Artificial Intelligence, Machine and Deep learning, Internet of Things (Iot) in next Generation Sustainable Agriculture

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Abstract

The Internet of Things (IoT) is revolutionizing both residential and commercial landscapes by enhancing safety, convenience, productivity, monitoring capabilities, and resource optimization across various sectors. In agriculture, IoT and robotics are reshaping traditional practices, from soil preparation to product distribution. Tasks like crop monitoring, intelligent irrigation, pest management, harvesting, and secure distribution are now seamlessly integrated, ensuring efficiency and quality throughout the supply chain. This fusion of technology has led to automated solutions that not only address global food demands but also generate employment opportunities for millions worldwide. Artificial intelligence (AI) spearheads this agricultural revolution, safeguarding production against challenges like population growth, climate volatility, job scarcity, and food insecurity. This chapter aims to scrutinize AI's applications in agriculture, particularly in tasks such as precision spraying, weed management, and irrigation, facilitated by sensor-equipped drones and robots. By minimizing water, pesticide, and herbicide usage, preserving soil health, optimizing labor, and boosting yields, these technologies foster sustainable farming practices. The study delves into automated weeding methods and soil moisture sensing systems, spotlighting two prominent weeding strategies, and explores drone technology's role in crop monitoring and spraying, emphasizing its significance in modern agriculture. Additionally, a Remote Sensing Assisted Control System (RSCS) has been devised to enhance greenhouse farming efficiency, leveraging AI and machine learning to optimize resource allocation and drive innovative agricultural practices. This chapter advocates for strategic marketing initiatives aimed at expanding access to nutritious foods and supporting the growth of local and international organic producers. By prioritizing these recommendations, stakeholders can foster a sustainable food ecosystem while nurturing agricultural innovation on a global scale.

Keywords: Artificial intelligence, Herbicide, Pesticide, Automation, Irrigation.

Introduction

The global population is projected to increase by over a third, or 2.3 billion people, from 2009 to 2050 (Dunwell, J. M. et at.2013). This represents a slower growth rate compared to the past four decades, during which the population expanded by 3.3 billion, or more than 90 percent. Nearly all of this future growth is expected in developing countries, with sub-Saharan Africa experiencing the fastest growth (+114 percent) and East and Southeast Asia the slowest (+13 percent) (Meyers, W. H et al.20120). Urbanization is also expected to accelerate, with urban areas projected to house 70 percent of the global population by 2050, up from 49 percent today (Bhattacharya, B.et al. 2010). In contrast, the rural population is anticipated to peak in the next decade and then decline. By 2050, per capita incomes are forecasted to be significantly higher than today's levels. In the agricultural sector, India's food grain production reached a record 316.06 million tonnes in 2021-22, as per the 2nd Advance Estimates. This figure is 5.32 million tonnes higher than the previous year and 25.35 million tonnes above the five-year average from 2016-17 to 2020-21(Tripathi, S. et al.2022). Record outputs were seen in rice, maize, pulses, oilseeds, gram, rapeseed, mustard, and sugarcane. Analysts agree that developing economies have been growing faster than developed ones, a trend likely to continue. However, not all land is arable due to factors like soil quality, climate, topography, and variability within seemingly homogeneous land. The decline of arable land outpaces its recovery due to pollution, soil erosion, and land degradation, highlighting the need for advancements in agriculture.

Artificial Intelligence

Artificial intelligence (AI) broadly refers to any human-like behavior displayed by a machine or system. At its core, AI involves programming computers to "mimic" human actions using extensive data from past examples (Samoili, S. et al.2022). This can range from distinguishing between a cat and a bird to performing complex tasks in manufacturing facilities.AI encompasses various forms, including deep learning and strategic thinking, primarily applied in scenarios requiring rapid responses (Nishant, R et al.2020). AI systems can process vast amounts of data almost instantaneously, solving problems through supervised, unsupervised, or reinforced learning. Companies like HPE are pioneering AI at the edge, harnessing real-time data for automation, prediction, and control. This approach helps businesses realize the value of their data faster, driving innovation, growth, and success.

A Brief History of Artificial Intelligence

Before 1949, computers could execute commands but couldn't store them. In 1950, Alan Turing's paper "Computing Machinery and Intelligence" laid the groundwork for intelligent machines and testing their intelligence (Ignotofsky, R.et al.2022). The first AI program was presented at the 1956 Dartmouth Summer Research Project on Artificial Intelligence (DSPRAI), sparking decades of research. From 1957 to 1974, computers became faster, cheaper, and more accessible, improving machine learning algorithms. However, limitations in memory and processing speed hindered progress. The 1980s saw a resurgence in AI with an expanded algorithmic toolkit and increased funding. John Hopfield and David Rumelhart introduced "deep learning" techniques, enabling computers to learn from experience. Edward Feigenbaum developed "expert systems" that mimicked human decision-making. Despite fluctuating government funding and public interest, AI achieved significant milestones in the following decades. In 1997, IBM's Deep Blue defeated World Chess Champion Gary Kasparov, and Dragon Systems' speech recognition software was implemented on Windows (McBee, M. P et al.2018). Cynthia Breazeal's robot, Kismet, could recognize and display emotions.

Types of Artificial Intelligence

AI is classified into two main categories: functionality-based and capability-based.

Functionality-Based AI

Reactive Machines: These AIs have no memory and cannot learn from past actions. IBM's Deep Blue is an example.

Limited Memory: These AIs use past information to make better decisions, such as GPS location apps.

Theory of Mind: This AI is under development and aims to deeply understand human minds.

Self-Aware AI: Hypothetical AI that could understand and evoke human emotions and possess its own.

Capability-Based AI

Artificial Narrow Intelligence (ANI): Performs narrowly defined tasks with reactive and limited memory capabilities. Most current AI applications fall into this category.

Artificial General Intelligence (AGI): Capable of training, learning, understanding, and performing like a human.

Artificial Super Intelligence (ASI): Hypothetical AI that would surpass human abilities in data processing, memory, and decision-making. No real-world examples exist today.

AI, Machine Learning, and Deep Learning

Artificial intelligence is a branch of computer science aimed at simulating human intelligence in machines. AI systems use algorithms powered by techniques such as machine learning and deep learning to exhibit "intelligent" behavior.

The Role of IoT and AI in Agriculture

The adoption of Internet of Things (IoT) technologies offers significant advancements in agriculture, providing capabilities such as data acquisition, communication infrastructure, cloud-based data analysis, decision-making, user interfaces, and operational automation (Elijah, O et al.2018). These technologies open new dimensions in agriculture, promoting sustainable food production with minimal resources. This chapter explores the application of IoT in smart agriculture, including practical case studies, white papers, and articles on sustainable food production and implementation challenges. Smart farming, or precision agriculture, leverages advanced technology like big data, the cloud, and IoT for tracking, monitoring, automating, and analyzing agricultural operations. This approach is increasingly important due to the expanding global population, higher crop yield demands, efficient natural resource use, advanced information and communication technology, and climate-smart agriculture needs.

Technological Integration in Agriculture

Agricultural production involves detecting and measuring crops using technologies like remote sensing and fixed position components (Lee, W. S.et al.2010). Combined with deep learning, sensors can map soil and vegetation, monitor crop phenology and height, estimate yields, assess fertilizer impact, detect water stress and drought conditions, manage pests, detect weeds, and monitor greenhouses.

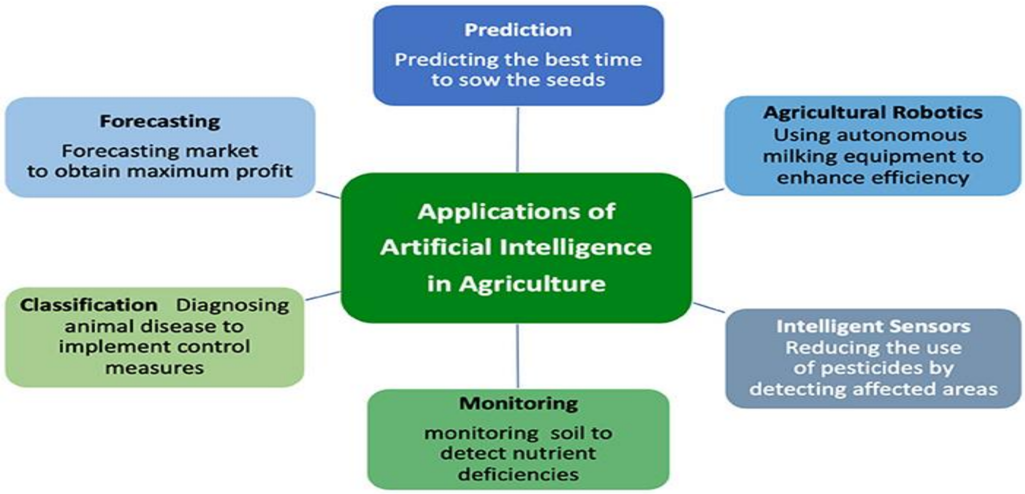

Figure.1: Application of artificial intelligence in agriculture

Smart Agriculture Methods and Techniques

For centuries, humans have strived to enhance food production to meet growing demands. Today, advanced agricultural techniques like vertical farming, hydroponics, and phenotyping have significantly improved with the integration of IoT, making them more efficient and cost-effective. These methods help manage resources efficiently, including inputs, labor, and operations, while also yielding higher outputs. IoT applications in agriculture include geospatial and temporal sampling and mapping, disease and pest monitoring, smart irrigation, and fertilization (Zhang, L et al.2018). Common technologies used in these applications include sensors, UAVs, and IoT-based machinery and communication systems.

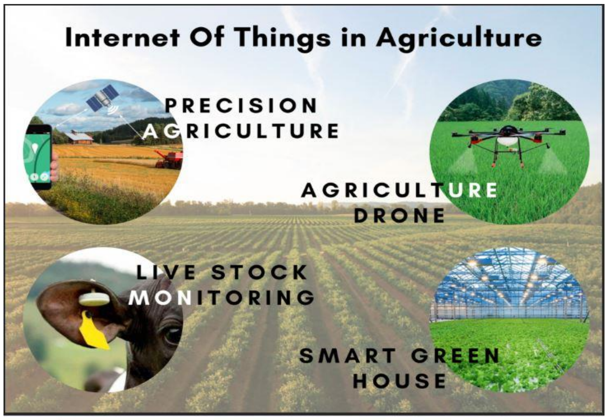

Figure.2: Smart Agriculture Methods and Techniques

Precision Agriculture

Although precision agriculture has existed for some time, it was not viable for small and medium-sized farmers, especially in developing countries like Pakistan. Challenges such as climate change, the food demand-supply gap, urbanization, and declining arable land necessitate new solutions. IoT has enabled a new dimension in precision agriculture, integrating technologies such as WSN, RFID Gateways, cloud computing, communication protocols, middleware components, and user interfaces (Ferrández-Pastor, F. J et al.2016). Precision agriculture focuses on efficient natural resource utilization and environmental protection. Implementing precision agriculture involves four steps: characterizing soil and crop variability, interpreting its significance and causes, managing it spatially and temporally, and monitoring the outcomes (Oliver, M. A et al.2013). IoT facilitates these processes by enabling yield monitoring and the development of spatial and temporal databases for land management.

Remote Sensing Assisted Control System (RSCS)

This paper presents an innovative approach for automated implementation and sensing in agricultural products. It explores IoT technology integration in control networks and communication systems based on real-time agricultural productivity conditions.

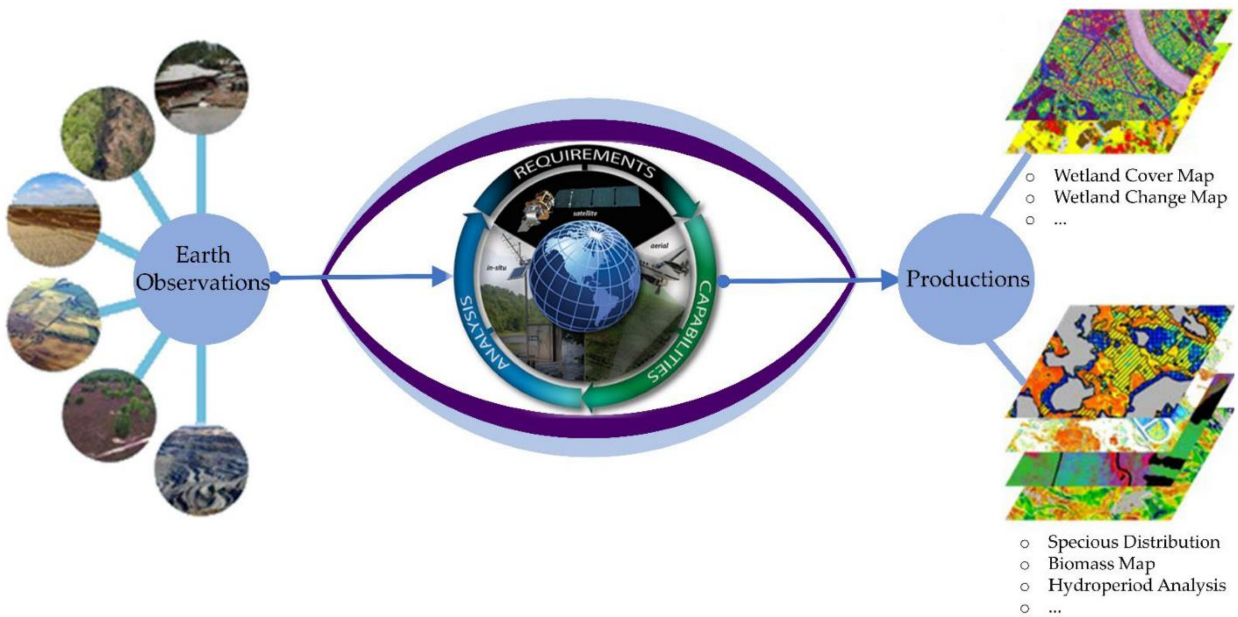

Figure.3: Remote Sensing Assisted Control System use in agriculture

The sensing and actuating system for agricultural and greenhouse production environments utilizes IoT to manage resources efficiently and enhance the development of agricultural products. This system collects real-time data on temperature, moisture, and soil conditions, which is essential for informed decision-making in production.The system includes remote sensing monitoring equipment, data receivers, remote acquisition applications, and mobile web applications. Components like computer vision, robotics, and machine learning help farmers combat weeds and optimize pesticide use through AI. AI can also assist in real-time detection of areas needing irrigation, fertilization, or pesticide treatment, reducing chemical use and enhancing resource efficiency.

Advanced Farming Techniques

Techniques such as vertical farming can increase food production while using fewer resources. Precision agriculture allows farmers to use less water, fertilizer, and seed while increasing yields. Sensors and field mapping provide micro-scale insights into crops, conserving resources, and minimizing environmental impact. IoT technology in agriculture enhances overall performance, knowledge communication, and information transfer between mobile applications.

Green Crop Production

Crop production is a major source of food, including grains, sugar crops, fruits, vegetables, and oil crops. Addressing challenges like soil pollution and nitrogen fixation requires establishing green crop production systems. These systems involve creating new crop plants, using green pesticides, and developing sustainable crop rotation and intercropping systems to achieve high efficiency and resource utilization.

Figure.3: Role of IoT and AI in Green Crop Production

Green crop production aims to transform traditional agriculture into a model with higher productivity, efficient resource use, and minimal environmental impact. This transformation involves green input and management practices, enhancing soil quality and agricultural productivity.

Livestock Production

Livestock production, including meat, eggs, and milk, provides essential nutrients and raw materials for industries like textiles. Managing livestock waste and crop production efficiently is crucial for green agriculture.

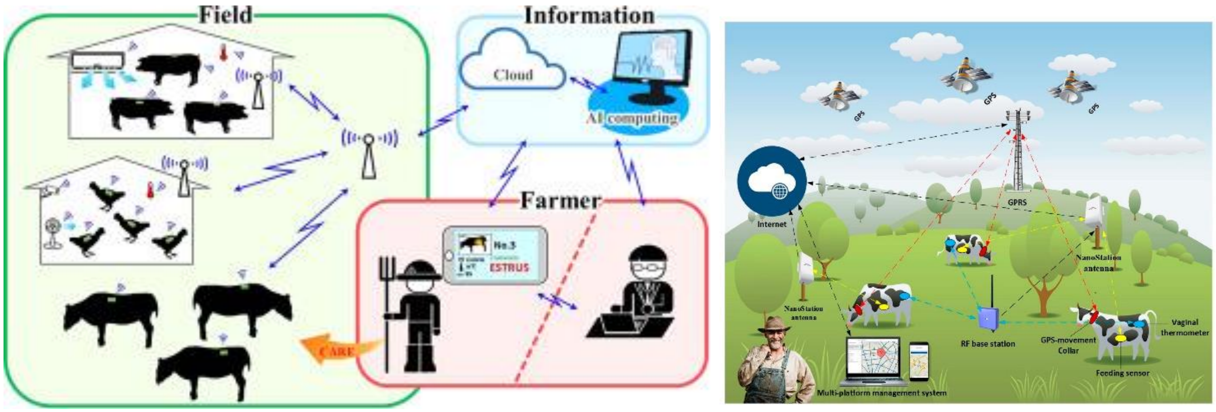

Figure.4: Role of IoT and AI in Livestock Production

Integrated animal-crop systems can optimize nutrient use and reduce pollution by connecting livestock production with crop farming. smart agriculture, facilitated by IoT and other advanced technologies, offers sustainable solutions to meet global food demands. These techniques improve resource efficiency, increase yields, and minimize environmental impact, contributing to a sustainable agricultural future.

Challenges and Future Scope Agriculture:

Agriculture faces numerous challenges including inadequate irrigation, temperature fluctuations, groundwater depletion, food scarcity, and wastage. The future of farming heavily relies on adopting various cognitive solutions, though large-scale research is ongoing and some applications are available, the industry remains underdeveloped (Shobila and Mood et al. 2014). Addressing real-world agricultural challenges with autonomous decision-making and predictive solutions is still in its infancy. For AI to fully realize its potential in agriculture, applications must become more robust (Slaughter et al., 2008). This robustness will enable real-time decision-making, efficient data collection, and adaptation to changing external conditions. One significant barrier is the high cost of current cognitive solutions, which need to be more affordable to ensure widespread adoption among farmers. An open-source platform could reduce costs, resulting in rapid adoption and higher penetration. This would help farmers achieve higher yields and better seasonal crops. In many countries, like India, farmers rely on monsoon predictions for cultivation. AI technology can predict weather and other agricultural conditions such as land quality, groundwater levels, crop cycles, and pest attacks, reducing farmers' uncertainties.AI-driven sensors play a crucial role in extracting important agricultural data, enhancing production. These sensors can provide information on soil quality, weather, and groundwater levels, improving cultivation processes. AI-enabled sensors in robotic harvesting equipment can also gather data, potentially increasing production by 30%. Crop damage due to disasters, including pest attacks, is a significant challenge. Often, farmers lose crops due to a lack of timely information. AI-enabled image recognition can help monitor and protect crops from such attacks. Companies have successfully used drones for production monitoring and pest detection, inspiring further development of crop monitoring systems. For instance, Nature Fresh Farms uses AI algorithms to predict tomato ripening times, aiding sales and improving the bottom line (Bradley).AI is poised to revolutionize agriculture by helping to address the global challenge of feeding an additional 2 billion people by 2050, despite climate change and resource constraints. The United Nations estimates a 50% increase in food production is needed by mid-century. Unlike the past reliance on expanding agricultural land, future gains must come from increased efficiency and sustainability.AI can transform agriculture by enabling farmers to understand hybrid cultivations for higher income within limited time frames. Proper AI implementation will improve cultivation processes and market dynamics. Addressing food wastage through AI algorithms will save time and money, promoting sustainable development. Digital transformation in agriculture, supported by AI, holds great promise, although gathering large datasets remains challenging due to the seasonal nature of production. Nonetheless, farmers are adapting to digital transformation, leveraging AI to enhance agricultural productivity and sustainability.

Summary of Artificial Intelligence and Machine Learning for the Green Development of Agriculture Using IoT Platform:

The Green Revolution has been instrumental in preventing food shortages by combining high-yielding crops, chemical fertilizers, and irrigation, benefitting millions in developing countries (Maddikunta et al., 2021). However, the extensive and often inappropriate use of agrochemicals, particularly chemical fertilizers, has led to concerns about its sustainability and environmental impact (Seyhan et al., 2021). High-yield crops typically demand substantial amounts of fertilizer and water, which poses additional challenges. Greenhouses, constructed primarily from flexible plastic, are designed to enhance crop production by adapting to the growth needs of plants, thereby improving both crop quality and quantity (Shakeel et al., 2020). Traditional greenhouses, especially in arid regions, often overlook crucial environmental factors such as moisture and temperature. Effective greenhouse management requires precise environmental control and multi-parameter management systems. Fresh vegetables are a staple of a healthy diet (Pérez-Pons et al., 2021). However, environmental conditions and food safety are not always guaranteed (Tran et al., 2021). Additionally, there is often a shortage of labor to adequately monitor the planting process (Nguyen et al., 2020). Automated technologies, such as quadcopters, are increasingly being used in agriculture to monitor crop development and meet the growing demand for food production (Manogaran et al., 2021). Innovative irrigation systems, including mechanical and organic systems, ensure efficient allocation and maintenance of water resources (Vangala et al., 2020; Sagheer et al., 2021). Crop productivity is now evaluated with greater emphasis on field conditions and plant health, which are crucial for both profitability and food security (Manogaran et al., 2019). One of the major challenges in modern agriculture is the lack of comprehensive knowledge about agricultural conditions and the slow adoption of emerging technologies (Manogaran et al., 2020). The development of remote sensing technologies for greenhouse environments offers cost-effective solutions for farmers to enhance production (Shamshiri et al., 2020). A well-designed greenhouse with appropriate light sources can maintain optimal temperature, moisture, and light levels necessary for healthy plant growth (Gao et al., 2020; Lv et al., 2020)

Conclusion

The agricultural industry faces several challenges, including ineffective irrigation systems, weeds, difficulties in plant monitoring due to crop height, and extreme weather conditions. However, technological advancements can address these issues and enhance agricultural performance. AI-driven techniques, such as remote sensors for detecting soil moisture content and automated irrigation using GPS, offer significant improvements. Precision weeding techniques help prevent the loss of large quantities of crops during the weeding process. Autonomous robots not only enhance efficiency but also reduce the need for excessive pesticides and herbicides. Additionally, drones enable farmers to spray pesticides and herbicides more effectively and simplify plant monitoring. AI can also address resource and labor shortages in agriculture. Traditional methods required substantial labor to measure crop characteristics like plant height and soil texture, which was time-consuming. Advanced systems now allow for rapid and non-destructive high-throughput phenotyping, offering flexible and convenient operations, on-demand data access, and spatial resolution.

References

Bhattacharya, B. (2010). *Urbanization, Urban Sustainability and the Future of Cities*. concept publishing company.

Dunwell, J. M. (2013). Global population growth, food security and food and farming for the future. *Successful Agricultural Innovation in Emerging Economies: New Genetic Technologies for Global Food Production*, *100*, 23.

Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y., & Hindia, M. N. (2018). An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges. *IEEE Internet of things Journal*, *5*(5), 3758-3773.

Ferrández-Pastor, F. J., García-Chamizo, J. M., Nieto-Hidalgo, M., Mora-Pascual, J., & Mora-Martínez, J. (2016). Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture. *Sensors*, *16*(7), 1141.

Gao, Z., Wanyama, T., Singh, I., Gadhrri, A., & Schmidt, R. (2020). From industry 4.0 to robotics 4.0-a conceptual framework for collaborative and intelligent robotic systems. *Procedia manufacturing*, *46*, 591-599.

Ignotofsky, R. (2022). *The History of the Computer: People, Inventions, and Technology that Changed Our World*. Ten Speed Press.

Lee, W. S., Alchanatis, V., Yang, C., Hirafuji, M., Moshou, D., & Li, C. (2010). Sensing technologies for precision specialty crop production. *Computers and electronics in agriculture*, *74*(1), 2-33.

Lv, Z., Lou, R., & Singh, A. K. (2020). AI empowered communication systems for intelligent transportation systems. *IEEE Transactions on Intelligent Transportation Systems*, *22*(7), 4579-4587.

Maddikunta, P. K. R., Hakak, S., Alazab, M., Bhattacharya, S., Gadekallu, T. R., Khan, W. Z., & Pham, Q. V. (2021). Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges. *IEEE Sensors Journal*, *21*(16), 17608-17619.

Manogaran, G., Alazab, M., Saravanan, V., Rawal, B. S., Shakeel, P. M., Sundarasekar, R., ... & Montenegro-Marin, C. E. (2020). Machine learning assisted information management scheme in service concentrated IoT. *IEEE transactions on industrial informatics*, *17*(4), 2871-2879.

Manogaran, G., Alazab, M., Shakeel, P. M., & Hsu, C. H. (2021). Blockchain assisted secure data sharing model for Internet of Things based smart industries. *IEEE Transactions on Reliability*, *71*(1), 348-358.

Manogaran, G., Shakeel, P. M., Fouad, H., Nam, Y., Baskar, S., Chilamkurti, N., & Sundarasekar, R. (2019). Wearable IoT smart-log patch: An edge computing-based Bayesian deep learning network system for multi access physical monitoring system. *Sensors*, *19*(13), 3030.

McBee, M. P., Awan, O. A., Colucci, A. T., Ghobadi, C. W., Kadom, N., Kansagra, A. P., ... & Auffermann, W. F. (2018). Deep learning in radiology. *Academic radiology*, *25*(11), 1472-1480.

Meyers, W. H., & Kalaitzandonakes, N. (2012). World population growth and food supply. *The role of technology in a sustainable food supply*, 1-16.

Nguyen, T. T., Nguyen, Q. V. H., Nguyen, D. T., Yang, S., Eklund, P. W., Huynh-The, T., & Hsu, E. B. (2020). Artificial intelligence in the battle against coronavirus (COVID-19): a survey and future research directions. *arXiv preprint arXiv:2008.07343*.

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, *53*, 102104.

Oliver, M. A., Bishop, T. F., & Marchant, B. P. (Eds.). (2013). *Precision agriculture for sustainability and environmental protection* (pp. 1-283). Abingdon: Routledge.

Pérez-Pons, M. E., Alonso, R. S., García, O., Marreiros, G., & Corchado, J. M. (2021). Deep q-learning and preference based multi-agent system for sustainable agricultural market. *Sensors*, *21*(16), 5276.

Sagheer, A., Hamdoun, H., & Youness, H. (2021). Deep LSTM-based transfer learning approach for coherent forecasts in hierarchical time series. *Sensors*, *21*(13), 4379.

Samoili, S., Cobo, M. L., Gómez, E., De Prato, G., Martínez-Plumed, F., & Delipetrev, B. (2020). AI Watch. Defining Artificial Intelligence. Towards an operational definition and taxonomy of artificial intelligence.

Seyhan, K., Nguyen, T. N., Akleylek, S., Cengiz, K., & Islam, S. H. (2021). Bi-GISIS KE: Modified key exchange protocol with reusable keys for IoT security. *Journal of Information Security and Applications*, *58*, 102788.

Shakeel, J., Mardani, A., Chofreh, A. G., Goni, F. A., & Klemeš, J. J. (2020). Anatomy of sustainable business model innovation. *Journal of cleaner production*, *261*, 121201.

Shamshiri, R. R., Bojic, I., van Henten, E., Balasundram, S. K., Dworak, V., Sultan, M., & Weltzien, C. (2020). Model-based evaluation of greenhouse microclimate using IoT-Sensor data fusion for energy efficient crop production. *Journal of Cleaner Production*, *263*, 121303.

Shobila, P., & Mood, V. (2014). Automated irrigation system using robotics and sensors. *Int. J. Sci. Eng. Res*, *3*(8), 9-13.

Slaughter, D. C., Giles, D. K., & Downey, D. (2008). Autonomous robotic weed control systems: A review. *Computers and electronics in agriculture*, *61*(1), 63-78.

Tran-Dang, H., & Kim, D. S. (2021). The physical internet in the era of digital transformation: perspectives and open issues. *IEEE Access*, *9*, 164613-164631.

Tripathi, S. (2022). *Time Spent on Unpaid Care Work and Women's Employment Status: Evidence from India* (Doctoral dissertation, Fordham University).

Vangala, A., Das, A. K., Kumar, N., & Alazab, M. (2020). Smart secure sensing for IoT-based agriculture: Blockchain perspective. *IEEE Sensors Journal*, *21*(16), 17591-17607.

Zhang, L., Dabipi, I. K., & Brown Jr, W. L. (2018). Internet of Things applications for agriculture. *Internet of things A to Z: technologies and applications*, 507-528.