBay, Facebook, YouTube, and other e-commerce websites, data mining via machine learning techniques are increasingly being used to find the most loved and hated elements of already existing products. The development of new products or technologies according to consumer preferences can be guided by insights derived from natural language processing (NLP) and sentiment analysis (see section 5.2) of social media and e-commerce data, aiding in the determination of crucial design decisions to more precisely satisfy customer needs. This strategy gives a sector of the economy the knowledge it needs to produce highly inventive, consumer-friendly, durable products that also adhere to market demands. Keep in mind that in these situations, internet platforms serve as the primary source of the creative inspiration for the new or better product.

It's important to keep in mind that corporations use digital media as a way to create and disseminate information and values, in addition to unsolicited user created content. Social media platforms are being used more often to connect, communicate, and work with customers. Multinational food firms, for instance, have recently used social media marketing efforts to involve consumers in the co-creation of new flavor and texture for their products. When consumers answer to a campaign using a certain hashtag or media handle, all user responses and the associated data can be collected to create a massive body of knowledge. An effective technique to gain insights and promote segmented brands is to analyze the textual data acquired from social campaigns and overlay it with user-related metadata like geolocation, age, occupation, time of content production, etc. It is also important to note that many businesses use web scraping and big data analysis to compare product pricing and determine where your products' sales prices fall within a given product category in the e-commerce space. To sum up, businesses should think about including big data analytics as one of their research tools and take a cue from the programs that are already proving to be effective. Businesses may create superior value propositions that are more pertinent to their target audience by learning what consumers value and actively engaging in conversation and interaction.

b. **Analysis of Attitude**

Big data analysts perform Sentiment Analysis on the enormous corpus of text data from social websites, commercial websites, and blogs to ascertain the sentiments-positive, negative, or neutral—that customers connect with a specific product, brand, or firm. In order to monitor social media attitudes at high frequencies, many businesses have either created or are now constructing "digital acceleration teams," also known as "social listening teams". Several new firms built on the idea of "Data-as-a-Service" provider (DAAS) have exploded in recent years for the purpose of collecting extensive reviews on a regular basis. DaaS providers offer the necessary computational resources to continuously extract high-quality data from social media and e-commerce websites.

The primary goal of the majority of sentiment analysis workflows is to break down the information barrier created by social slang, non-textual expressions, and language. A pre-built, pre-classified custom lexicon dictionary of terms is typically compared to user-generated words after this. The digital teams of businesses can quickly identify impending difficulties and possibilities by using technologies for real-time analysis of streaming social data. Then, in order to seize the chance or overcome the difficulty, businesses might interact with the parties in question, including customers, groups, suppliers, or governmental agencies. For instance, the food business can track the changes in sentiment ratings related to a product that has been reformed and determine whether the reformulation was successful in reversing the unfavorable feelings.

6. SAFETY OF FOOD

a. **Foodborne Outbreaks and Big Data**

All global stakeholders now view ensuring the safety of food from farm to fork as a top priority. In response to the recent foodborne outbreaks of fresh produce in the United States, which included two significant cases of romaine lettuce contaminated with Escherichia coli in 2018, a lot of food (which also included large quantities of the safe produce) was disposed of in order to safeguard the public's health. The existing methods of protecting the public health from foodborne outbreaks may not be an effective alternative in the future given that the demand for food is anticipated to rise by 50% between 2012 and 2050. Technology improvements and integrated informatics measures can play a major role in mitigating the risks to food safety and preventing future outbreaks, saving millions of dollars and many lives. This is because outbreaks have a large economic impact. Every day, the food industry generates a sizable amount of data related to food safety. Finding ways to extract reliable data from various sources would help with microbial risk assessment, outbreak prevention, and trend identification through pathogen surveillance, all of which will help with the outcomes and decision-making related to food safety. One of the many benefits that informatics can provide to the future of food safety is the capacity to monitor food in real-time while it is being stored and transported, to use digital labeling techniques that are simple to synchronize with cloud data, and to improve traceability using blockchain.

Protecting the general population's health and limiting the damage are the main considerations while managing an outbreak. It entails hazard detection, efficient containment, and risk reduction in a constrained amount of time. FoodNet, PulseNet, and GenomerTrakr are three web-based technologies developed by the US Centers for Disease Control and Prevention (CDC) to swiftly identify and prevent food related illness outbreaks in order to minimize the impact on the public's health. The FoodNet, which monitors trends for illnesses frequently spread through food, is the Foodborne Diseases Active Surveillance Network. GenomeTrakr, an FDA-managed database with 27 domestic and 3 international laboratory facilities, provides data on foodborne bacterial germs from food products and the environment. PulseNet employs DNA fingerprinting to identify patients and locate clusters of disease that may signal prospective outbreaks. To obtain the pathogen's entire genome sequence, the pathogen is isolated from samples taken from ill persons and DNA fingerprinting is carried out. Using the Foodborne Disease Outbreak Surveillance System, matches are found in the data gathered from 83 laboratories (PulseNet Network) in the United States (FDOSS). By employing big data analytics to pull information from these web tools, the CDC's division of Foodborne, Waterborne, and Environmental Diseases can spot trends in foodborne illness cases. Additionally, CDC collaborates with partners in Canada, Europe, Asia Pacific, Africa, the Middle East, Latin America, and the Caribbean to share WGS data through international laboratory networks and support foodborne disease surveillance and outbreak response. This international database, called PulseNet International, is part of CDC's global network of labs. With the help of clusters of related data, PulseNet can isolate an unexpected outbreak by recognizing the pathogen's fingerprints (whole genome sequences) from sick individuals.

Through the food safety platform FOSCOLLAB, WHO has lately delved into big data analytics to assist decision making in worldwide food safety outbreaks. This platform includes data (both structured and unstructured) derived from analyses of the Global Environment Monitoring System (GEMS) database, Joint FAO/WHO Expert Committee on Food Additives (JECFA) database, Joint FAO/WHO Meeting on Pesticide Residues (JMPR) database, among others, to cover multiple segments including animal, agriculture, food, public health, and economics that are integrated and accessible to all stakeholders.

b. **Traceability**

Public confidence in the food supply chain is severely undermined by the food regulatory agencies' inability to pinpoint the source of contamination in foodborne outbreaks. For instance, it took two weeks to isolate the contaminant during the 2006 spinach incident, and a lot of resources were used. Another recent example is the 2018 epidemic of romaine lettuce, when all of the lettuce was withdrawn from the market without knowing where the contamination originated. Due to the food control officials' ineffective backtracking, all lettuce was thrown out. Following 67 days from the first instance of a romaine lettuce-related illness being recorded, the FDA issued a recall (Fig. 8). The ineffective record-keeping practices in use, such as the frequently used "One Up, One Down - OUOD approach," are to blame for the inability to trace products. Up and down the supply chain, the only people who can be held accountable are the immediate suppliers and the immediate buyers, and it often takes days for epidemic investigations to connect the dots and pinpoint the source of contamination. Due to this, customer confidence declines, which has a negative impact on produce growers (such as spinach and lettuce growers). Blockchain technology might be utilized to solve this problem. By enabling quick and precise tracking through the use of blockchain, food waste costs will be reduced and priceless human lives will be preserved.

7. FUTURE TRENDS, OBSTACLES, AND REQUIREMENTS

a. **Iot, big data, and computation**

Due to the enormous amount of data that IoT devices and social media platforms generate, it is frequently necessary to have the right infrastructure in place to store, process, or analyze the data and to take the relevant automatic actions based on the insights gained. The "platform as a service" business model is gaining popularity due to the high cost of such infrastructure. Amazon Web Services (AWS), Microsoft Azure, ThingWorx IoT Platform, IBM's Watson, Cisco IoT Cloud Connect, Salesforce IoT Cloud, Oracle Integrated Cloud, and GE Predix are a few of the major IoT platforms available today. Database management, cloud computing, and analytics as a service are anticipated to be the preferred business models in the future due to the anticipated decline in sensor costs and the ensuing quick increase in demand for cloud computing.

b. **Agriculture**

The expense of collecting data in data-driven agriculture is still very expensive, which considerably reduces the productivity-boosting effects of IoT and AI. Only developments that result in reasonably priced sensing technologies will be able to ameliorate the situation, and that doesn't seem to be happening anytime soon. Who holds and owns the data will continue to be a major focus for both farmers and technology businesses as the collaboration between the big data technology industry and the farming community develops. Only highly developed nations utilize cutting-edge technology in agriculture, whereas the majority of farmers elsewhere in the world struggle to make ends meet. Large factory farms, like those found in North America or Europe, are typically well-suited to use the modern technologies. This means that internet-based technologies are not likely to become significant forces in altering the productivity of agriculture worldwide. As a result, only strong political will that results in governmental assistance for farmers may increase the success of these technologies in developing and poor nations.

c. **Social Media**

As this period progresses, social media and individual user data are gradually replacing traditional resources as the "most valuable resource." Cyberattacks, the use of bots and fake social media accounts by anti-enterprise organizations to harm the reputation of companies and promote the marketing of fake/counterfeit goods on the internet are just a few of the new challenges that are arising. Consumers and businesses are also becoming more concerned about data privacy. As a result, businesses' digital teams need to be continually creative in order to address blunders on social media platforms and deal with challenging situations. Modernizing the food supply chain: There have not yet been any quantitative studies on the advantages of IoT in the supply chain. It is a difficult problem that requires more research on an individual basis to integrate IoT with food industry procedures for supply chain control. Considering that product-level tracking utilizing sensors was a well-known concept to this industry, IoT adoption in the food supply-chain business is generally improving quickly. The new trends that are anticipated to continue to gain traction are the decentralized food diversion and consignment redirection depending on anticipated shelf life. By reducing food waste dramatically, these developments will aid in. Due to the involvement of several stakeholders and players, including end-consumers, end-to-end supply chain traceability in the agri-food business is likely to be realized in the future through technology implementations that slightly diverge from blockchain techniques.

d. **Food Supply-Chain Modernization**

Using spectral data to measure food quality is becoming more widespread than ever before in the food sector. UV-Vis spectrophotometers and hyperspectral cameras are both utilized to check food quality. In response to millennials' attention to their health, tech start-ups are creating consumer-focused, pocket-sized spectral gadgets. The needs of the industry are actively taken into consideration when designing and developing smaller, quicker hyperspectral cameras. Spectral sensors can now be purchased for as little as $300, but commercial spectrophotometers can cost up to $100,000. Depending on the specifications, hyperspectral cameras can cost as much as several million dollars, with a starting price of around USD 20,000. The databases of spectral properties for foods are likewise still in the development stage and are not yet suitable for commercial use. The food business is severely lagging behind, despite analogous problems in the field applications of precision agriculture being quickly handled. However, it is anticipated that the demand for spectral technology for food applications would only increase.

e. **Food Safety**

Regarding food safety, the emphasis has shifted from reaction and response to prediction and prevention as a result of recent changes to the laws governing food safety. Due to the current challenges in food safety, comprehensive and coordinated approaches are needed to deal with upcoming foodborne outbreaks, including the collection and analysis of vast amounts of genetic data for the early detection of food safety problems. The need to improve systems of tracking food supply chains that protect both food and public health is mandated by upcoming threats to food safety. The future of sustainable agriculture will depend on being able to provide the increasing global food demand. In order to improve food safety, important information would need to be gathered from around the world and connected to various disease and outbreak databases. This would need the deployment of cutting-edge technology like whole genome sequencing, blockchain, and digital process data logging. In order to make the food supply chain safer and more secure, with better accountability and transparency, future food safety measures will necessitate stronger digital advances.

f. **Data Ownership, Security, and Privacy**

Data ownership, security, and privacy issues are three of the new cybersecurity difficulties brought on by the agri-food industry's increased reliance on big data, cloud computing, and the Internet of Things. This is due to the vulnerability of technology like business management systems, data platforms, RFID, wireless sensor networks, and wireless sensor networks to malfunction, abuse, and misuse. In terms of lost revenue or damaged reputation, a data security breach might be devastating for businesses. In spite of the fact that software companies frequently update their platforms for data and applications, updating can be particularly challenging in specific situations, such as with process management software. A frequent problem that affects farm-based IT systems that results in outages is power loss.

Despite the fact that using data for AI methods is thought to be very beneficial, there are still many uncertainties, problems, and unanswered questions regarding data ownership and privacy that need to be resolved. Companies are reluctant to contribute to AI efforts since there is no assurance that data leakage upon sharing can be stopped. Farmers, consumers, and smaller company players are frequently faced with a difficult decision on whether to give up their privacy or a financial share in order for the data to be used for commercial gain. Blockchain, which is a peer-to-peer network that enables each user to own his or her own data and engage in trade, may be able to prevent data monopolies in terms of ownership. In order for blockchain technology to be widely adopted and for AI to be integrated into it in order to guarantee robust data immutability, increased transparency, and improved security, efforts must be made to standardize the protocols that are employed. Two key methods for ensuring that the value of data is spread without losing the parties' trust are smart contracts for data sharing and robust algorithms for data privacy.

8. CONCLUSIONS

IoT is garnering a lot of interest from a variety of businesses and is seen as one of the most crucial areas of future technology. Farming will become more efficient, intelligent, and connected with the use of IoT infrastructure, and farmers will be able to provide analysts with a wealth of data on crop yields, soil mapping, fertilizer applications, weather information, machinery, and animal health. In order to enable early inspections for public health and safety, the use of sensors is progressively expanding in early reporting of issues relevant to crop health in farms. To create a viable and effective IoT system, efforts must be made to make it simple for different IoT devices to integrate into the data and instruction flow from farm to consumer.

To trace shipments and real-time reroute them, the food supply chain is leading the way in IoT usage. It has become common practice in the business to evaluate the quality and authenticity of food using tiny spectral cameras, and efforts are being made to give customers access to this technology via their cellphones. For traceability in the event of disease outbreaks and to guarantee food safety, the industry is also investigating the advantages of next-generation genome sequencing and blockchain technology. People are crowdsourcing ideas for the creation of new food products by analyzing the massive amounts of social media data for customer behavior.

Final thoughts: The economic, environmental, and social key performance indicators that IoT and big data technologies may have an impact on are higher productivity, reduced production costs, and higher quality (e.g. improved public health, consumer demand driven, quality of life improvement). Tasks that were unachievable a few years ago have now been implemented with remarkable success thanks to the astonishing pace of progress in the fields of IoT, big data, and AI. Modern agriculture and the food sector must embrace technological developments and use them to their advantage if they are to succeed.

REFERENCES

[1] P. Rashi, M. C. Lohani, N. Luftiani, T. Hermansyah, and I. N. Hikam, "New Personalized Social Approach Based on Flexible Integration of Web Services," *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 1–17, 2022.
[2] A. S. Bist, V. Agarwal, Q. Aini, and N. Khofifah, "Managing Digital Transformation in Marketing:" Fusion of Traditional Marketing and Digital Marketing"," *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 18–27, 2022.
[3] M. R. Anwar, F. P. Oganda, N. P. L. Santoso, and M. Fabio, "Artificial Intelligence that Exists in the Human Mind," *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 28–42, 2022.
[4] H. T. Sukmana, A. E. Widjaja, and H. J. Situmorang, "Game Theoretical-Based Logistics Costs Analysis: A Review," *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 43–61, 2022.
[5] M. Wahyudi, V. Meilinda, and A. Khoirunisa, "The Digital Economy's Use of Big Data," *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 62–70, 2022.
[6] U. Rahardja, "Camera Trap Approaches Using Artificial Intelligence and Citizen Science," *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 71–83, 2022.
[7] A. Ramadhan and T. Nurtino, "Integrated Energy System Systems and Game Theory A Review," *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 84–101, 2022.
[8] C. Sriliasta, D. S. S. Wuisan, and T. Mariyanti, "Functions of Artificial Intelligence, Income Investment Instrument, and Crypto Money in Era of The Fourth Revolution," *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp.

117–128, 2022.
[9] P. A. Sunarya, “Machine Learning and Artificial Intelligence as Educational Games,” *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 129–138, 2022.
[10] A. G. Prawiyogi, S. Purnama, and L. Meria, “Smart Cities Using Machine Learning and Intelligent Applications,” *Int. Trans. Artif. Intell.*, vol. 1, no. 1, pp. 102–116, 2022.
[11] S. A. Putra, “Virtual Reality’s Impacts on Learning Results in 5.0 Education: a Meta-Analysis,” *Int. Trans. Educ. Technol.*, vol. 1, no. 1, pp. 10–18, 2022.
[12] A. Rachmawati, “Analysis of Machine Learning Systems for Cyber Physical Systems,” *Int. Trans. Educ. Technol.*, vol. 1, no. 1, pp. 1–9, 2022.
[13] N. N. Azizah and T. Mariyanti, “Education and Technology Management Policies and Practices in Madarasah,” *Int. Trans. Educ. Technol.*, vol. 1, no. 1, pp. 29–34, 2022.
[14] N. Ramadhona, A. A. Putri, and D. S. S. Wuisan, “Students’ Opinions of the Use of Quipper School as an Online Learning Platform for Teaching English,” *Int. Trans. Educ. Technol.*, vol. 1, no. 1, pp. 35–41, 2022.
[15] C. S. Bangun, S. Purnama, and A. S. Panjaitan, “Analysis of New Business Opportunities from Online Informal Education Mediamorphosis Through Digital Platforms,” *Int. Trans. Educ. Technol.*, vol. 1, no. 1, pp. 42–52, 2022.
[16] U. Rahardja, “Using Highchart to Implement Business Intelligence on Attendance Assessment System based on YII Framework,” *Int. Trans. Educ. Technol.*, vol. 1, no. 1, pp. 19–28, 2022.
[17] M. K. van der Hulst *et al.*, “A systematic approach to assess the environmental impact of emerging technologies: A case study for the GHG footprint of CIGS solar photovoltaic laminate,” *J. Ind. Ecol.*, vol. 24, no. 6, pp. 1234–1249, 2020.
[18] A. Belhadi, S. S. Kamble, S. A. R. Khan, F. E. Touriki, and D. Kumar M, “Infectious waste management strategy during COVID-19 pandemic in Africa: an integrated decision-making framework for selecting sustainable technologies,” *Environ. Manage.*, vol. 66, pp. 1085–1104, 2020.
[19] E. Igos, E. Benetto, R. Meyer, P. Baustert, and B. Othoniel, “How to treat uncertainties in life cycle assessment studies?,” *Int. J. Life Cycle Assess.*, vol. 24, pp. 794–807, 2019.
[20] S. M. Moni, “A Framework for Life Cycle Assessment (LCA) of Emerging Technologies at Low Technology Readiness Levels.” Clemson University, 2020.
[21] V. Prado *et al.*, “Sensitivity to weighting in life cycle impact assessment (LCIA),” *Int. J. Life Cycle Assess.*, vol. 25, pp. 2393–2406, 2020.
[22] S. Cucurachi, C. F. Blanco, B. Steubing, and R. Heijungs, “Implementation of uncertainty analysis and moment‐independent global sensitivity analysis for full‐scale life cycle assessment models,” *J. Ind. Ecol.*, vol. 26, no. 2, pp. 374–391, 2022.
[23] S. M. Moni, R. Mahmud, K. High, and M. Carbajales‐Dale, “Life cycle assessment of emerging technologies: A review,” *J. Ind. Ecol.*, vol. 24, no. 1, pp. 52–63, 2020.
[24] C. G. Bhat, “Life cycle information models with parameter uncertainty analysis to facilitate the use of life-cycle assessment outcomes in pavement design decision-making.” Michigan Technological University, 2020.
[25] S. Merschak, P. Hehenberger, S. Schmidt, and R. Kirchberger, “Considerations of life cycle assessment and the estimate of carbon footprint of powertrains,” SAE Technical Paper, 2020.
[26] K. Molina‐Besch and H. Pålsson, “A simplified environmental evaluation tool for food packaging to support decision‐making in packaging development,” *Packag. Technol. Sci.*, vol. 33, no. 4–5, pp. 141–157, 2020.

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