Available online at www.rajournals.in

RA JOURNAL OF APPLIED RESEARCH
ISSN: 2394-6709
DOI:10.47191/rajar/v9i6.01
Volume: 09 Issue: 06 June-2023

International Open Access

Impact Factor- 8.174

Page no.- 306-330

Deployment of IoT Sensors in the Revolution of Agriculture

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ARTICLE INFO

Published Online
31 May 2023

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ABSTRACT

Internet of Things sensors are increasingly deployed in sustainable agriculture and food security. This review article discusses the history and importance of agriculture as a source of food and other products for human consumption and the challenges facing the agriculture industry, including climate change, soil degradation, and water scarcity. The various revolutions that have occurred in agriculture were also explored, from the adoption of modern agriculture to the green process and precision agriculture. This article also summarises by exploring the prospects for the fourth agricultural revolution, which centres on deploying technology to foster environmentally responsible farming methods. This review emphasised the significant potential of IoT sensors in agriculture to enhance sustainability and improve food security.

KEYWORDS: IoT sensors, sustainable agriculture, food security, agricultural revolution

I. INTRODUCTION

Agriculture is cultivating soil and crops and raising animals for food, fuel, fibre, and other products. It includes various activities such as preparing the ground, planting seeds or seedlings, watering and fertilising the crops, protecting them from pests and diseases, and harvesting and processing the crops for consumption or sale. Veraart (2018) noted that agriculture also includes plants for fabrics such as cotton, wool, and leather. Agriculture also provides wood for construction and paper products. The development of agriculture since 12,000 years ago has significantly changed how people live. Human societies globally transitioned from a nomadic hunter-gatherer lifestyle to settled communities engaged in agriculture, forming the basis of numerous societies and economies. The development of agriculture has closely intertwined with the growth of the global population, making it the largest industry worldwide. With over one billion people employed in the agricultural sector, it contributes to the production of over USD 1 trillion worth of food annually. Approximately half of the Earth's habitable land is used for pasture and cropland, serving as both habitat and a source of sustenance for various species (National Geographic, 2022).

Agriculture is essential because it provides food for human consumption. Agriculture also plays a vital role in the food supply chain by transporting, processing, and distributing food to consumers. In a study by Nasreddine et al. (2006) on the food consumption patterns of the adult population in an urban area, the average food consumption was about 3 kilogrammes within 450 samples. When we multiply food demand by population size, the data becomes enormous, indicating that food security will become the most significant challenge for the world. The global population is expected to reach 9.7 billion by 2050, representing 20.6% of the current population (Jiang et al., 2008). Climate, accessibility, trade, and culture are just some of the geographic factors that influence the popularity of a food crop in a particular region. Maize, wheat, and rice are the most popular food crops in the world. These crops are often the basis for staple foods (National Geographic, 2022).

Wheat plays a vital role in global nutrition as a staple food. It provides a significant portion of food calories (21%) and protein (20%) for more than 4.5 billion people in 94 developing countries (Bhateshwar et al., 2020). The nutrient composition of wheat green forage has been studied by Mondal et al. (2020), revealing variations in dry matter (74.89%), crude protein (24.16%), crude ash (3.75%), crude fat (5.7%), crude fibre (14.48%), nitrogen-free extractants (26.7%), total carbohydrate (40.79%), and total digestible nutrient (60.76%). Moreover, Anteneh and Asrat (2020) conducted a case study in Ethiopia, observing a consistent growth rate of 4.3% per year in wheat production from 2003 to 2013. However, despite this growth, Ethiopia still faces challenges meeting the demand for wheat due to population growth and dietary changes. In 2013, the production of wheat in Ethiopia reached 4.6 million metric tonnes, while the demand amounted to 6.4 million metric tonnes, resulting in the need to rely on imports to bridge the gap.

According to the research by Gutierrez et al. (2015), there are a variety of factors that affect the factors that determine international wheat prices. Their study emphasises the positive relationship between oil prices and international wheat prices, as higher oil prices lead to increased production and transportation costs for wheat. Moreover, fluctuations in exchange rates and interest rates also significantly impact global wheat prices. Understanding the effects of real and financial shocks on international wheat prices is crucial due to their profound implications for poverty and food security worldwide. In Bosnia and Herzegovina, wheat cultivation has experienced a positive trend, as noted by Dončić et al. (2019). From 2010 to 2016, the area dedicated to wheat cultivation expanded by approximately 1% annually, reaching 63,606.30 hectares. With an average yield of 3.58 metric tonnes per hectare, wheat holds significant economic importance for the country. Examining the relationship between wheat grain yield and drought conditions in Saudi Arabia, Leilah and Al-Khateeb (2005) employed various statistical procedures, including simple correlation, path analysis, multiple linear regression, stepwise regression, factor analysis, principal components, and cluster analysis. Their findings indicate a negative impact of drought conditions on wheat yield. Additionally, Asseng et al. (2014) predicted a decline in global wheat production of approximately 6% for every one-degree Celsius increase in temperature. Their study involved testing 30 different wheat crop models against field experiments, consistently demonstrating that the ensemble median of the models provided more accurate simulations of crop temperature response than any single model, regardless of the input data used.

II. REVOLUTION IN AGRICULTURE

Three pivotal agricultural revolutions have shaped human history and evolution, each marked by significant turning points. The Holocene period witnessed the commencement of plant and animal domestication across various regions globally, likely prompted by climate fluctuations and population growth. Archaeological evidence highlights this transformative shift towards agriculture, which presently accounts for over 80% of the world's food supply and is derived from a small number of plant species domesticated long ago. Similar to the industrial revolution, an agricultural revolution transpired, characterised by substantial advancements in farming techniques within a relatively short timeframe. This revolution aimed to enhance food production efficiency while minimising labour requirements. Herrera and Garcia-Bertrand (2018) argue that despite notable achievements, the agricultural industry confronts several challenges that jeopardise its sustainability and productivity.

The transition from hunting and gathering to agricultural practices marked the onset of the first agricultural revolution approximately 10,000–12,000 years ago. This transformative period witnessed humans domesticating plants and animals, enabling the production of larger quantities of food with greater predictability (National Geographic, 2022) (Figure 1).

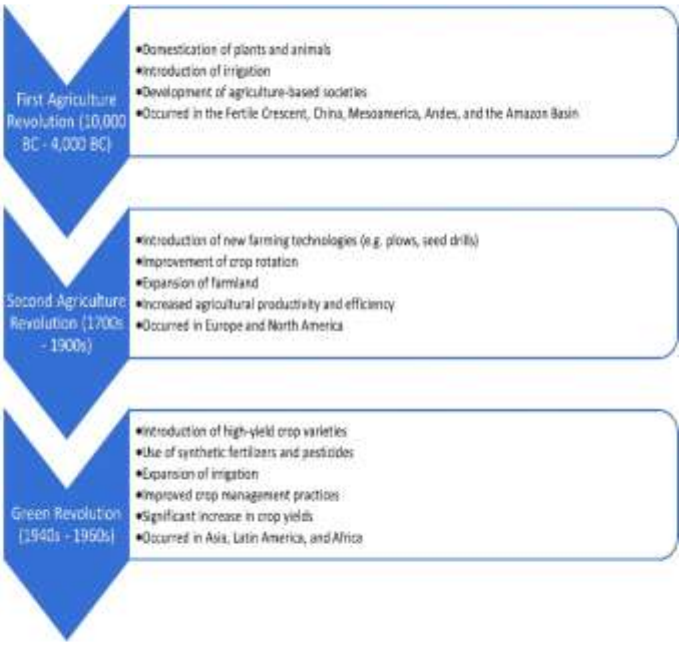

Figure 1: Agriculture revolution

Consequently, sedentary societies emerged, and the foundations of civilization were laid. The second agricultural revolution occurred during the
18th and 19th centuries in Europe and North America. This revolution was characterised by increased agrarian productivity achieved through mechanisation and improved transportation for better access to market areas. It represented a shift from traditional farming methods to modern practices, incorporating mechanisation, scientific techniques, and new crop varieties (Holderness & Beckett, 1991). The third agricultural revolution, also known as the Green Revolution, took place in the mid-20th century. It was a period of significant agricultural innovation that involved product hybridization, genetic engineering, and the widespread use of pesticides and fertilisers. The introduction of high-yielding crop varieties, along with the adoption of chemical inputs and expanded irrigation systems, contributed to increased food production and the alleviation of hunger in many regions worldwide (Campos, 2020). To summarise, the first agricultural revolution initiated modern agriculture, the second revolutionised farming through mechanisation, and the third revolution, known as the Green Revolution, focused on innovation and increased productivity (Clay & Zimmerer, 2020).

To meet the growing demands of a rapidly increasing global population, there is a pressing need for a Golden Revolution in agriculture, as highlighted by Evans and Lawson (2020).

Sustaining constant per capita grain production will require a continuous increase in global grain production. This necessitates the implementation of the fourth agricultural revolution, also known as Agriculture 4.0, which seeks to optimise the value chain of world agriculture through the application of new technologies that bring disruptive solutions at every stage of the agricultural production process (da Silveira et al., 2021). Agriculture 4.0 embraces technology to promote sustainable agricultural practices, leveraging advancements such as biotechnology and Big Data. Science and technology are poised to revolutionise the agricultural sector, enhancing its efficiency and productivity. These developments have given rise to a range of innovative practices in recent years, focusing on precision agriculture technologies that reduce greenhouse gas emissions while maintaining or improving farm productivity and profitability (Barrera, 2011). One example is the research conducted by Balafoutis et al. (2017), which explores how precision agriculture technologies can effectively reduce greenhouse gas emissions in the farming sector. Precision agriculture utilises advanced equipment to apply inputs, such as fertilisers and pesticides, in a targeted manner based on the specific spatial and temporal requirements of each field. By minimising the overapplication of inputs, precision agriculture plays a vital role in reducing greenhouse gas emissions.

However, it is important to acknowledge that the 4.0 revolution in agriculture is currently limited to a small number of innovative companies. The availability of affordable food has accompanied each significant wave of capitalist development, according to Zambon et al.'s (2019) examination of the effects of technological development on various sectors, including industry and agriculture. Successive agricultural revolutions have played a crucial role in expanding food surpluses. The paper identifies the "first" agricultural revolution, which took place during the long sixteenth century, and suggests that signs of its exhaustion began to emerge sometime after 1760 (Moore, 2010).

III. CHALLENGES IN AGRICULTURE

The agricultural revolution has brought about profound transformations in the production, processing, and distribution of food. Technological advancements, improved transportation, and enhanced communication have enabled us to achieve unprecedented levels of food production, contributing to enhanced global food security and improved nutrition. However, despite these achievements, the agricultural industry continues to face numerous challenges that pose threats to its sustainability and productivity. Climate change, soil degradation, water scarcity, pest and disease outbreaks, and shifting consumer preferences are among the many obstacles that farmers, researchers, and policymakers must address. Overcoming these challenges is crucial to ensuring that agriculture can effectively meet the increasing demand for food in the future.

Climate change has had a significant negative impact on the agricultural sector, which has negatively impacted crop yields and global food security. Alam et al. (2011) conducted a study that revealed a decline in crop yields of major staples such as wheat, rice, and maize due to climate change. The research indicated that for every one-degree Celsius increase in temperature, wheat yields decreased by approximately five percent, rice yields declined by three to seven percent, and maize yields decreased by three percent. For example, the drought experienced in California from 2011 to 2017 severely reduced surface water supplies for ecosystems, agriculture, and human consumption, necessitating coordinated efforts to protect water resources. Given that agriculture accounts for the largest water usage in California, a logical response to a severe drought would be to reduce the cultivation of low-value, high-water-use crops such as alfalfa (Cantor et al., 2022).

Ensuring food security has emerged as a critical global challenge, particularly with the projected increase in the global population to 9.7 billion by 2050, which represents 20.6% growth from the current population (Veraart, 2018). Food security encompasses the availability, accessibility, and affordability of food for all individuals. According to the International Food Policy Research Institute (IFPRI) (2014), population growth, climate change, income growth, and the depletion of natural resources can have substantial impacts on food prices and the number of people vulnerable to hunger in developing nations. Without addressing these factors, the report highlights a potential increase in the number of people at risk of hunger in the developing world from 881 million in 2005 to over one billion by 2050. Additionally, the study indicates that the prices of key commodities like maize, rice, and wheat would experience significant increases between 2005 and 2050 if appropriate measures were not taken to address these challenges.

Soil degradation poses a significant challenge in the realm of food security and sustainable agriculture, referring to the decline in the soil's productive capacity resulting from the loss of soil fertility, biodiversity, and overall degradation. Soil degradation can be attributed to various factors, including agricultural, industrial, and commercial pollution; urban expansion leading to the loss of arable land; overgrazing; unsustainable farming practices; and long-term climate changes. Disturbingly, nearly one-third of the world's arable land has vanished over the past four decades, as reported to the United Nations (Maximillian et al., 2019). This global issue is closely connected to increased anthropogenic activities, leading to the presence of pollutants, decreased organic matter content, reduced water-holding capacity, and an increased tendency for nutrient leaching and soil nutrient loss (Mitchell et al., 2022). According to a study by Ferreira et al. (2022), soil degradation affects approximately 33% of the world's land area and significantly diminishes crop yields. Erosion, nutrient depletion, and chemical pollution are key factors contributing to soil degradation. Over the years, there has been a noticeable reduction in usable agricultural land per capita worldwide, decreasing from 0.41 to 0.21 hectares since 1960. The impact of soil degradation has intensified in recent decades, with an estimated 5–10 million hectares of agricultural land being abandoned annually due to land degradation as well as the construction of buildings and infrastructure (Jie et al., 2002). Consequently, only a portion of the land on Earth is arable due to factors such as soil quality, climate, topography, and high variability within the homogeneous land. In addition, the rate of decline of arable land exceeds the recovery rate due to pollution, soil erosion, and land degradation (Gomiero, 2016). Another reason for the occurrence of soil degradation is when farmers apply more fertilisers than crops need or apply them at the wrong time or in the wrong way. Excessive fertiliser application can lead to nutrient imbalances in the soil, resulting in lower crop yields, soil acidification, and contamination of water resources (Kopittke et al., 2019).

Water scarcity poses a significant challenge to agriculture, with agriculture accounting for approximately 70% of global freshwater withdrawals, leading to water scarcity in many regions (FAO, 2017). The availability of naturally hygienic water falling below 1000 m3 per person per year in a country or region is what defines water scarcity, which refers to a situation where water demand exceeds the available supply (Kumari et al., 2021). Water scarcity impacts a larger population within a specific geographic region over extended periods of time. It can arise from natural factors such as low water availability or human-induced activities that degrade existing water resources. Water pollution is a key factor that exacerbates water scarcity by degrading the quality of water resources (Kumari et al., 2021).

Water scarcity occurs when there is insufficient water to meet the needs of both humans and ecosystems simultaneously (White, 2014). It can stem from a fundamental lack of water, known as physical water scarcity. Additionally, economic water scarcity can arise when appropriate infrastructure is lacking to access abundant water resources. Physical water scarcity can be caused by natural phenomena such as drought or human influences like desertification and water storage, with these factors often interconnected (Pereira et al., 2002; White, 2014). For instance, desertification often begins due to water overuse during transient droughts, which are more prevalent in arid regions (Alisher & Jianguo, 2022; World Health Organization, 2018).

The National Integrated Drought Mapping System (NIDMS) has shown that over 42% of the lower 48 states in the US experienced some degree of drought by the end of January (Dan, 2023). The permanence and reversibility of these different processes play a crucial role in understanding their impacts.

In the case of drought and water overuse, for example, the effects may be temporary. Understanding both the consequences and potential mitigation options is crucial in addressing water scarcity (Sabater et al., 2019). According to Shiferaw et al. (2003), increasing private irrigation investment and the depletion of freely accessible aquifers in many drylands are major factors contributing to groundwater depletion. Frequent droughts and water scarcity pose significant challenges to improving agricultural productivity and livelihoods, especially in rain-fed tropics like India. Groundwater depletion can further exacerbate these problems and reduce agricultural productivity, leading to negative economic and environmental consequences. It is important to note that increased investment in irrigation has also resulted in a shift towards water-intensive irrigated crops, a practice that may need to be reconsidered in water-scarce areas.

By reassessing cropping patterns, implementing efficient irrigation practices, promoting water conservation measures, and exploring alternative water sources, it may be possible to mitigate the impact of water scarcity on agricultural productivity and reduce the strain on water resources in water-scarce regions. Integrated water management approaches that consider the needs of both agriculture and the environment can play a crucial role in achieving sustainable water use and addressing water scarcity challenges.

The rate of urbanisation is rapidly increasing. According to Desa (2018), it is projected that by 2050, 68% of the global population will reside in cities, a significant increase from the 54% reported in 2018. This urban migration will lead to a decline in available arable land. People are attracted to urban areas for various reasons, such as the potential for economic prosperity and employment opportunities. By 2050, urban regions will be home to two-thirds of the world's population, which currently represents half of the total population. However, urban areas also face significant challenges, including poverty and environmental degradation. The concentration of people in urban spaces exacerbates problems such as poor air and water quality, limited water supply, waste management issues, and high energy consumption. Addressing these and other challenges in urban areas will require effective city planning, as highlighted by National Geographic (2016).

According to Tellnes (2005), urbanisation brings about positive changes in people's lives by creating more educational and employment opportunities, improving infrastructure and public transportation, promoting cultural diversity and exchange, and driving economic growth and development. However, urbanisation also has negative consequences. Unlike rural areas where the soil and vegetation can absorb and reflect energy, urban landscapes consisting of concrete, asphalt, and bricks retain heat, resulting in warmer nights. Pollutants are often dispersed throughout urban areas or concentrated in industrial zones and landfills. For instance, lead-based paint, previously used on roads, highways, and buildings, has contaminated the soil. Additionally, large quantities of waste are dumped into municipal and industrial landfills, posing environmental challenges. Lastly, urbanisation has contributed to a decline in water quality over time, leading to increased sedimentation and the presence of pollutants in runoff (Bhuvandas et al., 2012).

Crop losses and decreased agricultural productivity can be attributed to the presence of pests and diseases. One example is the fall armyworm (FAW), a destructive pest that targets maize crops and has had a significant impact on several African countries. The infestation of this pest leads to annual maize production losses ranging from 45% to 67%, resulting in a financial burden of over USD 6.2 billion. To combat this issue, researchers have proposed an integrated pest management (IPM) system utilising push-pull technology (Khan et al., 2018). This approach involves planting intercrops of pest-repelling plants to deter pests from the main crop and trap plants to attract and trap them. Additionally, this method enhances soil fertility, prevents further soil degradation, and promotes the presence of natural parasitoids and predators in the area (Niassy et al., 2022).

Consumer preferences in the realm of food are undergoing a transformation, as there is a growing inclination towards locally produced, sustainable, and organic food options. This shift in demand has had a notable impact on farming practices, particularly in the United States, where the organic food market has experienced substantial growth. Consequently, farmers have been compelled to adapt their methods accordingly. The adoption of organic farming practices has gained momentum both at the national and international levels. Nevertheless, farmers face challenges when transitioning to organic farming, including the USDA's three-year transition period and the increased production costs and risks associated with organic agriculture (Klonsky & Greene, 2005).

The agricultural sector in numerous countries is grappling with challenges related to migration and labour shortages. As highlighted by Sommarribas et al. (2015), factors such as ageing populations, rapid technological advancements, increased demand for highly skilled labour, and economic uncertainties in European nations contribute to this crisis. The lack of an adequately trained agricultural workforce can lead to reduced output, lower productivity, heightened labour costs, and delays or cancellations of projects. The report further discusses several strategies implemented by various Member States to manage economic migration, including the use of quotas, labour market assessments, points-based systems, and other measures. These tools aim to address observed labour shortages by, for instance, exempting third-country nationals seeking employment in occupations facing a shortage from labour market testing.

IV. RECENT CASES IN AGRICULTURE

These concerns exert a significant influence on the acceptance and advancement of agriculture. With the global population on the rise and increasing demand for food, the challenge of meeting the world's food requirements through agriculture has become increasingly critical. Consequently, the price of eggs, which serve as a vital source of protein for many individuals, has been steadily climbing over time. Egg purchases have become exceptionally costly, with the average price of a dozen eggs in the United States reaching USD 4.25 in December 2022, more than twice the price compared to the previous year. According to the Minister of Domestic Trade and Consumer Affairs, Datuk Seri Alexander Nanta Linggi (Ashley, 2023; Williams, 2023), the escalating operational expenses for poultry breeders have compelled them to downsize their livestock, leading to disruptions in the supply of chicken eggs across various states' marketplaces. The production of these eggs relies on the hens that lay them, and similar to other factors, the increased cost of feeding hens their traditional diet of grains like corn, oats, and barley has impacted egg farmers.

In addition, a significant proportion of the global wheat and grain supply originates from Russia and Ukraine. The United States Department of Agriculture (USDA) identifies Russia and Ukraine as key producers and exporters of wheat and grains. For the 2021–2022 marketing year, Russia is projected to be the largest wheat exporter globally, with Ukraine ranking third. The USDA estimates that Russia's wheat exports will reach 38 million metric tonnes, while Ukraine's wheat exports are expected to reach 20 million metric tonnes in the same marketing year. Furthermore, both Russia and Ukraine play substantial roles in corn and barley exports, which are essential grains in the global food trade (USDA, 2023a). However, due to the conflict in Ukraine last year, these shipments were significantly constrained, leading to a global supply shortage and subsequent price increases. Egg farmers have been grappling with escalating energy costs for farm operations, higher fuel prices for transportation, and more expensive chicken feed. In 2022, the emergence of highly contagious avian influenza resulted in a significant decline in US egg production. Over 44 million egg-laying hens, accounting for approximately one in ten of the pre-outbreak population, perished as farmers culled infected flocks to prevent the spread of the disease. It takes several months for farmers to resume egg production after an outbreak, as they must clean facilities, introduce new chickens, wait for them to mature and start laying eggs, and eliminate any contaminated flocks. Despite recent price increases, the demand for eggs has remained steady. Experts suggest that more substantial price hikes would be required to slightly reduce demand. Currently, even if only the more expensive egg cartons are available on grocery store shelves, it is likely that consumers will still purchase them. Some individuals have sought alternatives, such as plant-based options (Ashley, 2023).

Moreover, there has been a notable decline in fruit and vegetable sales among major retailers in the UK due to shortages. According to governments and businesses, the situation has worsened due to unfavourable weather conditions in Spain and North Africa. The British Retail Consortium (BRC) reported a rise in overall shop price inflation to 8.9% in February, the highest increase since records began in 2005 (The Sun Daily, 2023). According to farmers in one of the UK's prominent agricultural regions, the shortage of certain fruits and vegetables may persist until May (Smith, 2023). Additionally, it is predicted that prices for fruits and vegetables will continue to increase in 2023 (USDA, 2023). Similarly, the retail price of tomatoes in Malaysia has reached a record high of RM 12 per kg, while the wholesale price stands at RM 10 per kg. This price surge can be attributed to the impact of the rainy season in January on agricultural regions like Johor and Cameron Highlands (San, 2023).

The scarcity of eggs, crops, and vegetables is a significant concern that can be attributed to the evolution of agriculture. Meeting the demands of a growing global population and increasing food requirements may necessitate moving beyond traditional farming methods. In this regard, agriculture technology, particularly the Internet of Things (IoT), plays a crucial role. By employing IoT sensors, farmers can monitor crucial factors like crop growth, soil moisture levels, and temperature, enabling data-driven decision-making and optimising crop yields. Furthermore, IoT-enabled smart farming allows for better livestock monitoring and control, leading to improved animal health and increased egg production. The integration of IoT in agriculture is part of the broader agricultural revolution that has been unfolding for centuries. As technology continues to advance, more innovative solutions are expected to emerge to address the challenges faced by the agriculture sector (Boursianis et al., 2022). Notably, the Internet of Things (IoT) in agriculture market analysis and size has been witnessing growing demand. According to Data Bridge Market Research, the IoT in agriculture market was valued at USD 13.76 billion in 2022 and is projected to reach USD 29.71 billion by 2030, with a compound annual growth rate (CAGR) of 10.10% during the forecast period from 2023 to 2030.

Furthermore, one of the most significant emerging global public health concerns is antibiotic resistance, which poses a serious threat. The misuse of antibiotics by farmers in animal farming is believed to contribute to this challenge. Krnjaić et al. (2005) conducted a study that demonstrated the presence of antibiotic resistance in most isolated E. coli strains. Similarly, Eltayb et al. (2012) found that many farmers lacked awareness of antibiotic resistance and the potential transfer of zoonotic infections between humans and animals. This study emphasises the urgent need for interventions to address the knowledge and practical gaps related to antibiotic use and resistance in animal farming, particularly in Sudan. McKellar (1999) discusses the therapeutic use of antibiotics in animals, where the aim is to treat bacterial infections at an appropriate concentration and duration to ensure recovery. However, the paper also highlights the importance of prudent antibiotic use, even for therapeutic purposes, to minimise the exposure of non-target bacteria in the animal’s gut to selection pressure for resistance.

V. IOT AND SMART AGRICULTURE

The agriculture sector has the potential to undergo a transformative revolution through the adoption of the Internet of Things (IoT), which addresses the numerous challenges it faces. IoT refers to a network of interconnected devices that autonomously gather and exchange data through the Internet. These devices include sensors, actuators, and intelligent machines capable of communication. By providing real-time data on critical factors like crop growth, soil moisture, and weather conditions, the IoT has the power to effectively address agricultural challenges. This ground-breaking technology is reshaping the current world by creating an intelligent environment with trillions of sensors and actuators. The scientific research community recognises the immense potential of sensors, considering them a promising field. The widespread deployment of sensors allows for shared information, fostering the development of a common operating picture. In various IoT applications, sensors play a crucial role in creating intelligent environments (Sehrawat & Gill, 2019). The integration of IoT technology enhances business and industrial performance by facilitating data collection, analysis, and decision-making processes. Real-time data from IoT devices offers valuable insights into various aspects of business operations, including inventory levels, equipment performance, and customer behaviour. This data can be utilised to optimise processes, reduce costs, and enhance overall efficiency. Furthermore, IoT technology enables predictive maintenance, effectively preventing equipment failures and minimising downtime (Villamil et al., 2020).

The Internet of Things (IoT) is a concept that has been defined differently by various authors, reflecting its evolving nature and the diverse perspectives surrounding it. Villamil et al. (2020), as well as Yadav and Kumar (2021), emphasise the absence of a standardised definition or architecture for IoT, highlighting the ongoing discussions and challenges associated with its increasing popularity. Nord et al. (2019) describe the IoT as the interconnection of machines and devices through the internet, generating valuable data for analytics and supporting new technologies. Sengupta et al. (2020) view the IoT as a network of interconnected static and mobile objects equipped with communication, sensors, and actuators connected through the internet. Luthra et al. (2018) define the IoT as a system wherein physical objects establish independent communication among themselves. Asplund and Nadjm-Tehrani (2016) perceive the IoT as internet-connected embedded systems that can be upgraded and adapted to changing needs, enabling efficient fault diagnosis and system restarts. Wang et al. (2022) highlight that IoT involves connecting sensing devices to the internet for information exchange. Siboni et al. (2019) conceptualise the IoT as a global ecosystem of information and communication technologies aimed at connecting any object, anytime and anywhere, to each other and the internet. Al-Kadhim and Al-Raweshidy (2019) point out that the IoT comprises a vast number of sensor nodes with limited processing, storage, and battery capabilities. These different perspectives collectively contribute to our understanding of the IoT and its multifaceted nature.

Smart materials represent a subset of smart systems or smart structures operating at microscopic or mesoscopic scales. Unlike conventional machines, they exhibit characteristics similar to those of biological systems. According to Kamila (2013), smart materials are a class of substances capable of altering their properties under controlled conditions. They have the ability to receive, transmit, or process stimuli and respond by producing beneficial effects. These materials are also referred to as intelligent or responsive materials and can be categorised into two types: active and passive. Active smart materials can transduce energy and serve as sensors, actuators, or transducers, while passive smart materials function as sensors but lack actuation or transduction capabilities. The applications of smart materials span various fields such as engineering, medicine, and the environment. Recent studies have explored different types of smart materials, including covalent organic frameworks (COFs), magnetic iron oxide-fabricated layered double hydroxide/cellulose composites (Fe_3O_4@LDH/poly), polydiacetylene (PDA), and lipoyl ester-terminated star poly(lactic-co-glycolic acid) (sPLGA-LA) (Ammavasi & Mariappan, 2018; Gan et al., 2022; Huo et al., 2017; Wang et al., 2018). These materials possess adaptive structures that enable them to excel in their respective environments, outperforming traditional materials.

Smart agriculture leverages technology, data analytics, and sensors to enhance agricultural production and operational efficiency. This approach involves gathering data from diverse sources, analysing it, and utilising the insights gained to better manage crops, livestock, and agricultural resources. The adoption of Internet of Things (IoT) solutions in agriculture is steadily increasing, with COVID-19 even positively impacting the market share of IoT in the agricultural sector. The disruptions caused by the pandemic in supply chains and the scarcity of skilled labour have contributed to a compound annual growth rate (CAGR) of 9.9% (Baltic et al., 2021; The Heavy Impact of COVID-19 on the Agriculture Sector and the Food Supply Chain, Penang Institute, 2020). In fact, recent reports suggest that the market share of intelligent farming is projected to reach USD 28.56 billion by 2030.

Numerous studies have compared the yields of IoT-based agriculture with conventional farming methods. For instance, in a study published in the Journal of Sensors, researchers examined the cultivation of greenhouse cucumbers using IoT-based systems compared to traditional methods. The findings indicated that the IoT-based approach resulted in higher yields (40%), reduced water consumption, and improved plant quality (Lasantha & Adikaram, 2020). Similarly, a study by Kayad et al. (2021) observed a 31% average increase in corn yield over ten years, with yields surpassing 14 tonnes/ha of dry matter in 2018. While the overall yield increased, the application of nitrogen decreased by approximately 23%, leading to an increase in partial factor productivity from less than 54 to about 87 kg of corn grain per kg of nitrogen applied. In another study featured in the Journal of Sensors, researchers compared the yield of IoT-based tomato cultivation with conventional methods. According to a survey conducted by Akhter and Sofi (2022), precision agriculture based on IoT can potentially enhance crop yields by up to 10%, reduce water usage by up to 70%, and minimise chemical usage by up to 90%. IoT sensors enable the monitoring of soil moisture, temperature, and nutrient levels, empowering farmers to optimise irrigation and fertilisation practices. Furthermore, research on monitoring the health, behaviour, and stress of cows using prototype IoT-based systems has shown promising results in animal farming (Evstatiev et al., 2022).

VI. APPLICATION OF IOT/SMART FARMING

IoT technology plays a crucial role in supporting farmers by enabling real-time monitoring and analysis of essential data such as soil moisture, temperature, humidity, and more. This data can be utilised to optimise irrigation, fertilisation, and other inputs, leading to increased crop yields and improved crop quality. According to Vitali et al. (2021), the IoT has the potential to assist in crop management by providing affordable devices that can sense crop fields and alert a broader range of farmers about stress conditions and diseases in a timely manner. Furthermore, this technology enables reliable storage, access to diverse data, and the implementation of machine learning techniques to develop and deploy farm services. Overall, the IoT enhances crop management by providing farmers with precise and timely information, empowering them to make informed decisions and improve their crop yields.

For instance, CropX offers a soil moisture monitoring system that employs IoT sensors to provide real-time data on soil moisture levels, enabling farmers to optimise irrigation practices and reduce water usage. They can also make informed decisions regarding fungicide application, monitor nitrogen absorption by plants, and identify salt accumulation in the soil (Dan, 2023). Additionally, John Deere's Field Connect system, as utilised by Vitali et al. (2021), employs IoT sensors to monitor soil moisture, temperature, and other environmental factors in crop fields. The gathered information is transmitted to a cloud-based platform, allowing farmers to access it and optimise their irrigation and fertilisation practices.

Weather stations equipped with smart farming sensors are among the most popular IoT devices in intelligent agriculture. These stations are strategically placed across fields to collect environmental data, which is then sent to the cloud. The gathered measurements can be used to map climate conditions, select suitable crops, and implement precision farming techniques to enhance crop productivity (Alexey, 2023). Adoghe et al. (2017) emphasise the significance of smart weather stations in providing localised and timely weather information to local communities in Africa, as access to short-term forecasts remains limited. These stations, developed by integrating meteorological sensors with microcontrollers, significantly reduce the cost of obtaining accurate, localised weather information, contributing to food security in arid and semi-arid African countries. Notable examples of such agriculture IoT devices include allMETEO, Smart Elements, and Pycno. By effectively monitoring crop growth and detecting anomalies, farmers can proactively prevent diseases and infestations that may harm their yields. Real-life applications of this approach can be seen through companies like Arable and Semios (Alexey, 2023). However, it is important to note that different monitoring technologies may introduce variability in the accuracy of measured weather parameters (Tenzin et al., 2017). Moreover, agro-weather solutions should be customised and affordable for small-scale farmers in developing countries (Faid et al., 2022).

The use of IoT sensors in livestock management offers valuable insights into the health and behaviour of animals. These sensors play a crucial role in smart livestock management, allowing farmers to remotely monitor the biological and environmental data of their livestock. By doing so, it improves livestock production efficiency while reducing physical labour and associated costs. This technology revolutionises livestock management by establishing a connection between IoT sensor data and farmers located in remote areas through cloud-based platforms. Consequently, farmers can make informed decisions regarding their livestock and enhance their overall management practices. For instance, IoT sensors can effectively monitor temperature and humidity levels in barns, ensuring optimal conditions for animal comfort and well-being. Prominent companies, such as Allflex, provide a range of smart ear tags and collars that enable the monitoring of individual animal location, activity, and health. Cainthus offers a computer vision system that utilises cameras to monitor the behaviour and health of animal groups. Connecterra introduces a collar-mounted sensor employing machine learning to monitor the behaviour and health of individual cows. Moreover, Quantified AG provides a comprehensive system that employs sensors to monitor the weight, feed intake, and behaviour of animal groups (Iwasaki et al., 2019).

Marine agriculture faces various challenges related to environmental monitoring, fish farming operations, and sustainability. The Internet of Things (IoT) offers solutions to address these challenges by enabling real-time data collection and analysis. One notable project, SmartOysters, utilises IoT sensors to monitor water quality and temperature in oyster farms, empowering farmers to optimise their operations and enhance product quality (Xu et al., 2019). Tseng et al. (2018) emphasise the importance of reducing energy consumption and ensuring sustainability. They propose the Sustainable Fish Farming System (SFFS) prototype, which integrates solar cells and LEDs to enhance energy efficiency and support photosynthesis during the night, surpassing traditional pumping methods.

In the realm of precision agriculture (PA) or smart farming, intelligent data collection plays a vital role in assisting farmers with informed decision-making and improving overall productivity. Advanced technologies like unmanned aerial vehicles (UAVs) and multispectral optical sensors are employed to collect data efficiently and accurately. Various applications of intelligent data collection include Geographic Information Systems (GIS) for spatial data analysis and management, Free and Open-Source Software (FOSS) for data processing and sharing, and WebGIS platforms for interactive data visualisation and collaboration (Belcore et al., 2021). IoT devices equipped with sensors gather valuable information such as climatic conditions, soil quality, and crop progress, allowing for comprehensive farm monitoring, worker performance evaluation, and appliance efficiency assessment.

Predictive analytics encompasses empirical methods that generate data predictions and plans to evaluate predictive power. These techniques, including statistical models and other approaches, contribute to the creation of practical and useful models (Shmueli & Koppius, 2011). In the agricultural domain, IoT data plays a crucial role in developing predictive models that assist farmers in anticipating and managing potential risks. For instance, IoT sensors can monitor weather patterns and soil conditions to predict the likelihood of pest infestations and disease outbreaks. By leveraging this information, farmers can take proactive measures to mitigate these risks. Intelligent agriculture sensors collect vast amounts of data, including weather conditions, soil quality, crop growth progress, and livestock health. This data serves to monitor overall farm performance, assess staff efficiency, and evaluate equipment effectiveness (Sabu & Kumar, 2020). Predictive analytics in agriculture also offers the ability to forecast agricultural commodity prices, enabling stakeholders along the supply chain to make informed decisions about minimising and managing price fluctuations. Farmers can optimise their crop selection and timing of sales to maximise profits and mitigate losses due to market volatility. Furthermore, food processors and retailers can strategize their procurement and inventory management, ensuring a stable supply of food products for consumers. This stability reduces uncertainty and fosters economic efficiency throughout the agriculture supply chain, benefiting both producers and consumers. Ultimately, effective price risk management is crucial for the long-term viability and sustainability of the agriculture industry.

This has led to the emergence of precision farming, also known as precision agriculture, which emphasises efficiency and data-driven decision-making. Precision farming challenges the conventional practice of uniformly treating fields with fertilisers and pesticides, proposing instead that farmers adopt a "by the inch" approach to address yield variations within a plot. It utilises various tools and techniques such as yield monitors, satellite imagery, yield mapping, soil mapping, and precision drilling. The primary goal of precision farming is to enhance efficiency and minimise waste in agricultural practices (Tsouvalis et al., 2000).

Yield mapping, a precision farming technique, involves using yield monitors to measure crop yields across a field. The data obtained from yield maps, combined with other information like soil maps, soil sampling and analysis, weather records, weed maps, assessments of pest and disease levels, chlorophyll monitors, and the farmer's expertise, can be utilised to optimise input levels and ensure optimal crop output. Research conducted by Weis et al. (2008) indicated that site-specific techniques could be employed for weed detection and management in precision farming. For instance, weed maps can be automatically generated using systems capable of discriminating between different weed species and crops based on images. Additionally, models for estimating the yield impact of weeds have been developed and applied in on-farm research experiments. Companies like Mothive offer similar services, aiding farmers in waste reduction, yield improvement, and the promotion of sustainable farming practices.

Agricultural drones, also known as UAVs (uncrewed aerial vehicles), represent a promising technological advancement in intelligent farming. Drones outperform aeroplanes and satellites in collecting agricultural data, and their applications in precision farming are diverse. UAVs can monitor crop health, conduct soil analysis, manage irrigation, and assist in pest control. Equipped with advanced sensors and imaging capabilities, these drones provide farmers with innovative methods to increase yields and minimise crop damage (KRISHNA, 2021). In addition to surveillance capabilities, drones can also perform tasks that previously required human labour, including crop planting, pest and disease control, agriculture spraying, and crop monitoring. For example, DroneSeed develops drones for reforestation projects, achieving six times the efficiency of human labour. The senseFly eBee SQ Drone utilises multispectral image analysis to assess crop health and is available at an affordable price (Dileep et al., 2020). Agricultural drones come in various types, including fixed-wing, multi-rotor, and hybrid drones. Fixed-wing drones excel at covering large areas quickly, while multi-rotor drones are more suitable for smaller spaces and precise tasks. Hybrid drones combine the advantages of both types to optimise performance in different scenarios.

The concept of the "expert-farmer interface" is discussed in the research conducted by Tsouvalis et al. (2000). This term refers to the interaction between agricultural experts and farmers, specifically in the context of implementing precision farming techniques. The study explores the challenges that arise due to the different knowledge cultures of experts and farmers, emphasising the importance of understanding these cultures for effective communication and collaboration. An example of such challenges is evident in how experts and farmers perceive and utilise technology. The paper cites a farmer who expressed, "They have had to get better and need to be brighter to understand modern technology. No place for thick old farm hands." This quote highlights the potential intimidation or exclusion some farmers may feel towards new technologies, while experts may assume resistance to change or an unwillingness to learn. By recognising and appreciating these different perspectives, experts and farmers can enhance their cooperation and effectiveness.

In agriculture, waste can originate from various sources, including crop residues, animal manure, and agricultural chemicals. Waste in agriculture encompasses water, fertilisers, pesticides, and energy; its improper management can have detrimental environmental impacts. IoT sensors play a crucial role in reducing wastewater in agriculture by enabling farmers to optimise inputs and minimise the excessive use of water, fertilisers, and pesticides. Intelligent devices can accurately detect any abnormalities in crop conditions, leading to cost reductions and a more sustainable agricultural system. For instance, Blue River Technology offers a smart weeding system that utilises machine learning and computer vision to identify and target weeds, thereby reducing the need for herbicides (Yeshe et al., 2022).

As a result, the prevention of crop yield-damaging infestations becomes more efficient. Moreover, cost savings can be achieved through streamlined irrigation and fertilisation processes. Agricultural machinery is equipped with sensors that provide valuable soil information. Additionally, these sensors can be programmed to send notifications indicating the optimal harvest time (Yang et al., 2021). Consequently, agricultural waste can be significantly reduced. The combination of IoT and intelligent sensor technology offers real-time data that can be analysed to make informed predictions about crop harvesting time, disease and infestation risks, and expected yield volume. Leveraging data analytics tools makes crop management and prediction more feasible, particularly considering their dependence on weather conditions. For instance, a crop performance platform grants farmers access to advanced information regarding yield volume, quality, and vulnerability to adverse weather conditions like floods and droughts. It also empowers farmers to optimise water and nutrient supply for each crop and select desired yield traits to enhance quality. Implementing solutions like SoilScout in agriculture can potentially reduce irrigation water usage by up to 50%, minimise fertiliser losses caused by excessive watering, and provide actionable insights regardless of the season or weather conditions (Lal et al., 2023). In summary, IoT-based smart agriculture has the potential to assist farmers in waste reduction and sustainability improvement by providing real-time data and automation to optimise farming practices.

IoT technology has played a role in reducing environmental pollution in agriculture. Agricultural activities can contribute to pollution through the use of pesticides and fertilisers, as well as the generation of farm waste. Zhu (2004) mentioned that non-point sources account for a growing proportion of environmental water pollution, with farming being the most significant factor among agricultural non-point sources. Conway et al. (2009) stated that agriculture can cause different types of pollution, including:

1. Pesticide pollution: Pesticides used in agriculture can contaminate water bodies, such as rivers and lakes, leading to the death of aquatic organisms. For example, the use of the pesticide DDT in the mid-20th century led to the decline of bird populations, such as the bald eagle, due to the accumulation of the pesticide in their bodies (Tiwana et al., 2009).
2. Fertiliser pollution: Excessive use of fertilisers can lead to the contamination of groundwater, causing health problems for people who rely on it for drinking water. For example, in the midwestern United States, the use of fertilisers has led to the contamination of the Ogallala Aquifer, which provides drinking water for millions of people (Li & Zhang, 1999).
3. Farm waste pollution: Improper disposal of animal waste can lead to the contamination of nearby water bodies, causing negative impacts on aquatic ecosystems. For example, in North Carolina, large-scale hog farms have been linked to the contamination of rivers and streams with animal waste (BECK, 1989).
4. Air pollution: Agriculture can contribute to air pollution through the release of greenhouse gases such as methane and nitrous oxide, as well as through the emission of particulate matter from farm machinery and the burning of crop residues. For example, in California's Central Valley, air pollution from agriculture has been linked to respiratory problems in nearby communities (Aneja et al., 2009).

Wallace and Kock (2012) introduced the concept of the "food footprint" to examine the interplay between food, agriculture, and the environment. The food footprint refers to the environmental impact associated with food production and consumption, encompassing factors such as greenhouse gas emissions, water usage, and land utilisation. Jaiswal and Agrawal (2020) highlight that the agriculture sector significantly contributes to greenhouse gas (GHG) emissions, referred to as the carbon footprint of agriculture. According to the Food and Agricultural Organization (FAO), agriculture is responsible for approximately 14% of global GHG emissions (FAO, 2022). In their study, Korunoski et al. (2019) proposed a model that identifies the evolution of pollution fields and the potential sources of air pollution. By utilising deep learning techniques, future pollution levels and the time required to reach critical thresholds can be predicted. Deploying this system on an IoT sensing architecture enhances data spatial resolution and performance. Simultaneously, Saha et al. (2017) focus on leveraging IoT technology to prevent air and noise pollution. Their system employs sensors such as the UVI-01 sensor for ultraviolet light detection and the 2-in-1 temperature and pH sensor to monitor water quality. The collected data is then transmitted to the cloud for analysis. The Precision Agriculture Technologies (PAT) highlighted by the European Commission et al. (2019) contribute to greenhouse gas emission reduction through various means. These technologies enable the precise application of fertilisers and inputs, reducing excess nutrient usage that contributes to GHG emissions. They also minimise tillage, which can release carbon from the soil into the atmosphere; optimise irrigation to conserve water and energy; and utilise sensors and other technologies to monitor crop growth and health, facilitating informed decision-making regarding input application. For example, machine guidance and variable-rate nitrogen application technologies effectively reduce excess nutrients contributing to GHG emissions.

Giles et al. (2011) conducted research on target-sensing sprayer technology for pesticide application on plants. This technology offers environmental and economic benefits by reducing pesticide wastage that does not reach the intended target, thereby lowering pesticide usage rates and deposition in non-target areas. In multi-season experiments, it was observed that this technology could reduce pesticide application rates by 15% to 40% and nontarget orchard floor deposition by 5% to 72%.

Traceability involves tracking and tracing the entire production process of a product or item, from raw material sourcing to the end consumer (Chun-Ting et al., 2020). The European Commission (2013) emphasises that monitoring the movement of food products will possibly enable the rapid identification of contamination or foodborne illness sources so that appropriate actions can be taken to prevent further spread, thus ensuring food safety.

Traceability plays a crucial role in identifying supply chain bottlenecks and inefficiencies, enabling improvements that reduce waste and enhance productivity. The Food and Agriculture Organization of the United Nations (2018) emphasises the importance of meeting regulatory requirements in many countries, which necessitate traceability throughout the food supply chain. Implementing traceability systems and process automation ensures compliance with these regulations. Automation through intelligent devices like irrigation, fertilisation, and pest control enables greater accuracy, improved product quality, and resource conservation by eliminating manual interventions. This ultimately ensures higher standards of quality for agricultural harvests. To achieve traceability in agricultural products, Chun-Ting et al. (2020) proposed the adoption of the Agriculture Blockchain Service Platform, which utilises IoT sensors and blockchain technology. This platform, built on the Ethereum blockchain, leverages smart contracts to ensure data integrity and reliability. It connects all stakeholders in the food production chain, including producers, processors, and distributors, providing a tamperproof record of the entire production process from farm to fork (Misra et al., 2022).

As products progress through the supply chain, additional information such as harvest dates, processing facility locations, and shipment dates can be added to the blockchain. Authorised parties, including regulators, retailers, and consumers, can access this information. Blockchain-based digital traceability enables rapid identification of contamination sources and other issues. For instance, in the case of lettuce contaminated with E. coli, the blockchain can be traced back to the originating farm, facilitating swift action to prevent further spread and safeguard public health.

In the context of winemaking, Medela et al. (2013) presented a smart architecture based on the Internet of Things (IoT) to enhance the winemaking process. This architecture integrates wireless and distributed sensor devices that capture essential environmental data such as soil condition, vine growth, and fermentation status. Implemented in a real-world scenario in Zamora, Spain, covering crops and a winery, the system offers a predictive approach to precision farming. It simplifies vineyard and winery management while improving traceability throughout the winemaking process.

Improved control over internal processes leads to reduced production risks and enables better planning for product distribution. Various researchers have proposed IoT-based solutions to enhance control in agriculture. Saxena and Dutta (2020) introduce an IoT-based wireless sensor system that monitors and controls crop growth and productivity by utilising energy harvesting to power sensor nodes distributed across the designated area. Ahmed et al. (2018) presented a network architecture for smart farming and agriculture, incorporating IoT and fog computing to monitor and control multiple aspects of farming operations in rural areas. This architecture facilitates the monitoring of soil moisture, temperature, humidity, livestock health, and movement. It also enables remote control of irrigation systems, lighting, and other equipment, resulting in time and resource savings for farmers.

Moreover, Ping et al. (2018) proposed the application of IoT technology in machine-to-machine (M2M-based) devices and process control for improved governance in agricultural production. M2M-based device and process control involve communication between devices and a central control system, enabling real-time monitoring and control of production processes. This technology enhances operational efficiency, reduces labour costs, and promotes the quality and safety of agricultural products. Examples of M2M-based applications include automated irrigation systems that adjust water delivery based on soil moisture levels; precision agriculture systems that monitor crop growth and optimise the application of fertilisers and pesticides; cold chain monitoring systems that track temperature and humidity during transportation and storage; and traceability systems that ensure the quality and safety of agricultural products by tracking their movement from farm to table using RFID and other sensors.

Process automation has significantly improved business efficiency, and several studies highlight the role of IoT and data analytics (DA) in achieving this. Elijah et al. (2018) provided examples of how IoT sensors enable the monitoring of soil moisture, temperature, and environmental factors, allowing farmers to optimise irrigation and fertilisation practices for cost savings and increased crop yields. DA further enhances efficiency by analysing data from various sources, enabling informed decisions regarding planting, harvesting, and selling crops, thereby increasing profits and reducing risks. Madushanki et al. (2019) emphasise the use of IoT technology in agriculture and farming industries to enhance productivity and efficiency. Automation and sensor-based data collection contribute to reduced human intervention and improved yields, particularly in sub-verticals like water and crop management. Recommendations are provided for future research, focusing on scalability, system architecture, data analysis methods, and security protocols.

Lee et al. (2013) proposed a system that utilises IoT sensors to gather environmental information for monitoring crop growth and production. By analysing this data, the system can predict future harvests and assist farmers in making informed decisions, leading to efficient resource utilisation and improved crop quality. Additionally, the system provides a unified platform encompassing the entire agricultural production process, ensuring consistency and quality from seed sowing to product sale. Gupta et al. (2018) highlight how IoT adoption in agriculture enhances product quality and volumes through timely and accurate information on crop yields, rainfall, pest infestations, and soil nutrition. For instance, monitoring soil moisture levels helps determine optimal irrigation timing, preventing under- or over-watering and ensuring crop quality and yield. Similarly, early detection of pest activity enables targeted pest control measures, reducing pesticide usage, improving product quality, and minimising costs.

End-to-end farm management systems encompass a comprehensive approach to farm management, integrating various technologies and services to optimise operations (Kaloxylos et al., 2014). Akhtar (2017) discusses an integrated IoT system platform with AI for agriculture management, enabling data collection, monitoring, control, and communication. This system monitors multiple parameters such as temperature, humidity, vibration, soil moisture, soil conductivity, air temperature, and humidity. Collected data is stored in the cloud for predictive and real-time data analysis, facilitating proactive and preventive actions to increase crop yield, reduce water consumption, and minimise food waste during storage and distribution. Farm productivity management systems, a more advanced approach to IoT in agriculture, involve multiple IoT devices and sensors on the farm premises, along with a powerful dashboard for analytics and reporting. This enables remote farm monitoring and streamlines various business operations. Patodkar et al. (2015) presented an end-to-end farm management system that combines modern technology with traditional farming practices. Their software application supports farmers in achieving sustainable development by offering features such as crop-specific fertiliser schedules, reminders for fertiliser application based on sowing dates, and advice based on soil type and climate conditions. The application also enables farmers to monitor farming costs per crop, field, task, and individual task inputs while facilitating financial budgeting. Kaloxylos et al. (2012) proposed a farm management system designed to enhance farming activities, replacing outdated and complex systems with modular software tools leveraging the capabilities of the "Future Internet." Similar solutions include FarmLogs and Cropio. Beyond the mentioned IoT agriculture use cases, opportunities exist for vehicle tracking, storage management, and logistics.

According to Sistler (1987), robotics and intelligent machines involve advanced technology that enables devices to perform tasks autonomously or with minimal human intervention. These machines find applications in agriculture for activities like planting, harvesting, and crop monitoring. They use sensors and other technologies to gather and process data (Bechar & Vigneault, 2016). Equipped with sensors, manipulators, and algorithms, these robots can operate independently in unstructured agricultural environments. The development of such machines aims to enhance efficiency, productivity, and food quality while reducing labour costs. Examples include autonomous tractors capable of planting and harvesting without human involvement, drones equipped with sensors and cameras for crop health monitoring and pest detection, robotic arms for fruit and vegetable picking and sorting, automated irrigation systems adjusting water usage based on weather and soil conditions, smart sensors for monitoring soil moisture, temperature, and nutrient levels for optimised crop growth, and spraying robots that apply pesticides and herbicides to crops (Bechar & Vigneault, 2016; Sistler, 1987). For example, Bear Flag Robotics is a company actively working on automated tractors that operate on designated routes, send notifications, and start work at predetermined hours, reducing labour costs for farmers. Eco Robotics provides robots that employ computer vision and AI technology for delicate tasks such as weed detection, seed planting, and watering, minimising harm to plants and the environment.

Unmanned aerial vehicles (UAVs) are another important tool in smart agriculture, providing valuable data on crops, soil, and other agricultural parameters. Small UAVs have been employed for various commercial purposes, including high-resolution imaging, traffic monitoring, and powerline inspection (Morris & Jones, 2004). Quadcopters, fixed-wing drones, and other small, unmanned aircraft are used for tasks such as aerial photography, surveying, mapping, and surveillance. UAVs contribute to precision agriculture by enabling techniques that optimise water, fertiliser, and pesticide usage, thereby reducing environmental impact. Equipped with cameras, multispectral sensors, and thermal sensors, UAVs collect data on crops, soil, and other relevant factors. It is essential for the sensors to be suitable for the specific application and provide accurate and reliable data. Furthermore, UAVs require sufficient battery life to cover large farmland areas and collect data over extended periods without frequent recharging (Reddy Maddikunta et al., 2021). UAVs can also generate 3D models and map fields, aiding farmers in making informed decisions about crop management, as highlighted by Al-Turjman and Altiparmak (2020).

Additionally, Al-Turjman and Altiparmak (2020) proposed the adoption of multispectral imaging in smart farming. Multispectral imaging involves capturing images of objects or scenes using multiple wavelengths of light, extending beyond the human eye's perceptible range. It provides valuable insights into the imagined object or scene. In the context of smart agriculture, multispectral imaging can be utilised to monitor crop health, detect plant diseases, and optimise irrigation and fertilisation practices. The application of thermal imaging, as explained by Roopaei et al. (2017), enables the assessment of the relationship between plant or field water status and radiation emission. Therefore, multispectral imaging serves as a measure of water stress and irrigation distribution. Consequently, thermal imaging assists farmers in identifying areas of their fields experiencing insufficient water supply, allowing them to adjust their irrigation systems accordingly. For instance, if certain areas emit more radiation than others, it indicates water stress, prompting the farmer to increase the water supply. This ensures uniform water distribution throughout the field, thereby enhancing crop quality.

Furthermore, Atlam et al. (2018) conducted a comparison between the Internet of Things (IoT) and cloud computing. IoT connects physical objects, while cloud computing facilitates on-demand, convenient, and scalable network access. Both IoT and cloud computing rely on the Internet as a means of connectivity. Moreover, IoT generates big data, while cloud computing provides the means to manage such data. The features of IoT and cloud computing are highly complementary, as illustrated in the comparison table presented in the study. Atlam et al. (2018) suggest that integrating IoT with cloud computing can address numerous challenges faced by IoT, including limited capabilities in terms of protocols, reliability, scalability, interoperability, security, availability, and efficiency.

In conclusion, Friha et al. (2021) highlight several emerging technologies for IoT-based smart agriculture that can enhance various aspects of agricultural practices. These technologies encompass unmanned aerial vehicles, wireless technologies, open-source IoT platforms, software-defined networking (SDN), network function virtualization (NFV), cloud or fog computing, and middleware platforms. The paper provides real-life project examples that demonstrate the potential of these emerging technologies in improving different facets of agriculture, such as monitoring, water management, agrochemical applications, disease management, harvesting, supply chain management, and agricultural practices.

The advantages of implementing smart agriculture are evident in the substantial yield improvements compared to traditional farming methods. Conducting comparisons of different outcomes holds significant value for several reasons. It allows individuals to assess the effectiveness of various approaches or solutions to a specific problem. For instance, when comparing the accuracy of different machine learning algorithms, one can leverage the comparison results to identify the most optimal algorithm for their task. Comparisons aid in optimising processes or systems by identifying areas that require improvement. Through analysing and comparing the performance of diverse approaches, individuals can make necessary changes to enhance overall outcomes. Comparing results serves as a crucial validation tool for scientific research, enabling researchers to ascertain the consistency of their findings with prior studies. Ultimately, comparing different outcomes is a vital practice that promotes informed decision-making, process improvement, and knowledge advancement in a given field.

Seufert et al. (2012) conducted a comprehensive meta-analysis to compare the yield performance of organic and conventional farming systems on a global scale. Their findings indicated that organic yields generally tend to be lower than conventional yields. However, the magnitude of yield differences is highly dependent on system and site characteristics. The range of yield differences varied from 5% lower for organic products to 34% lower when comparing the most similar conventional and organic systems. The study concluded that under certain conditions, such as effective management practices, specific crop types, and favourable growing conditions, organic farming systems can nearly achieve yields comparable to traditional methods. These conditions can be related to IoT-based management systems. Additionally, a report by the Food and Agriculture Organization (FAO) of the United Nations highlighted the potential of IoT in increasing agricultural productivity, improving efficiency, reducing waste, and enhancing farming systems' resilience to climate change. Although the adoption of IoT in agriculture is still in its early stages, it has the potential to transform agricultural practices (FAO, 2021).

In their book, Turner and Stephen (1988) compare different farming systems and their methodologies, including mixed-technique and production systems. This approach involves blending traditional and modern techniques to enhance productivity and efficiency. Mixed-technique systems often encompass a combination of subsistence and commercial farming, with farmers utilising diverse tools and methods for crop and livestock production. Case studies exploring the integration of traditional and modern techniques include examples such as irrigation and mechanised agriculture in Upper Egypt and intensive paddy and garden agriculture in Bangladesh. The first case study delves into how farmers in Upper Egypt have adopted modern irrigation and mechanised farming techniques to boost crop yields and improve their livelihoods. The second case study examines the intensification of rice and vegetable production in Bangladesh through the utilisation of modern inputs and techniques. These studies underscore the significance of access to credit and markets, the role of the state in promoting agricultural development, and the challenges associated with water resource management and extension services in driving agricultural progress and poverty reduction.

Lacoste et al. (2016) conducted research comparing the farming systems of 36 farms in a Western Australian wheat belt region. The study revealed that management practices, including crop specialisation, were influenced by land types, which also explained some of the regional variations in grain yield and enterprise mix. The findings indicated that crop rotations varied according to soil type and farm type, with break crops being more common on light sandy soils compared to heavier fine-textured soils.

In a study by Srilakshmi et al. (2018), various IoT techniques and intelligent decision-support systems used in agriculture were compared. For instance, the authors examined the predictions of crop yield using ANFIS and PLSR models. The study found that both techniques effectively predicted crop yield, with ANFIS demonstrating higher accuracy than PLSR for crops such as wheat and maize. Another aspect of comparison in the paper focused on different sensors used in agriculture, specifically pH, oxygen, and moisture sensors. The authors discovered that these sensors were efficient in monitoring soil conditions and optimising crop production.

However, Roberts and Swinton (1996) reviewed 58 recent studies at the time, comparing alternative crop production systems with conventional systems. The review emphasised that evaluating systems designed with environmental objectives cannot be reasonably accomplished solely based on productivity, as is often done in economic studies of alternative methods. The paper proposed four criteria for comparison: expected profit (financial returns expected from the system), stability of profits (consistency of financial returns over time), expected environmental impacts (potential ecological effects such as soil and water quality, greenhouse gas emissions, and biodiversity), and stability of environmental impacts (consistency of ecological effects over time). The authors suggested that a balanced environmental-economic analysis could be achieved by integrating biophysical simulation models with economic optimisation methods to model the trade-offs among profitability, environmental impact, and system stability (both financial and environmental). The paper provided examples of studies that employed this approach, including the work of Antle and Stoorvogel (2008) on the sustainable intensification of agriculture in Africa. The paper also discussed the challenges associated with this approach, such as the requirement for accurate data on both financial and environmental factors and the complexity of modelling systems with numerous interconnected variables.

While IoT has the potential to revolutionise agriculture, there are several challenges that need to be overcome for its full realisation. One significant challenge is the limited access to reliable and affordable high-speed internet in rural farming areas, which hinders the effectiveness of IoT devices in transmitting real-time data. The lack of internet connectivity in these regions poses difficulties in deploying and managing IoT systems. Additionally, the implementation costs of IoT technology, including hardware, software, and maintenance, can be expensive. Moreover, the substantial amount of data generated by IoT devices requires businesses to ensure effective integration and analysis within existing systems. Data security is another concern, as IoT devices are susceptible to cyberattacks, necessitating robust security measures.

To address these challenges, Adesta et al. (2017) proposed the development of "table stakes" capabilities, such as proficient management and analysis of large datasets, integration of diverse portfolios, and fostering relationships with IoT-related companies. The paper highlights examples of IoT technology in agriculture, such as low power wide area (LPWA) applications for water metering and precision livestock tracking. Ayaz et al. (2019) mention SourceTrace, a company that has developed cloud-based mobile applications catering to the agriculture industry. SourceTrace has considered the connectivity issues faced by farms in remote and low-bandwidth environments during the development of their applications, providing visibility and traceability along the value chain.

Interoperability is another critical challenge in IoT implementation, referring to the seamless exchange of information between different systems and devices. In the context of smart farming, interoperability involves the ability of various systems to share and utilise data. However, the use of different communication protocols and standards among IoT devices complicates integration with other systems. Interoperability issues can lead to communication delays, hamper decision-making processes, and reduce efficiency and productivity. Moreover, inconsistent data exchange may result in errors and impact the quality of products and services.

To tackle interoperability challenges, Kalatzis et al. (2019) proposed the gaiasenseTM solution, which offers cost-effective smart-farming services without requiring substantial technological investments from farmers. This solution includes a network of sensors, a cloud-based platform, and a mobile application that provides farmers with real-time information about their crops. The paper introduces the concept of the "Data Interoperability Zone" as a standardised framework for data exchange between different smart farming systems. Furthermore, the "Information Management Adapter" is introduced to facilitate data interoperability by translating data between systems.

As IoT devices and systems continue to advance, the management and maintenance of these technologies become increasingly challenging, particularly in large-scale deployments. Farms with extensive areas require numerous devices and sensors to cover the entire space. Terence and Purushothaman (2020) proposed several solutions to address this challenge. One approach is cloud computing, which involves utilising remote servers to store, manage, and process data from IoT devices. By leveraging cloud-based platforms like Microsoft Azure and Amazon Web Services, the burden on individual devices can be reduced, enabling more efficient data analysis.

Another solution is edge computing, which involves processing data closer to the source, such as IoT devices or nearby servers. This approach helps minimise latency and facilitates real-time decision-making. An example of edge computing in precision agriculture is the local processing of data from sensors on tractors and equipment to optimise farming operations.

Furthermore, Tong-ke (2013) explains that cloud computing is a technology that allows users to access computing resources, including servers, storage, and applications, over the Internet. Third-party service providers manage and maintain the infrastructure, offering various cloud-based services. Cloud storage services such as Google Drive, Dropbox, and OneDrive enable users to store and access files from any location with an internet connection. Cloud-based productivity tools like Google Docs, Microsoft Office 365, and Salesforce enable real-time collaboration on documents and projects. Additionally, cloud hosting services like Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform allow businesses to host their applications and websites on remote servers.

In the context of agricultural modernization, cloud computing plays a crucial role in storing and processing vast amounts of agricultural production-related data, including weather patterns, soil conditions, and crop yields. This data can be analysed to improve farming practices and enhance overall efficiency.

Farmers face the challenge of inadequate knowledge and skills, impeding their adoption of modern technology and new practices. To overcome this, it is crucial to provide farmers with training on smart agricultural technologies, enabling them to better understand and manage farming processes using digital techniques. This, in turn, can lead to increased efficiency, productivity, and profitability. A study by Chuang et al. (2020) suggests that farmers who possess a better understanding of intelligent agriculture (SA) and hold positive attitudes towards it are more likely to adopt smart agriculture technologies. This emphasises the role of farmers' knowledge and attitudes in their decision to embrace new technologies.

In Thailand, Suebsombut et al. (2020) conducted research on the intelligent agriculture literacy of farmers in Chiang Mai and Khon Kaen provinces. The results revealed varying levels of intelligent agriculture literacy among farmers, highlighting the need to enhance their skills and knowledge of intelligent agricultural technologies. Similarly, in Taiwan, Chuang et al. (2020) explored how farmers' knowledge and attitudes regarding smart agriculture (SA) influence their adoption of intelligent technologies. The study found a positive relationship between farmers' attitudes towards SA and their adoption of SA technologies.

Additionally, Ayre et al. (2018) discusses the slow uptake of digital tools and services by farmers and agricultural advisors globally. The term "slow uptake" refers to the slower-than-expected adoption or utilisation of these technologies in agriculture. This hesitation may stem from farmers' uncertainty about the benefits or their lack of the necessary skills and knowledge to effectively use new technologies. Similarly, agricultural advisors may hesitate to recommend unfamiliar technologies if they do not fully understand their potential benefits. To address this issue, the paper proposes the development of a digital value assessment tool (DVA tool) for agricultural advisors. This tool serves as a decision support system, helping advisors and their clients assess the costs and benefits of intelligent farming tools or services. Integrating the DVA tool into routine business practices can maximise opportunities for engaging with digital technologies in agriculture.

In agriculture, security is a significant concern due to the vulnerability of IoT devices to cyber-attacks, posing a risk to sensitive data such as crop yield, soil quality, and livestock information. Rettore de Araujo Zanella et al. (2020) outline various challenges and issues related to security in smart agriculture, particularly in open-field agriculture. These include compatibility issues among different resources within smart agriculture systems, constrained resources in remote areas, handling massive amounts of data, a lack of standardisation, and the presence of cybersecurity threats.

To address these challenges, the paper suggests several future directions for research and development in intelligent agriculture security. One solution involves developing lightweight security protocols that are compatible with constrained resources. Additionally, implementing edge computing and fog computing solutions can reduce the need for extensive data transmission over the network. Establishing industry-wide standards for security and interoperability is another recommended approach. Artificial intelligence and machine learning techniques can be integrated to detect and respond to cybersecurity threats effectively. Furthermore, educating farmers and other stakeholders about cybersecurity and best practices for securing smart agriculture systems is crucial. Ultimately, the reliability and consistent performance of IoT devices and procedures are essential to ensuring their trustworthiness for critical applications in agriculture.

Data management is a crucial aspect of the IoT in agriculture. The sheer volume of data generated by IoT devices can pose challenges for farmers. They need proper infrastructure and tools to effectively store, process, and analyse this data in order to derive valuable insights. Belanche et al. (2019) conducted a case study on conventional dairy goat farms and highlighted the challenges faced due to intensification processes, resulting in the generation of large amounts of data known as "big data." To address this challenge, the Eskardillo tool was developed, which simplifies data recording, processing, and analysis while providing interactive feedback to optimise farm management. Implementation of the Eskardillo tool improved productivity monitoring, animal selection for breeding or culling, and optimisation of conception timing without negatively impacting milk yield.

Interoperability is another issue in IoT agriculture. Many devices and sensors in IoT systems are proprietary and not designed to work seamlessly with other systems or devices, leading to compatibility problems and difficulties in integrating multiple IoT systems. Ensuring reliability is crucial for an effective intelligent agriculture system, as it ensures accurate information and enables better decision-making. Ait Issad et al. (2019) highlight the importance of data mining in smart agriculture for real-time data analysis, predicting crop yields, identifying diseases, optimising irrigation, and improving livestock management. Sushanth and Sujatha (2018) proposed an alternative solution using Short Message Service (SMS) technology. Sensors monitor environmental conditions, and in case of discrepancies, the system sends SMS notifications to the farmer's smartphone, allowing for timely actions to be taken.

Overall, managing and analysing data and addressing interoperability challenges are essential for maximising the benefits of IoT in agriculture. Reliable systems, data mining techniques, and innovative communication methods can contribute to the successful implementation of intelligent agriculture practices.

IoT devices and sensors can be costly to install and maintain, creating a barrier for small and medium-sized farms, particularly in developing countries. Limited access to electricity, the internet, and transportation in remote or underdeveloped areas further hinders the adoption of modern technology. In order to address these challenges, Varghese and Sharma (2019) proposed an affordable intelligent farming module that utilises IoT and machine learning. This module consists of ground sensors to monitor crop conditions and an IoT device for connectivity to the cloud infrastructure. Real-time analytics based on machine learning algorithms are performed in the cloud to predict future crop states. The system aims to be cost-effective and requires minimal human intervention, enhancing the accuracy of results and automating crop monitoring.

Another solution proposed by Faid et al. (2020) focuses on wireless sensor network technology to support smart farming. The architecture utilises plug-and-play nodes, allowing for easy integration of new nodes into the network. Data is collected by cluster heads and sent to the base station for processing and storage. This low-cost architecture increases accessibility for farmers in developing countries.

In the context of irrigation, Xie et al. (2017) introduced an on-demand irrigation scheduling system that reduces costs by considering the time-of-use price model of electricity. The system utilises hourly weather predictions to optimise irrigation, avoiding over-irrigation and reducing water and energy waste. By scheduling irrigation during off-peak hours when electricity is cheaper, the overall cost of irrigation on intelligent farms is reduced.

Ethical considerations are also crucial in the field of intelligent farming. Mark (2019) highlights ethical questions surrounding data ownership, access, distribution of power, and impacts on human life and society. Similarly, van der Burg et al. (2022) simplify the ethical issues into four main topics: data ownership and access, distribution of power, impacts on human life and society, and accuracy and availability of data. These topics address concerns regarding data ownership, power dynamics, potential impacts, and the accuracy and availability of data. The authors emphasise the need for responsible and sustainable development and implementation of smart farming technologies. They also discuss issues such as data ownership by farmers, privacy and security measures, employment implications, environmental impact, and the potential deskilling of staff due to technology reliance.

Mark (2019) examined the ethical implications of utilising smart information systems (SIS) in agriculture and proposed strategies to address these concerns. These strategies include implementing robust security measures to safeguard privacy and ensuring that SIS complements human expertise. Similarly, van der Burg et al. (2022) recommended the development of guidelines for smart farming that strike a balance between stakeholder goals and incorporate sustainability considerations. Eastwood et al. (2019) emphasise the importance of embedding responsible research and innovation (RRI) principles in smart dairy research and development (R&D) activities. They proposed the creation of a roadmap to support capacity building for implementing RRI, which involves anticipating potential consequences, addressing stakeholder concerns, and minimising environmental and social impacts.

According to Wolfert et al. (2017), smart farming utilises information and communication technology, including the Internet of Things (IoT) and cloud computing, to enhance farm management. Big data plays a crucial role in smart farming by capturing and analysing vast amounts of diverse data to facilitate better decision-making. The future of smart farming is envisioned to incorporate robots, artificial intelligence, and predictive analytics, enabling real-time operational decisions and innovative business models. The applications of big data extend beyond primary production and have an impact on the entire food supply chain. Two contrasting scenarios for the future of smart farming are proposed: closed, proprietary systems where farmers are integrated into highly interconnected food supply chains, or open, collaborative systems that offer flexibility in choosing partners for both technology and food production.

Terence and Purushothaman (2020) discuss the potential of smart farming to enhance agricultural efficiency and productivity through IoT technologies. By integrating sensors, devices, and data analytics, smart farming empowers farmers to make informed decisions regarding crop management, irrigation, and other farming practices. The paper emphasises the advantages of smart farming, such as waste reduction, increased yields, and improved sustainability.

Saiz-Rubio and Rovira-Más (2020) emphasise the utilisation of data management and advanced technologies in smart farming to optimise decision-making in agriculture. By leveraging sensors to acquire objective information and employing artificial intelligence for analysis, farmers can enhance resource utilisation, minimise waste, and reduce environmental impact. The main aim is to increase productivity and sustainability in agriculture while improving profitability and reducing costs for farmers. Smart farming is envisioned as a transformative approach to food production that can address the challenges posed by future population growth sustainably.

Wolfert et al. (2017) suggested several areas for future research in smart farming, including the consideration of broader innovation perspectives and ethical aspects, the prioritisation of organisational issues, and the development of data and application infrastructures to support open and collaborative systems. Additionally, Jayakumar et al. (2021) proposed an IoT monitoring system for livestock farming that enables continuous vital signs monitoring and disease prevention, while Raj (2020) focuses on the utilisation of big data in real-time healthcare environments to achieve minimal delays and better performance compared to conventional models.

Terence and Purushothaman (2020) underscore the objective of enhancing agricultural efficiency and productivity through IoT technologies, such as sensors, devices, and data analytics, in smart farming. This approach empowers farmers to make well-informed decisions regarding crop management, irrigation, and other farming practices, leading to waste reduction, increased yields, and improved sustainability. Similarly, Pathan et al. (2020) highlight the expectations of intelligent agriculture or precision farming, which involve the incorporation of advanced technologies like AI, machine learning, and robotics to optimise crop yields, minimise chemical usage, and increase productivity. Smart farming also plays a crucial role in disease detection, crop phenotyping, and effective crop management, as well as soil fertility, which are all essential considerations in the face of unpredictable climate changes, population growth, and concerns about food security.

Government policies play a vital role in the advancement of smart farming, and their impact varies across different countries and regions. Torquebiau et al. (2018) emphasise the importance of integrated measures in government policies to support climate-smart agriculture practices. In India, the government has made significant investments in enhancing climate change resilience, including initiatives such as micro-irrigation and conservation agriculture, as highlighted by Kishore et al. (2018). Furthermore, government initiatives can involve funding research and development of big data technologies in agriculture and implementing policies that facilitate data sharing, as recommended by Islam Sarker et al. (2019). Public-private partnerships, exemplified by collaborations between technology companies like John Deere and the Climate Corporation with agricultural organisations, serve as additional instances of how government policies can contribute to the promotion of smart farming.

VII. CONCLUSION

The agricultural sector encounters numerous challenges, including unpredictable weather conditions, pest outbreaks, and inefficient resource utilisation. Nevertheless, the adoption of IoT technologies, specifically smart farming systems, can mitigate or overcome these challenges by providing real-time data and valuable insights for improved decision-making in areas such as planting, irrigation, and pest management. Smart farming leverages IoT tools like sensors, devices, and data analytics to enhance agricultural productivity and efficiency. The future of smart farming envisions the utilisation of closed or open systems, incorporating collaborative approaches, and the integration of robots and artificial intelligence. Government policies play a pivotal role in promoting smart farming through financial support for research and development as well as fostering public-private partnerships. Ultimately, the goal of smart farming is to optimise decision-making in agriculture and ensure sustainable food production to meet the demands of future population growth.

VIII. ACKNOWLEDGEMENT

We would like to thank to the Malaysian Agricultural Research and Development Institute (MARDI) for publication funding.

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