Adoption of IoT in Agriculture - Systematic Review

Syed Mosaddik Hossain Ifty [1], Bayazid Hossain [3], Md Rahatul Ashakin [2], Mazharul Islam Tusher [4], Rashedul Haque Shadhin [5], Jahedul Hoque [6], Redoyan Chowdhury [7*], Atiqur Rahman Sunny [8*]

Abstract

This study aimed to elucidate the diverse applications and concrete advantages of incorporating IoT technology into the agricultural sector of the United States. This paper highlights the potential of IoT to address difficulties and create possibilities for resilience and sustainable advancement in agriculture. It does so by examining numerous case studies across different aspects of agricultural production. Recent findings indicate that the United States has significant potential for the use of Internet of Things (IoT) technology in agriculture. This has the potential to completely transform farming methods and enhance productivity, sustainability, and profitability. Utilising IoT technology in precision agriculture enables specific methods for irrigation, fertilisation, and insect control, resulting in increased crop production and decreased environmental impact. Nevertheless, there are significant obstacles that continue to exist, such as the upfront investment required for IoT infrastructure, apprehensions about the confidentiality and security of data, challenges related to compatibility, and the widespread lack of access to digital technology in rural regions. To tackle these problems, it is essential for stakeholders to work together, which involves providing financial support, establishing legislative frameworks, offering expert technical guidance and education, and improving accessibility to infrastructure. By taking coordinated and determined steps, the agriculture industry may overcome these challenges, thereby harnessing the complete capabilities of IoT technology to promote sustainable development and adaptability.

Keywords: IoT; Smart Agriculture; Smart Aquaculture; Weather; United States of America

Significance | Exploring IoT advancements in agriculture is crucial for addressing food security challenges, enhancing productivity, and fostering sustainable practices amid rising global demands.

*Correspondence: Redoyan Chowdhury, Department of Business Administration, International American University, Los Angeles, CA 90010, USA. And and Atiqur Rahman Sunny, Pathfinder Research and Consultancy Center, Bangladesh
E-mail: c.redoyan@gmail.com, atiksunny@yahoo.com

Edited by Md. Shamsul Haque Prodhan, Shahjalal University of Science and Technology, Bangladesh. And accepted by the Editorial Board Feb 19, 2023 (received for review Jan 09, 2023)

Introduction

The agricultural sector stands on the brink of a transformative revolution, driven by technological advancements like the Internet of Things (IoT). IoT is expected to revolutionize traditional farming methods all around the globe. It is characterized by interconnected devices that enable automation and data exchange (Waher, 2015). Through its applications which include weather forecasting, livestock monitoring, soil analysis, and precision agriculture. It provides historically unprecedented chances for farmers to maximize the utilization of resources and enhance productivity (Ray, 2017; Lohr, 2015). As forecasting indicate that the number of interconnected agricultural devices is going to increase significantly across the globe, IoT becomes growing significance in tackling critical challenges related to food security (Machina Research, 2016; Meola, 2016).

It is anticipated that by 2050, there will be 9.7 billion people on the planet, putting unprecedented pressure on the agricultural sector to grow food production in a sustainable manner (Chakma et al., 2022; Moniruzzaman et al., 2023). Concurrently, conventional

Author Affiliation:
[1] Department of EEE, Brac University, Bangladesh
[2] Department of EEE, Barishal Engineering College, Bangladesh
[3] Department of Information Technology, Washington University of Science and Technology, USA
[4] Department of Computer Science, Monroe College, New York, USA
[5] Bangladesh Bureau of Statistics (BBS), Dhaka, Bangladesh
[6] Department of Anthropology, University of Chittagong, Bangladesh
[7] Department of Business Administration, International American University, Los Angeles, CA 90010, USA
[8] Pathfinder Research and Consultancy Center, Bangladesh

Please cite this article:
Syed Mosaddik Hossain Ifty, Bayazid Hossain et al. (2023). Adoption of IoT in Agriculture - Systematic Review, Applied Agriculture Sciences, 1(1), 1-10, 9676

farming practices face never-before-seen difficulties due to resource constraint, climate change, and changing customer tastes (Sunny et al., 2017; Kuddus et al., 2020). Farmers and other agricultural stakeholders are using IoT solutions more frequently in response to these difficulties in order to obtain real-time insights, enhance decision-making procedures, and maximise operations throughout the agricultural value chain (Kuddus et al., 2021; Sazzad et al., 2023).

It will be feasible to increase global food production to feed billions of people in the coming decades by utilizing big data applications and IoT technologies together. By utilizing IoT-powered solutions, farmers can adopt data-driven, well-informed decisions that enhance the production of crops, preserve resources, and reduce risks regarding climate change (Johnston, 2014; Johnston and Pattinson 2016). Farmers may implement accuracy and precision farming techniques and encourage sustainable agricultural practices by using real-time monitoring of crop health, weather patterns, and soil conditions (Cukier and Mayer-Schoenberger, 2013; Noyes, 2014). IoT also renders supply chain management simpler, thereby guaranteeing that agricultural products are delivered on time to satisfy the demands of an expanding world population (Guerra, 2017; Bari et al., 2023).

IoT adoption in agriculture has fluctuated across different socio-economic contexts, but it has been especially significant in regions like the United States, where it has ushered in an era of advanced farming and data-driven decision-making (Lohr, 2015). IoT provides significant possibilities to deal with challenges related to food security in nations that possess distinct agricultural landscapes, such as Bangladesh and India (Sunny et al., 2021). IoT-enabled technologies are helping significantly in the global efforts to ensure food security by maximizing the effective utilization of available resources, increasing crop yields, and enhancing overall agricultural production.

This study attempts to clarify the varied uses and concrete advantages of IoT adoption in the US agriculture industry by means of a thorough analysis of case studies covering different aspects of agricultural production. This research also highlights the transformative potential of these technologies in addressing the issues facing the agricultural sector and opening up new opportunities for resilience and sustainable growth.

2. IoT's Function and Importance in Agriculture

A United Nations Organization report published on June 14, 2013, estimated that by 2050, there will be approximately 9.6 billion people on the planet, making food supply a significant challenge. Agriculture needs to leverage the most recent scientific and technical developments, including the Internet of Things, to meet food demand. The smart agriculture market is predicted to generate over 18.45 billion dollars in revenue in 2022 at a compound annual growth rate (CAGR) of 13.8 percent due to the Internet of Things' rapid expansion. Given that IoT devices have the potential to improve agriculture, "Business Insider," a significant American business platform, projects that over 75 million IoT devices will be exported for use in agriculture by 2020 at a compound annual growth rate of 20%.1. In light of these figures, numerous nations have made investments in agricultural IoT. The main areas of interest for agricultural IoT are weather forecasting, smart greenhouses, telematics, livestock management, food preservation, field monitoring, smart irrigation, soil and seed analysis, crop growth analysis, and much more. The research and applications of agricultural IoT conducted during the past ten years are covered in the next paragraph (Umme Salma & Narasegouda, 2020). Numerous applications exist for agricultural IoT, and a great deal of research is being done in this field. The following are some of the well-known agricultural IoT research areas:

2.1 Weather forecasting:

This involves projecting future variations in the climate and offering pertinent details about the security and safety of the agricultural crops, livestock and aquaculture. More than 90% of farming of crops and fish is dependent on the timing of rainfall. Weather forecasting using Internet of Things (IoT) can help plan cultivation well in advance. Agricultural risks are also decreased by weather forecasting. Weather stations employ sensors to gather copious amounts of climate data, which are then used to forecast rainfall and other natural events. This information is then disseminated to guarantee the safety and security of the crops (Tzounis et al. 2017). It is critical to have a consistent supply of power and internet because the agricultural Internet of Things depends on it. However, inclement weather disrupts the internet connection. Microsoft and the Massachusetts Institute of Technology have developed a novel approach dubbed FarmBeats, which is addressed in Vasisht et al. (2017), to address this issue. FarmBeats suggested a unique IoT base station design that considers the weather and adjusts its energy and bandwidth usage accordingly.

2.2 Field Study

Agricultural Internet of Things applications such as water quality, P^H, soil, seed, and crop growth analysis are all part of field analysis. IoT and cloud computing can be used to capture field data, such as crop growth, fertilizer, plant diseases, environmental conditions, etc. This data that has been recorded is utilized to analyze potentially very valuable hidden patterns. Additionally, future outcomes can be predicted using the recorded data (TongKe 2013). In the agro-industrial sector, IoT has been applied at many levels, benefiting a range of stakeholders from large industrialists to small farmers. IoT is used to evaluate the condition of the soil, the biomass of plants and animals, and the climate. According to

(Talavera et al. 2017), the Internet of Things (IoT) systems lessen human interference and create a robust network of strong devices that offer a useful feedback mechanism and analytical help. Many nations devote time and resources to soil analysis research, testing various soil types for bio-content (humus), pH level, moisture humidity, and chemical composition. Depending on the size of the sample and application, a variety of physical and electrochemical sensors are utilized to collect readings (data), and communication technologies such Bluetooth, LoRaWAN, GPRS, and Zigbee are used (Chen et al. 2014; Mafuta et al. 2013).

2.3 Smart Livestock Farming

Livestock management is a farming technique that involves the use of radio frequency identification (RFID) and other technologies for the purpose of identifying the cattle. The creatures are connected to sensors (like RFID) and allowed to look around freely. The animals' locations can be determined with the help of the identification sensors. Additionally, a variety of biomechanical sensors are utilized to track body temperature and pulse rate. Any variations are notified to the user so that treatment may begin right away. A few noteworthy studies on the management of cattle have been published (Havstad et al. 2018; Lopez-Ridaura et al. 2018; Qu et al. 2018).

2.4 Smart Aquaculture

The Internet of Things (IoT) has transformed traditional agricultural methods by decreasing labour expenses and enhancing efficiency in aquaculture. Through the integration of IoT devices, organisations have the ability to gather extensive quantities of data, which allows for immediate corrective actions and improvements in the well-being of fish (Chiu et al., 2022). Internet of Things (IoT) enabled aquaculture systems have the capability to monitor various parameters like as water quality and microclimate (Waterman et al., 2020). Additionally, they can also provide warning functions, hence improving the efficiency of early alerts and response times. A IoT systems can also manage equipment like as water wheels, pumps, and feed machines, leading to reduced labour requirements, stable water quality, energy conservation, and precise feeding. This can result in economic benefits and optimise production. The increasing demand for premium aquatic products has shifted the attention towards fish health, as the presence of unconsumed feed leads to the generation of ammonia and other toxic substances (Yang et al., 2021). In order to resolve this problem, it is necessary to implement an intelligent monitoring system for fish farming that utilises artificial intelligence frameworks. This system will allow for the prediction of future events and the establishment of effective feeding strategies for the animals.

2.5 Smart Agriculture

Using technology to gather agricultural data, do diagnostics, analyze data, conduct field operations, and evaluate is what sets precision agriculture (PA) apart from traditional agriculture. PA makes smart farming possible, which includes effective use of fertilizers and other nutrients needed for robust plant growth, as well as smart water management, weed and insect control, and more. PA is a crop management approach that uses IoT to improve crop quality and yield (Jawad et al. 2017). Rad et al. (2015) created an integrated PA management system based on a cyber-physical system, in which a smart system was created to raise Romania's potato crop's yield. The analysis aided in decision-making, which raised the potato crop's productivity. One of the cutting-edge technologies being utilized in agricultural IoT is nanotechnology. As an example, it being applied in precision farming, where the issue of soil nutrient depletion can be solved with nanofertilizers. In a similar vein, a variety of plant diseases can be avoided by using insecticides and nanopesticides. IoT-collected data are processed, and appropriate nanoproducts are employed to support crop growth appropriately based on the analysis (Kumar and Ilango 2018).

2.6 Greenhouse Management

Using technology to provide a regulated atmosphere that promotes healthy plant growth, smart greenhouses represent a novel way to monitor fields. To provide a good yield in an optimal environment, the Intelligent Greenhouse Management System (IGMS), a sophisticated comprehensive system, was proposed. Wireless sensor networks were used to generate a greenhouse climate by continuously measuring the soil's moisture content. The field received the necessary amount of water based on the moisture content. This technique conserves water and gives plants only the amount they need (Kassim et al. 2014).

2.7 Telematics

To enable connection between client and server devices and enable crop monitoring, agricultural telemetry is utilized. Oksanen et al. (2016) presented a proposal for one of the important telematics research projects. To transmit data about agriculture, the authors of this study created a client-side remote monitoring system and a client-side combine harvester system. It was discovered that the suggested system functioned well, with an internet latency of less than 250 ms. Recent advancement in telematics is Mobile to Mobile (M2M) communication where M2M plat-forms are integrated with cloud and IoT to render sensing and actuating services. Presents a literature survey that contains applications of M2M telemetry in all fields including agriculture Suciu et al. (2015).

2.8 Monitoring of intruders

In agriculture, intruders are identified by means of an intruder detecting system. Unauthorized individuals or animals who break in to harm crops are examples of intruders. Roy et al. (2015) presented a system named AID—Agricultural Intrusion Detection—to identify the intruder entering the field. In addition to sounding an alarm at the farmer's house, this system notifies him via text message on his mobile device to take the appropriate action. Zigbee communication technology and wireless sensor boards with Advanced Virtual RISC (AVR) microcontrollers were used in the system's design and implementation. Arshad et al. (2018) and Diro and Chilamkurti (2018) suggested an M2M-based intrusion detection system and deep learning-based multiple intrusion attack identifications, respectively.

2.9 Disease Detection

Research on agricultural requirements is done based on the nation conserved in order to discover illnesses in crops. A hybrid method was developed by Ramesh and Rajaram (2018) in India to detect disease in paddy crops, or rice. The authors created a hybrid Internet of Things architecture with modules for acquiring, quantifying, classifying, analyzing, and visualizing data. The farmers received the image data after it was processed using a variety of image processing methods on an MS-Azure cloud server. The main drawbacks of this proposed system are that it is time consuming and costly. Export of apples and berries from the USA being an important business, there is the need for developing a system that identifies the disease in fruit crops in the early stages. To address this issue, Ampatzidis et al. (2017) proposed an IoT-based framework to identify disease in various fruit crops. Many other works of similar type on various crops have also been available (for instance, Dang et al. 2013; Luvisi et al. 2016; Rad et al. 2015).

3. Technological development in Agriculture in the USA

According to the U.S. Department of Agriculture, a $1.420 trillion worth of contribution was made to the GDP by agriculture, food, and related industries, which equals around 5.5% share in 2022 (USDA ERS, n.d.). It was only possible with the integration of smart technologies with agriculture. The US adoption of technologies in the field of Agriculture can be realised with some case studies as below:

3.1 **Utilizing Satellite Imagery**

According to (Umme et al. 2020), crops are monitored using satellites to detect intruders and track crop health where Images of crops are taken and subjected to image analysis, where image processing-based software detects infection and/or illness in the plants at an early stage. Researchers like (Sabini et al. 2017) trained Convolutional Neural Networks to predict US crop yields using satellite photos. They used nine spectral and temperature bands from low-resolution images, minimizing data dimensionality and using pixel intensity histograms as features. A similar work (Nguyen et al. 2020) aims to create an intelligent system that uses imaging data from low-Earth orbiting satellites to identify crop and non-crop areas for paddy mapping where a unique multi-temporal high-spatial resolution classification method was proposed based on an advanced spatio-temporal-spectral deep neural network for locating paddy fields at the pixel level over the course of a year and per temporal instance. Another project (Song et al. 2017) aimed to create and test a method for predicting in-season crop acreage using a probability sample of field visits and generate wall-to-wall crop type maps on a national scale where A stratified, two-stage cluster sampling strategy was employed to acquire field data for estimating national soybean area. The field-based estimate identified and stratified soybean growing regions in the United States using historical soybean extent maps from the USDA's Cropland Data Layer with an overall accuracy 84%. Another researcher (Yang et al. 2020) developed an EVI-curve-based technique to detect patterns in cropping intensity and phenological stages in North America from 2000-2016 using vegetation index, satellite imagery and agricultural survey data.

3.2 **Field Inspection**

According to the author (Umme et al. 2020), aerial unmanned vehicles monitor fields not only by recording photographs of crops but also by recognizing infected plants, allowing pesticides to be sprayed only on infected crops rather than the entire field while Drone sensors aid in the collecting of data, which can then be analysed. Another paper (Guo et al. 2021) discusses the current state of UAS-based phenotyping platforms, identifies technical challenges, and highlights future trends in plant research, highlighting key questions for future UAS imaging modalities. A study (Zhang et al. 2022) collected high-resolution UAV photos of three growth stages of kiwifruit orchards from May to July 2021 where the correlated spectral and textural parameters were utilized to create univariate and multivariate regression models, with LAI calculated for each growth stage and the best model for LAI estimate and mapping was determined by comparing stepwise regression (SWR) and random forest regression (RFR). Another study (Bendig, 2015) proposes, an UAV-flight operation at three study sites shown that plant height and growth can be properly modelled using RGB images and Biomass estimation based on plant height is successful later on. Also, visible band vegetation indices from RGB imaging can predict early development, but their application is limited due to uncalibrated images. Researchers like (Das et al. 2021) utilized UAS footage from cornfields to assess Goss's Wilt severity, analyzing textural, color, and area features, and comparing the performance of different machine learning techniques.

3.3 Predictive monitoring

According to (Umme et al. 2020), data received from sensors can be utilized in predictive analytics to estimate future outcomes. Predictive analytics in agriculture is mostly used to anticipate rainfall, weather, natural disasters, yield, and so on. Here is a table that summarizes some of the current applications (Table 1).

3.4 Determining crop/soil condition with IoT sensors

Table 1. The current applications in agriculture to anticipate rainfall, weather, natural disasters, and yield.

Applications	Method	Description
Soil Managment	ANN	Can predict soil enzyme activity. Accurately predicts and classifies soil structure. (Tajik et al. 2012)
	ANN	Able to predict soil moisture (Zhao et al. 2009)
	SRC-DSS	Can classify soil according to associated risks (Lopez et al. 2008)
Crop Management	ANN	Predicts crop yeild (Snehal et sl. 2014)
	ANN	Above 90% success rate in detecting crop nutrition disorder (Song et al. 2005)
	FUZZY Cognitive Map	Predict cotton yield and improve crop for decision management (Papageorgiou et al. 2011)
Disease Management	Computer vision system (CVS)	Works at a high speed and can multitask in detecting diseases (Balleda et al. 2014)
	Web-Based Intelligent Disease Diagnosis System (WIDDS)	Good accuracy. Responds swiftly to the nature of crop diseases. (Kolhe et al. 2011)
	FuzzyXpest	provides pest information for farmers with high precision in forecast (Siraj et al. 2006)
	ANN	Has above than 90% prediction rate in detecting infection (Wang et al. 2006)

(Umme et al. 2020) states that, IoT sensors can be used for periodic monitoring of crop and soil health so that the yield obtained is both qualitatively and quantitatively strong. Author (Ramson, 2021) suggests the development, deployment, and validation of an IoT system for continuous soil health monitoring using solar-powered soil health monitoring units (SHMUs) which transmit data wirelessly using LoRaWAN technology, allowing users to view and analyze the data. Another study (Khanal et al. 2020) examines the application of Remote Sensing (RS) technologies in precision agriculture from 2000 to 2019, focusing on decision-making at different stages and finds out that countries like United States and China use RS technologies to optimize crop production, to address environmental quality, profitability, and sustainability. Study (Grimblatt et al. 2021) suggests using IoT with medium-cost sensors to provide real-time, inexpensive, and precise data processing for agriculture, resulting in Automated Decision-Making Systems (ADMS) while providing a complete review of plant characteristics, sensors, and their compatibility with low-cost ADMS-based IoT systems and some experimentation with essential parameters that demonstrates their effects on plant development and health. Another proposed approach (Shafi et al. 2020) integrates IoT, machine learning, and drone technology to monitor crop health, generating heterogeneous data with varying nature, temporal fidelity, and spatial resolution. IoT sensors provide real-time environmental parameters, while drone platforms generate multispectral data for Vegetation Indices (VIs) for crop health analysis.

3.5 Agri-bots

According to (Umme et al. 2020), these robots are intelligent enough to make decisions to assist the farmers in many stages of farming, from toiling to harvesting which not only cuts labour costs but also increases task efficiency and saves time. A primary research (Sistler, 1987), focused on the increasing international competition, computer technology advancements, and decreasing costs have led to the imminent widespread application of intelligent machines in agriculture which also stated that practical agricultural robots are expected to become common in developed countries within the next decade. Another study (CAST, 2020) discusses the promise that ground and aerial robots provide for improved crop and animal production, as well as the constraints that may impede their advancement and adoption where an overview of enabling variables that could boost robot deployment and adoption in agriculture is also provided with some insights into the workforce training requirements for next-generation agriculture. Another researcher (Mueller-Sim et al. 2017), offers a unique robotic ground-based platform that can navigate autonomously beneath the canopy of row crops like sorghum and maize and the robot may also deploy a manipulator to test plant stalk strength and collect phenotypic data using a modular array of non-contact sensors. Another paper (Fue et al. 2020; Alam et al., 2023a) examines opportunities in the agricultural robotics industry, focusing on the cotton harvesting robot industry and covers general robotic operations, advances in related fields, research progress in cotton harvesting robots, and challenges in commercializing and using these robots. Lastly, a unique research (Carolan, 2020) is done, based on interviews with (1) US farmers who have implemented automated systems; (2) individuals employed by North American enterprises that engineer, manufacture, and/or repair these technologies; and (3) US farm laborers (immigrant and domestic) and representatives from farm labor organizations to realise whether concepts like 'automation' and 'skill' provide sufficient analytic and conceptual clarity to critically engage these platforms.

4. Potential and Challenges of IoT Application

The USA has significant potential for adopting IoT in agriculture, which has the capacity to revolutionise farming operations and improve productivity, sustainability, and profitability. IoT devices provide the potential to gather up-to-the-minute information on soil conditions, weather patterns, crop health, and equipment performance (Hossain et al., 2023). This empowers farmers to make decisions based on data and maximise the efficiency of resource utilisation (Alam et al., 2023b). The utilisation of IoT technology in precision agriculture enables specific and focused approaches to irrigation, fertilisation, and insect management, resulting in higher crop yields and a diminished ecological footprint. Moreover, the implementation of Internet of Things (IoT) in supply chain tracking improves visibility and accountability, guaranteeing the excellence and security of agricultural goods throughout the entire production and distribution process. Nevertheless, there are still notable obstacles to overcome, such as the substantial upfront expenses associated with IoT infrastructure, apprehensions regarding the confidentiality and protection of data, compatibility problems, and the disparity in access to digital technology in rural regions. To overcome these problems, it is necessary for stakeholders to collaborate and take action by providing financial assistance, creating regulatory structures, enhancing technical assistance and training, and improving connectivity infrastructure. By doing so, the full potential of IoT in US agriculture can be realised.

Conclusion

To sum up, this research's case studies highlight how the adoption of IoT in American agriculture has had a revolutionary effect. It is clear that IoT technologies are transforming conventional farming methods through a thorough examination of a variety of applications, such as field analysis, precision agriculture, weather forecasting, smart greenhouse management, telematics, intruder identification, livestock management, and disease identification. These success stories of the research show how IoT solutions help farmers increase crop yields, minimise risks, maximise resource utilisation, and ultimately boost productivity and profitability. These case studies show the many advantages of integrating IoT into agricultural operations, from using real-time data analytics to make data-driven choices to deploying IoT-enabled sensors for environmental condition monitoring.

Furthermore, the USA's dedication to agricultural innovation and research is shown by the broad adoption of cutting-edge digital technologies like robots, artificial intelligence, and the Internet of Things at both the individual and industrial levels. In addition to encouraging sustainable agricultural methods, this proactive strategy sets up the agriculture industry for long-term growth and competitiveness in the international market. So, the stakeholders in the agriculture sector must embrace IoT as it develops and becomes more widely available in order to fully realise its promise to promote sustainability, resilience, and efficiency. Through assimilating the lessons and accomplishments delineated in these case studies, both farmers and policymakers can steer clear of obstacles and towards a more successful and resilient agricultural future.

Author Contribution

S.M.H.I., B.H., M.R.A., M.I.T., R.H.S., J.H., R.C., A.R.S. wrote, analysed data and reviewed the manuscript.

Acknowledgment

The authors were grateful to their department.

Competing financial interests

The authors have no conflict of interest.

References

Alam, K., Jahan, N., Chowdhury, R., Mia, M.T., Saleheen, S., Hossain, N.M & Sazzad, S.A. (2023a). Impact of Brand Reputation on Initial Perceptions of Consumers. Pathfinder of Research, 1 (1), 1-10.

Alam, K., Jahan, N., Chowdhury, R., Mia, M.T., Saleheen, S., Sazzad, S.A. Hossain, N.M & Mithun, M.H. (2023b). Influence of Product Design on Consumer Purchase Decisions. Pathfinder of Research, 1 (1), 23-36

Ampatzidis, Y., De Bellis, L., & Luvisi, A. (2017). iPathology: Robotic applications and management of plants and plant diseases. Sustainability, 9(6), 1010. Multidisciplinary Digital Publishing Institute.

Arshad, J., Abdellatif, M. M., Khan, M. M., & Azad, M. A. (2018). A novel framework for collaborative intrusion detection for m2m networks. In 2018 9th international conference on information and communication systems (ICICS), pp. 12–17. IEEE.

Balleda, K., Satyanvesh, D., Sampath, N. V. S. S. P., Varma, K. T. N., & Baruah, P. K. (2014, January). Agpest: An efficient rule-based expert system to prevent pest diseases of rice & wheat crops. Paper presented at the 8th International Conference on Intelligent Systems and Control, Coimbatore, India.

Bari, K. F., Salam, M. T., Hasan, S. E., & Sunny, A. R. (2023). Serum zinc and calcium level in patients with psoriasis. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online), 2(3), 7-14.

Bendig, J. (2015). Unmanned aerial vehicles (UAVs) for multi-temporal crop surface modelling: A new method for plant height and biomass estimation based on RGB-imaging. Applied Soft Computing Journal.

Carolan, M. (2020). Automated agrifood futures: Robotics, labor, and the distributive politics of digital agriculture. The Journal of Peasant Studies, 47(1), 184-207. https://doi.org/10.1080/03066150.2019.1584189

Carrasquilla-Batista, A., Chacón-Rodríguez, A., & Solórzano-Quintana, M. (2016). Using IoT resources to enhance the accuracy of overdrain measurements in greenhouse horticulture. In Central American and panama convention (CONCAPAN XXXVI), pp. 1–5. IEEE.

Chakma, S., Paul, A.K., Rahman, M.A., Hasan, M.M., Sazzad, S.A. & Sunny, A.R. (2022). Climate Change Impacts and Ongoing Adaptation Measures in the Bangladesh Sundarbans. Egyptian Journal of Aquatic Biology and Fisheries. 1;26(2):329-48.

Chen, K. T., Zhang, H. H., Wu, T. T., Hu, J., Zhai, C. Y., & Wang, D. (2014). Design of monitoring system for multilayer soil temperature and moisture based on WSN. In 2014 International Conference on Wireless Communication and Sensor Network (WCSN), pp. 425–430. IEEE.

Chiu, M. C., Yan, W. M., Bhat, S. A., & Huang, N. F. (2022). Development of smart aquaculture farm management system using IoT and AI-based surrogate models. journal of Agriculture and Food Research, 9, 100357.

Council for Agricultural Science and Technology (CAST). (2020). Ground and aerial robots for agricultural production: Opportunities and challenges. Issue Paper 70. CAST, Ames, Iowa.

Cukier, K. and Mayer-Schoenberger, V. (2013), “The rise of big data: how it’s changing the way we think about the world”, Foreign Affairs, Vol. 92, p. 28.

Dang, K., Sun, H., Chanet, J. P., Garcia-Vidal, J., Barcelo-Ordinas, J., Shi, H., & Hou, K. M. (2013). Wireless multimedia sensor network for plant disease detections. In: NICST’2103 new information communication science and technology for sustainable development: France-China international workshop, pp. 6–p.

Das, A. K., Friskop, A., Flores, P., Cannayen, I., Jose, J., Mathew, Z., & Zhang, Z. (2021). 2021 ASABE annual international virtual meeting [Conference session]. ASABE. https://doi.org/10.13031/aim.202100146

Diro, A. A., & Chilamkurti, N. (2018). Distributed attack detection scheme using deep learning approach for internet of things. Future Generation Computer Systems, 82, 761–768. Elsevier.

Fue, K. G., Porter, W. M., Barnes, E. M., & Rains, G. C. (2020). An extensive review of mobile agricultural robotics for field operations: Focus on cotton harvesting. AgriEngineering, 2(1), 150-174. https://doi.org/10.3390/agriengineering2010010

Grimblatt, V., Jégo, C., Ferré, G., & Rivet, F. (2021). How to feed a growing population—An IoT approach to crop health and growth. IEEE Journal on Emerging and

Selected Topics in Circuits and Systems, 11(3), 435-448. https://doi.org/10.1109/JETCAS.2021.3099778

Guerra, M. (2017), "Three ways the IoT is revolutionizing agriculture", available at: www.electronicdesign.com/analog/ 3-ways-iot-revolutionizes-farming (accessed 9 January 2018).USDA ERS. (n.d.). Ag and food sectors and the economy. Retrieved from [https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/ag-and-food-sectors-and-the-economy/]

Guo, W., Carroll, M. E., Singh, A., Swetnam, T. L., Merchant, N., Sarkar, S., Singh, A. K., & Ganapathysubramanian, B. (2021). UAS-based plant phenotyping for research and breeding applications. Plant Phenomics, 2021, Article 9840192. https://doi.org/10.34133/2021/9840192

Havstad, K., Brown, J., Estell, R., Elias, E., Rango, A., & Steele, C. (2018). Vulnerabilities of southwestern us rangeland-based animal agriculture to climate change. Climatic Change, 148(3), 371–386. Springer.

Hossain Ifty, S.M., Ashakin, M.R., Hossain, B., Afrin, S., Sattar, A., Chowdhury, R., Tusher, M.I., Bhowmik, P.K., Mia, M.T., Islam, T., Tufael, M. & Sunny, A.R. (2023). IOT-Based Smart Agriculture in Bangladesh: An Overview. Applied Agriculture Sciences, 1(1), 1-6. 9563, 10.25163/agriculture.119563

Jawad, H., Nordin, R., Gharghan, S., Jawad, A., & Ismail, M. (2017). Energy-efficient wireless sensor networks for precision agriculture: A review. Sensors, 17(8), 1781. Multidisciplinary Digital Publishing Institute.

Johnston, W.J. (2014), "The future of business and industrial marketing and needed research", Journal of Business Market Management, Vol. 7 No. 1, pp. 296-300.

Johnston, W.J. and Pattinson, H.M. (2016), "The internet of things (IoT), big data and B2B digital business ecosystems", National research University: Higher school of Economics, Doctoral consortium in Strategic Marketing.

Kassim, M. R. M., Mat, I., & Harun, A. N. (2014). Wireless sensor network in precision agriculture application. In 2014 International Conference on Computer, Information and Telecommunication Systems (CITS), pp. 1–5. IEEE.

Khanal, S., KC, K., Fulton, J. P., Shearer, S., & Ozkan, E. (2020). Remote sensing in agriculture—Accomplishments, limitations, and opportunities. Remote Sensing, 12(22), 3783. https://doi.org/10.3390/rs12223783

Kolhe, S., Kamal, R., Saini, H. S., & Gupta, G. K. (2011). A web-based intelligent disease-diagnosis system using a new fuzzy-logic based approach for drawing the inferences in crops. Computers and Electronics in Agriculture, 76(1), 16-27.

Kuddus, M. A., Datta, G. C., Miah, M. A., Sarker, A. K., Hamid, S. M. A., & Sunny, A. R. (2020). Performance study of selected orange fleshed sweet potato varieties in north eastern bangladesh. Int. J. Environ. Agric. Biotechnol, 5, 673-682.

Kuddus, M. A., Alam, M. J., Datta, G. C., Miah, M. A., Sarker, A. K., & Sunny, M. A. R. (2021). Climate resilience technology for year round vegetable production in northeastern Bangladesh. International Journal of Agricultural Research, Innovation and Technology (IJARIT), 11(2355-2021-1223), 29-36.

Kumar, S. A., & Ilango, P. (2018). The impact of wireless sensor network in the field of precision agriculture: A review. Wireless Personal Communications, 98(1), 685–698. Springer.

Lohr, S. (2015), "The internet of things and the future of farming", (accessed 17 December 2017).

Lopez, E. M., Garcia, M., Schuhmacher, M., & Domingo, J. L. (2008). A fuzzy expert system for soil characterization. Environment International, 34(7), 950-958.

Lopez-Ridaura, S., Frelat, R., Van Wijk, M. T., Valbuena, D., Krupnik, T. J., & Jat, M. (2018). Climate smart agriculture, farm household typologies and food security: An ex-ante assessment from eastern India. Agricultural Systems, 159, 57–68. Elsevier.

Luvisi, A., Ampatzidis, Y., & De Bellis, L. (2016). Plant pathology and information technology: Opportunity for management of disease outbreak and applications in regulation frameworks. Sustainability, 8(8), 831. Multidisciplinary Digital Publishing Institute.

Machina Research (2016), "Agricultural IoT will see a very rapid growth over the next 10 years", available at: https:// machinaresearch.com/news/agricultural-iot-will-see-avery-rapid-growth-over-the-next-10-years/ (accessed 17 December 2017).

Mafuta, M., Zennaro, M., Bagula, A., Ault, G., & Chadza, T. (2013). Successful deployment of a wireless sensor network for precision agriculture in malawi–wipam. In 3rd IEEE International Conference on Networked Embedded Systems For Every Application, 9(5). SAGE Publications.

Meola, A. (2016), "Why IoT, big data & smart farming are the future of agriculture", available at: www.businessinsider. com/internet-of-things-smart-agriculture-2016-10 (accessed 17 December 2017)

Mueller-Sim, T., Jenkins, M., Abel, J., & Kantor, G. (2017). The robotanist: A ground-based agricultural robot for high-throughput crop phenotyping. In Proceedings of the 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, pp. 3634-3639. https://doi.org/10.1109/ICRA.2017.7989418

Nguyen, T. T., Hoang, T. D., Pham, M. T., Vu, T. T., Nguyen, T. H., Huynh, Q.-T., & Jo, J. (2020). Monitoring agriculture areas with satellite images and deep learning. Applied Soft Computing, 95, Article 106565. https://doi.org/10.1016/j.asoc.2020.106565

Noyes, K. (2014), "Cropping up on every farm: big data technology", available at: http://fortune.com/2014/05/30/ cropping-up-on-every-farm-big-data-technology/ (accessed 17 December 2017).

Oksanen, T., Linkolehto, R., & Seilonen, I. (2016). Adapting an industrial automation protocol to remote monitoring of mobile agricultural machinery: a combine harvester with IoT. IFACPapersOnLine, 49(16), 127–131. Elsevier.

Papageorgiou, E. I., Markinos, A. T., & Gemtos, T. A. (2011). Fuzzy cognitive map based approach for predicting crop production as a basis for decision support system in precision agriculture application. Applied Soft Computing, 11(4), 3643-3657.

Qu, D., Wang, X., Kang, C., & Liu, Y. (2018). Promoting agricultural and rural modernization through application of information and communication technologies in china. International Journal of Agricultural and Biological Engineering, 11(6), 1–4. ABE Publishing.

Rad, C. R., Hancu, O., Takacs, I. A., & Olteanu, G. (2015). Smart monitoring of potato crop: a cyberphysical system architecture model in the field of precision agriculture. Agriculture and Agricultural Science Procedia, 6, 73–79. Elsevier.

Ramesh, S., & Rajaram, B. (2018). Iot based crop disease identification system using optimization techniques. ARPN Journal of Engineering and Applied Sciences, 13, 1392–1395.

Ramson, S. R. J., et al. (2021). A self-powered real-time LoRaWAN IoT-based soil health monitoring system. IEEE Internet of Things Journal, 8(11), 9278-9293. https://doi.org/10.1109/JIOT.2021.3056586

Ray, B. (2017), "An in-Depth Look at IoT in agriculture & smart farming solutions", available at: www.link-labs.com/ blog/rise-of-iot-in-agriculture (accessed 17 December 2017).

Roy, S. K., Roy, A., Misra, S., Raghuwanshi, N. S., & Obaidat, M. S. (2015). Aid: A prototype for agricultural intrusion detection using wireless sensor network. In 2015 IEEE International Conference on Communications (ICC), pp. 7059–7064. IEEE.

Sabini, M., Rusak, G., & Ross, B. (2017). Understanding satellite-imagery-based crop yield predictions. Stanford University. Retrieved from https://stanford.edu/555.pdf

Sazzad, S. A., Billah, M., Sunny, A. R., Anowar, S., Pavel, J. H., Rakhi, M. S., ... & Al-Mamun, M. A. (2023). Sketching Livelihoods and Coping Strategies of Climate Vulnerable Fishers. Egyptian Journal of Aquatic Biology & Fisheries, 27(4).

Shafi, U., et al. (2020). A multi-modal approach for crop health mapping using low altitude remote sensing, Internet of Things (IoT), and machine learning. IEEE Access, 8, 112708-112724. https://doi.org/10.1109/ACCESS.2020.3002948

Siraj, F., & Arbaiy, N. (2006, June). Integrated pest management system using fuzzy expert system. Paper presented at the Knowledge Management International Conference & Exhibition, Kuala Lumpur, Malaysia.

Sistler, F. (1987). Robotics and intelligent machines in agriculture. IEEE Journal on Robotics and Automation, 3(1), 3-6. https://doi.org/10.1109/JRA.1987.1087074

Snehal, S. S., & Sandeep, S. V. (2014). Agricultural crop yield prediction using artificial neural network approach. International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, 2(1), 683-686.

Song, H., & He, Y. (2005, July). Crop nutrition diagnosis expert system based on artificial neural networks. Paper presented at the 3rd International Conference on Information Technology and Applications, Sydney, Australia.

Song, X.-P., Potapov, P. V., Krylov, A., King, L., Di Bella, C. M., Hudson, A., Khan, A., Adusei, B., Stehman, S. V., & Hansen, M. C. (2017). National-scale soybean mapping and area estimation in the United States using medium resolution satellite imagery and field survey. Remote Sensing of Environment, 190, 383-395. https://doi.org/10.1016/j.rse.2017.01.008

Suciu, G., Vulpe, A., Fratu, O., & Suciu, V. (2015). M2M remote telemetry and cloud IoT big data processing in viticulture. In 2015 International on Wireless Communications and Mobile Computing Conference (IWCMC), pp. 1117–1121. IEEE.

Sunny, A. R., Mithun, M. H., Prodhan, S. H., Ashrafuzzaman, M., Rahman, S. M. A., Billah, M. M., Hussain, M., Ahmed, K. J., Sazzad, S. A., Alam, M. T., Rashid, A., & Hossain, M. M. (2021). Fisheries in the context of attaining sustainable development goals (Sdgs) in bangladesh: Covid-19 impacts and future prospects. Sustainability (Switzerland), 13(17), 1–22. https://doi.org/10.3390/su13179912.

Sunny, A. R., Hassan, M. N., Mahashin, M., & Nahiduzzaman, M. (2017). Present status of hilsa shad (Tenualosa ilisha) in Bangladesh: A review. Journal of Entomology and Zoology Studies, 5(6), 2099-2105.

Tajik, S., Ayoubi, S., & Nourbakhsh, F. (2012). Prediction of soil enzymes activity by digital terrain analysis: Comparing artificial neural network and multiple linear regression models. Environmental Engineering Science, 29(8), 798-806.

Talavera, J. M., Tobón, L. E., Gómez, J. A., Culman, M. A., Aranda, J. M., Parra, D. T., Quiroz, L. A., Hoyos, A., & Garreta, L. E. (2017). Review of IoT applications in agro-industrial and environmental fields. Computers and Electronics in Agriculture, 142, 283–297. Elsevier.

TongKe, F. (2013). Smart agriculture based on cloud computing and IoT. Journal of Convergence Information Technology, 8(2). Advanced Institute of Convergence IT.

Tzounis, A., Katsoulas, N., Bartzanas, T., & Kittas, C. (2017). Internet of things in agriculture, recent advances and future challenges. Biosystems Engineering, 164, 31–48. Elsevier.

Umme, S. M., & Narasegouda, S. (2020). Agricultural IoT as a Disruptive Technology: Comparing Cases from the USA and India. In K. Das, B. S. P. Mishra, & M. Das (Eds.), The Digitalization Conundrum in India (India Studies in Business and Economics). Springer. https://doi.org/10.1007/978-981-15-6907-4_7

Vasisht, D., Kapetanovic, Z., Won, J., Jin, X., Chandra, R., Sinha, S. N., Kapoor, A., Sudarshan, M., & Stratman, S. (2017). Farmbeats: An IoT platform for data-driven agriculture. In NSDI, pp. 515–529.

Waher, P. (2015). Learning internet of things. Packt Publishing Ltd.

Wang, X., Zhang, M., Zhu, J., Geng, S. (2006). Spectral prediction of phytophthora infestans infection on tomatoes using artificial neural network. International Journal of Remote Sensing, 29(6), 1693-1706. https://doi.org/10.1080/01431160600851801

Waterman, J., Yang, H., & Muheidat, F. (2020, December). AWS IoT and the Interconnected World–Aging in Place. In 2020 International Conference on Computational Science and Computational Intelligence (CSCI) (pp. 1126-1129). IEEE.

Yang, Y., Ren, W., Tao, B., Ji, L., Liang, L., Ruane, A. C., Fisher, J. B., Liu, J., Sama, M., Li, Z., & Tian, Q. (2020). Characterizing spatiotemporal patterns of crop phenology across North America during 2000–2016 using satellite imagery and agricultural survey data. ISPRS Journal of Photogrammetry and Remote Sensing, 170, 156-173. https://doi.org/10.1016/j.isprsjprs.2020.10.005

Yang, X., Zhang, S., Liu, J., Gao, Q., Dong, S., & Zhou, C. (2021). Deep learning for smart fish farming: applications, opportunities and challenges. Reviews in Aquaculture, 13(1), 66-90.

Zhang, Y., Ta, N., Guo, S., Chen, Q., Zhao, L., Li, F., & Chang, Q. (2022). Combining spectral and textural information from UAV RGB images for leaf area index monitoring in kiwifruit orchard. Remote Sensing, 14(5), 1063. https://doi.org/10.3390/rs14051063

Zhao, Z., Chow, T. L., Rees, H. W., Yang, Q., Xing, Z., & Meng, F. R. (2009). Predict soil texture distributions using an artificial neural network model. Computers and Electronics in Agriculture, 65(1), 36-48.