



Article

Disruptive Technologies in Smart Farming: An Expanded View with Sentiment Analysis

Sargam Yadav ^{1,†}, Abhishek Kaushik ^{2,*}, Mahak Sharma ³ and Shubham Sharma ⁴¹ School of Computing, Dublin Business School, D02 WC04 Dublin, Ireland; sargam.yadav@edhec.com² Department of Computing Science and Mathematics, Dundalk Institute of Technology, A91 K584 Dundalk, Ireland³ Department of Education, VBGI of Educational Studies, Udaipur RJ SH 32, India; mahak10sharma@gmail.com⁴ School of Food Science and Environmental Health, Technological University Dublin, D07 EWW4 Dublin, Ireland; shubham.sharma@tudublin.ie

* Correspondence: abhishek.kaushik@dkit.ie

† These authors contributed equally to this work.

Abstract: Smart Farming (SF) is an emerging technology in the current agricultural landscape. The aim of Smart Farming is to provide tools for various agricultural and farming operations to improve yield by reducing cost, waste, and required manpower. SF is a data-driven approach that can mitigate losses that occur due to extreme weather conditions and calamities. The influx of data from various sensors, and the introduction of information communication technologies (ICTs) in the field of farming has accelerated the implementation of disruptive technologies (DTs) such as machine learning and big data. Application of these predictive and innovative tools in agriculture is crucial for handling unprecedented conditions such as climate change and the increasing global population. In this study, we review the recent advancements in the field of Smart Farming, which include novel use cases and projects around the globe. An overview of the challenges associated with the adoption of such technologies in their respective regions is also provided. A brief analysis of the general sentiment towards Smart Farming technologies is also performed by manually annotating YouTube comments and making use of the pattern library. Preliminary findings of our study indicate that, though there are several barriers to the implementation of SF tools, further research and innovation can alleviate such risks and ensure sustainability of the food supply. The exploratory sentiment analysis also suggests that most digital users are not well-informed about such technologies.

Keywords: smart farming; precision farming; unmanned vehicles; wireless sensor networks; sentiment analysis; computer vision; Internet of things (IoT)



Citation: Yadav, S.; Kaushik, A.; Sharma, M.; Sharma, S. Disruptive Technologies in Smart Farming: An Expanded View with Sentiment Analysis. *AgriEngineering* **2022**, *4*, 424–460. <https://doi.org/10.3390/agriengineering4020029>

Academic Editor: Lin Wei

Received: 19 March 2022

Accepted: 22 April 2022

Published: 12 May 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Agriculture is an indispensable field of study, as the continued survival of the human race depends on it. New and updated technology has been implemented throughout the ages in order to improve agricultural output and sustainability. The world's population is expected to grow to approximately 9.7 billion by the year 2050 [1]. To keep up with this increase in population, food production needs to go up by 70%. However, the resources available to produce the required food output are steadily decreasing due to climate change and an increase in the number of settlements. Water levels are receding, arable lands are shrinking, and the environment is being rapidly degraded. The agricultural industry is also one the biggest contributors of greenhouse gases. The strain on the availability of food across the world is predicted to increase drastically with the increase in the world population over the next few decades [2,3]. Agriculture 4.0, or the fourth agricultural revolution, was discussed by the World Government Summit in 2018 in the report titled 'Agriculture 4.0—The Future of Farming Technology' [4]. The report highlights the need for more efficient food production practices that can overcome the increasing food demand in

coming years. It would be nearly impossible to keep up with this increase in demand without the integration of information and communication technologies (ICTs) and disruptive technologies (DTs) such as remote sensing, Internet of Things (IoT), machine learning, big data, etc., into the agricultural industry. Smart Farming is of great interest to researchers and scientists as it has yielded great results in reducing the ecological footprint of farming [5], improving production efficiency [6], reducing human labor through unmanned vehicles [7,8], detecting diseases through image processing [9,10], and more.

Precision farming is an approach that utilizes ICTs to monitor resources such as crops, fields, and animals [11]. It aims to maximize resource usage and crop yield while minimizing associated costs. The agricultural sector consumes a significant amount of resources in the form of water, land, fertilizer, and energy. Precision farming is concerned with calculating the exact amount of resources required to grow plants and sustain livestock. Smart Farming (SF), which could be considered an extension of precision farming, focuses on utilization of data obtained from precision farming in an intelligent way and making crop production more efficient by predicting crop yield [12,13], reducing wastage of resources, automating tasks [14], and providing agricultural management support [15]. It can also be used to perform soil analysis [16], so that crops of optimal quality can be grown. There have been several calamities in recent years that occurred due to climate change [17]. In light of these calamities, there is great need for smart farming to help manage agricultural activities. Due to the various risks and external factors associated with farming, such as weather extremities and plant diseases, implementation of data-driven predictive tools, which can be used to provide insights into farming operations such as crop yield, feed intake, weather conditions, soil conditions, etc., is crucial for mitigation [18]. Decisions can thereby be made based on real-time data rather than heuristic, thumb-rule data.

The availability of huge amounts of data from Internet of things (IoT) devices has allowed for application of big-data tools. The development of Artificial Intelligence (AI) tools has impacted the efficiency of a number of tasks associated with farming, suggesting that data-driven agriculture is a good approach to ensure agricultural sustainability. Climate change is predicted to disproportionately impact smallholder farmers [19]. Even a temperature variation of a few degrees will drastically affect smallholder farmers who are not adequately prepared for the situation. A substantial amount of crop losses occur due to weather events, which can be greatly mitigated through predictive weather modeling. This approach can help farmers navigate the agricultural risks that arise from the unprecedented deterioration of the environment, social and economic changes in the industry, and the increase in demand for food production. The availability of big data has the potential to revamp the entire food supply chain [20]. A global connectivity chain in farming will allow for the use of correctly priced products, better market positioning, and improved means of production. The use of ICT in farming will provide greater insight and advice on agricultural practices to farmers. The increase in visibility that comes with inter-connectivity of the supply chain is also likely to improve the productivity and confidence of farmers in such practices.

Agricultural tasks such as fertilizer and pesticide spraying, crop monitoring, seed planting, etc., can be automated through the use of Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs) [21]. Robots can be trained to autonomously plant saplings and move heavy pots, thus complementing human effort in the agricultural industry and reducing the farmer's workload [22]. Autonomous vehicles never tire and can work around the clock. They also provide better accuracy and speed to improve the size of yields. With computer vision, autonomous vehicles can identify if the crops are ripe, ready, and disease-free. Lightweight sensors can be deployed on aerial vehicles to collect detailed information about crops and soil parameters through hyper-spectral imaging [23]. Sensors can also be used to map various parameters such as type of land, crop, vegetation index, chlorophyll index, and water index [24]. Drones can help to create a precision map of a field so that each part can precisely receive the resources it needs [25]. IoT is a major enabling technology that allows communication between the various sensors installed on the farm.

IoT makes use of Wireless Sensor Networks (WSN), which can collect a large amount of data about the environment, crop production, cattle monitoring, and more [26]. Information generated by IoT devices allows farmers to track farm operations and performance, and make informed decisions to improve farm productivity and yield. The massive amounts of data collected from the WSNs can be analyzed through technologies such as big data and deep learning. These technologies provide the added advantages of predictive modeling, real-time decision making, and adaptability to external factors. With the number of smart devices increasing steadily, the implementation of IoT in farms will increase interoperability, decrease losses due to human errors, and provide seamless unification of information. Vertical farming, which is the practice of growing crops in a vertically stacked layer within a controlled environment for maximum growth, is one way to grow crops independently of local soil and climate conditions [27].

The widespread implementation of smart farming tools faces several limitations and challenges depending on the geographical location of the project. One prominent barrier is the lack of internet connectivity, especially in rural areas. Such technology is not affordable for everyone. Without a stable internet connection agricultural sensors cannot communicate with each other. The initial cost of installation is high for any SF project, making it especially difficult for smallholder farms to accept the risks. Further, the farmers implementing smart farming technologies may not fully understand the operation, find the system too complex to use, or may be skeptical about its benefits. Older farmers usually prefer traditional farming and are unwilling to learn to operate new technology [28]. The security and privacy of the data generated by sensors is also a concern, as there has to be an accountable party in case of mishandling or misuse [6]. This review paper highlights the current state-of-the-art ICTs and DTs that are applicable to the agricultural sector. The practical implementation of these technologies in particular projects across the world has also been covered, along with the limitations of the approaches and their potential to alleviate significant concerns faced by farmers. Exploratory sentiment analysis has also been performed on comments collected from YouTube videos relevant to smart farming in order to determine public opinion regarding the implementation of these tools. This work aims to serve as a reference and motivation for further research in the adoption of technological tools in the agricultural industry.

2. Motivation

In this study, an in-depth exploration of recent advancements in the field of smart farming is performed. It has always been a human endeavor to revolutionize agriculture by domesticating animals, planting crops in rotations, using pesticides and fertilizers, etc. The advent of ICTs has brought about the fourth agricultural revolution, or Agriculture 4.0, which focuses on the use of limited resources on targeted areas. As discussed in the previous section, this is achievable with the help of sophisticated technologies such as unmanned vehicles, satellite imagery, sensors, and more. DTs such as AI have also greatly impacted the agricultural sector by improving efficiency, providing predictive analysis of yield, and mitigating production and market risks. Studies have shown several benefits of using smart solutions in farming practices, such as reduction of necessary manpower, increase in yield, effective management of livestock, monitoring of crops and weather conditions, predictive analysis, and cost reduction. Several initiatives have been undertaken across the world that support the use of precision farming and smart farming while also providing insight on the specific limitations that were encountered. It is crucial that the ever-increasing global food demand is met, as the survival of the human race depends on it. Smart farming is capable of providing essential assistance to farmers to ensure sustainable food production. It can help farmers manage risks by providing specific weather forecasts, yield projections, likelihood of diseases, and more. It can thereby also increase profits for the farmer, as the availability of data on risk assessment and external conditions can allow for optimal cultivation of crops. The motivation for conducting this study is to streamline the current state-of-the-art ICTs and DTs applicable to the farming

sector, analyze components of various smart farming projects, discuss potential uses of such components, and list the common challenges that face the large-scale adoption of such techniques. The considerations for using smart farming in different geographical regions also needs to be discussed. The general attitude of people towards the adoption of any new technology is a great indicator of its perceived benefits. To determine the consensus of the opinion on smart farming, we have performed a surface-level sentiment analysis on comments collected from YouTube channels relevant to smart farming. Thus, this work can serve as a point of reference for future research in the area of smart farming and can help researchers explore diverse technologies that are relevant to the topic.

During this exploratory study, we formed the following two hypotheses, each with their respective research questions for further investigation:

Hypothesis 1. *ICTs and DTs can be used in the agricultural sector to make significant improvements in several farming applications. The following research question was crafted to accept or reject the hypothesis:*

1. *What are the state-of-the-art ICTs and DTs currently used in smart farming?*

Hypothesis 2. *There are certain significant challenges to the widespread adoption of smart farming tools, such as lack of awareness about the topic amongst the general population. The following research questions are explored in this context:*

1. *What are the challenges associated with the widespread adoption of smart farming tools?*
2. *What are the current opinions and expectations of the digital user with regards to smart farming?*

For this study, Google Scholar was used to perform exploratory analysis. Specific keywords, such as 'plant disease detection', 'unmanned ground vehicles', 'precision livestock', 'big data', etc., were selected. The searches were performed in the format [technology][smart farming]. For example, in order to search for articles that provided an overview of big-data applications in farming, the search phrase was 'big data smart farming'. A total of 30 keywords were grouped into six groups to analyze the number of citations for the top five results for each search. We attempted to exclude review papers that covered a few or all of the keywords. The number of citations for the top five results for each keyword is graphed in Figure 1 in six groups. The average number of citations for the top five results was calculated. The documents where the number of citations was greater than the average for that keyword were considered for the study.

The rest of this paper is structured as follows: Section 3 covers the various ICTs and DTs, such as big data, IoT, cloud computing, AI, unmanned vehicles, blockchain, and decision support systems, that enable smart farming initiatives. Research efforts and projects that utilize such technologies in the agricultural sector are also discussed. Section 4 covers state-of-the-art smart farming projects that have been launched and completed in the European Union and across the world. A brief overview of user sentiment towards smart farming technologies is conducted through comments collected from YouTube videos about smart farming in Section 5, in order to better encapsulate user perception towards such tools. Section 6 highlights the various challenges present in the widespread adoption of precision and smart agricultural practices. In Section 7, we discuss the findings of our study with respect to the two hypotheses formulated, followed by the conclusion in Section 8. The structure of the paper is displayed in Figure 2.

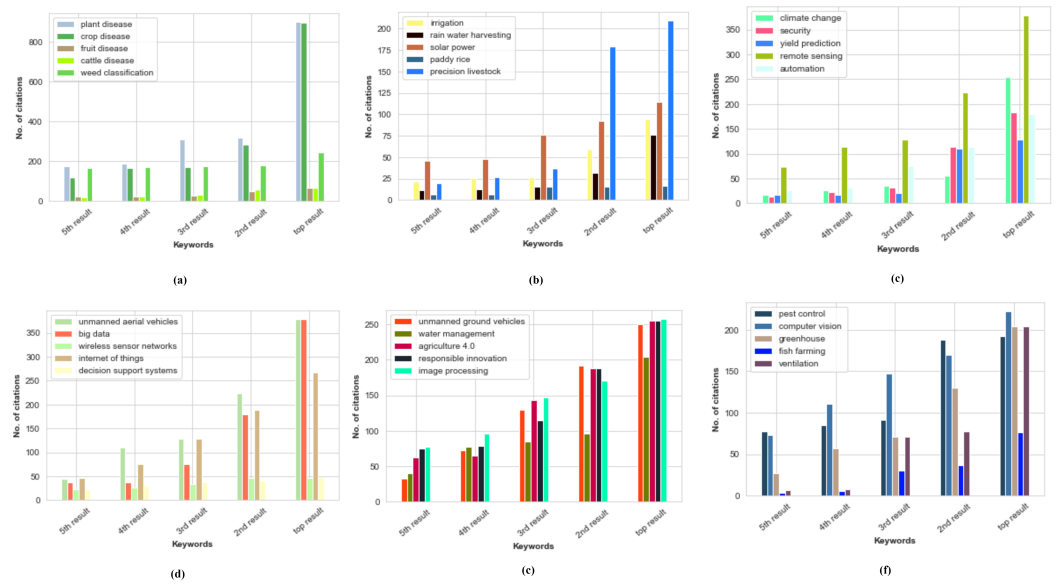


Figure 1. Number of citations per keyword for each of the 6 groups (a–f) of 5 closely related keywords. The number of citations are compared for the top 5 search results.

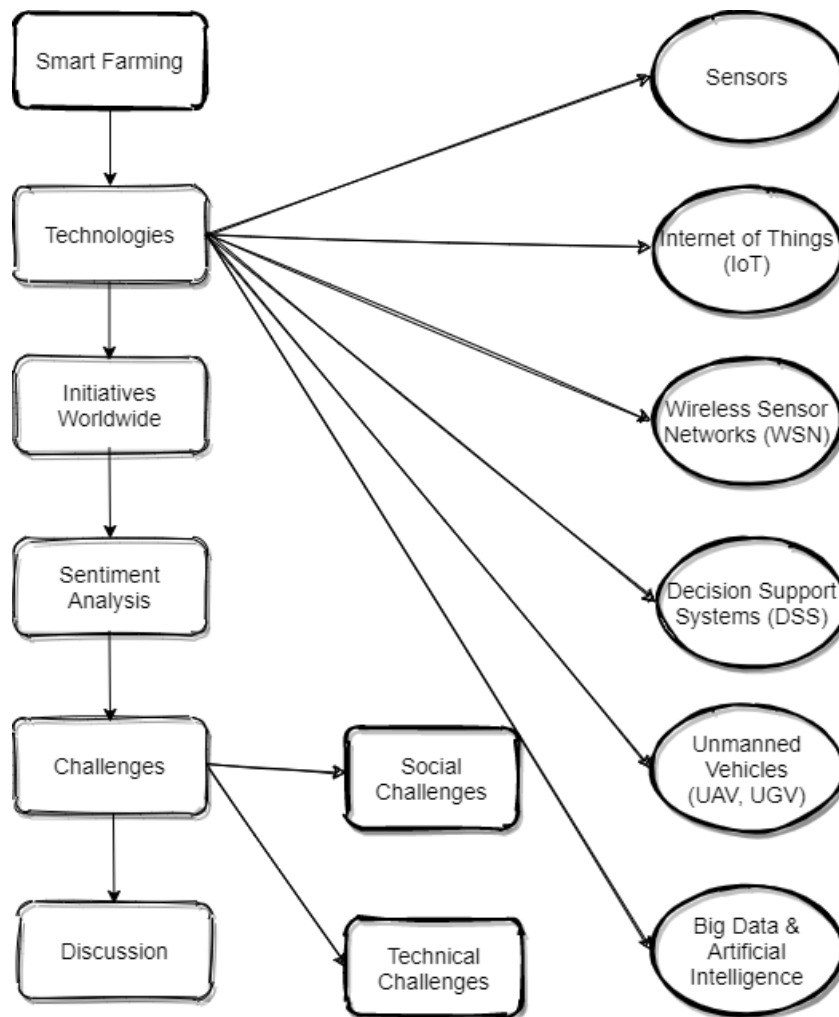


Figure 2. Structure of the paper.

3. Technologies

This section provides a thorough discussion of the key technologies that assist in the evolution of smart farming. These technologies include sensing systems, wireless sensor networks, IoT, unmanned vehicles, decision support systems, blockchain, and more. One or more of these tools has been used in collaboration for smart farming projects worldwide. The development of new sensors with improved sensitivity has allowed for the collection of higher-quality spatial and temporal data, which can be analyzed for more timely and efficient decision making. The advancements in remote sensing translate to reducing human time and effort, as less human intervention is required. Over the past few years, UAVs and UGVs have drastically improved in precision and have become more lightweight and cheaper, allowing for their easy adaption on large-scale farms. Wireless sensor networks can help the seamless functioning of sensors, autonomous vehicles, and decision-support systems to impact production at all stages. IoT platforms can allow control of daily farm activities through remote devices. Figure 3 classifies the technologies implemented in smart farming, along with their most common applications. Table 1 provides a brief description of each technology along with some related works and applications.

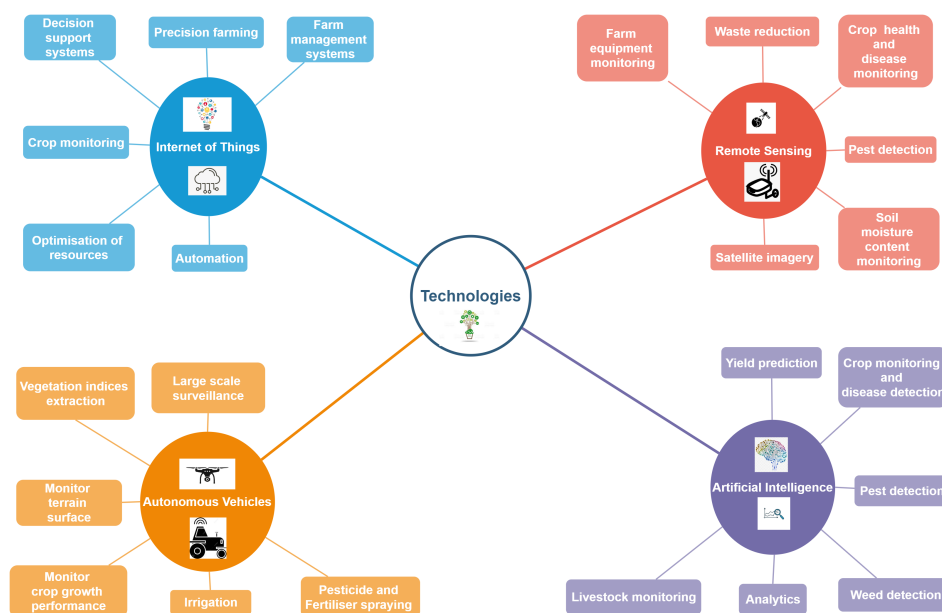


Figure 3. Technologies and applications.

Table 1. Overview of ICTs in smart farming.

Technology	Description	Applications
Sensors	A sensor is a device that detects changes in the physical environment and records this information for future analysis.	Smart collars for monitoring cattle well-being [29]; Hyperspectral imaging of crop field [24]; Greenhouse monitoring [30]
IoT platforms	IoT is a network of physical objects which share information across the internet.	Real-time monitoring and management system for wheat diseases, pests, and weed [31]; IOT platforms using sensors to measure and monitor humidity using the NETPIE protocol [32]; Monitoring health status of dairy cows using IoT and wireless body area networks (WBANs) using LoRa [33]; AgriTech- framework of optimizing resources using IoT [34]; IoT-based system for remote monitoring of soil characteristics using DS18B20 sensor [35]; Agri-IoT framework for IoT-based smart farming [36]; An IoT-based greenhouse monitoring system with Micaz motes [37]; IoT-based agricultural stick integrated with Arduino technology and Solar technology for temperature and moisture monitoring [37]

Table 1. Cont.

Technology	Description	Applications
Decision support systems	DSS is an information system that assists in operational decision making by providing additional predictive insights.	DSS for automatic climate control and minimizing diseases for greenhouse tomatoes [38]; AgriPrediction-LoRa IoT technology-based support system using ARIMA prediction model [39]; AgroDSS-cloud-based DSS for farm management [40]; Web-based decision support system capable of supporting farmers in selecting appropriate alternative crops [41]
Cloud/edge computing	Cloud computing is the online delivery of hosted services, such as software, storage, and computation power. Fog/edge computing is a decentralized computing architecture between the cloud and connected peripheral devices that allows computation and storage closer to the edge devices.	Cloud-computing-based system for early detection of borer insects in tomatoes [42]; cloud-computing-enabled spatio-temporal cyber-physical infrastructure (CESCI) for soil monitoring [43]; Cloud-based farm management system (FMS) developed within FIWARE [44]; IoT-based smart farming system built upon FIWARE for fruit quality control [45]; IoT platform based on edge and cloud computing for soil-less culture needs in greenhouses [46]; Fog-computing-based framework designed to provide a complete farming ecosystem [47]
Blockchain	A distributed, immutable ledger that keeps a record of all transactions of digital assets over a network.	Smart contract-based authentication scheme [48]; model ICT e-agriculture system with a blockchain infrastructure and evaluation tool [49]; Blockchain-based secure smart greenhouse farming [50]; Ecological food traceability system based on blockchain and IoT technologies [51]

3.1. Sensors

The implementation of ICTs and DTs in farming is dependent on the availability of wireless connectivity. Remote sensing is crucial for IoT devices to function. Sensors serve as the basic building block in a wireless sensor network (WSN), which then handles the seamless communication between IoT devices. The advancements in sensing technology translate to the use of additional wavelengths in the light spectrum to remotely monitor crops, manage weeds, capture imagery, and more. Satellites and UAVs are equipped with thermal, visual light (RGB), and near infrared (NIR) cameras to capture multi or hyper-spectral images of the crop field [24]. Hyper-spectral imaging divides light into thousands of smaller bands, which captures a lot of detail. Lightweight, hyper-spectral cameras can be used to monitor crop health, water and nutrient levels, and symptoms of a disease over large areas, which can be difficult to access by other means. The availability of detailed and precise data also allows for spot application of resources and better decision making.

The choice of technology to be used in a project relies heavily on the available bandwidth, transmission distance, and energy requirements. Wireless technologies that have been utilized in smart farming operations over the years include Bluetooth Low Energy (BLE), ZigBee, WiFi, 3G/4G/5G, LoRa, and more. Cellular networks (3G/4G/5G) serve the purpose of aggregating data from various sensors in a smart farming environment. Bluetooth Low Energy (BLE) provides coverage of 100 m and consumes less power than Bluetooth. It can be implemented in systems for livestock positioning [52], greenhouse monitoring [30], and more. BLE is not suitable for transferring large amounts of data [53]. ZigBee is a WSN protocol that provides a smaller coverage area and low energy consumption. It can be used for scenarios such as solar power monitoring [54], greenhouse monitoring, etc. WiFi is beneficial where high bandwidth and large amounts of data transfer is required. Cellular 3G/4G/5G networks offer wide coverage and low latency, but they drive up the cost and power consumption. LoRa can cover an area of 20 km and consumes less energy. Specialized sensors have been introduced for tasks such as pest identification and control, plant health monitoring, resource level monitoring, etc. Bug detection and classification can be performed using acoustic sensing devices and cameras, which capture factors such flight behavior and humming sound [55]. Similarly, parasite detection was performed in study [56] using a spectral sensor that measures light waves. The difference in the reflected light pattern can be an indicator of infestation in the plant.

López et al. [57] propose an autonomous monitoring system that uses a low-cost image sensor for visually inspecting bug traps deployed across the field. Bioacoustic sensors have also been deployed to detect red palm weevil infestation in palm trees [58]. Wireless sensors can be installed on leaves to monitor parameters such as humidity, water content, temperature, etc., to estimate the plant's health and required amount of resources [59]. The growth rate of the plant stem and trunk can also be used to determine its health. Various sensors, such as the stem micro variation sensors, sap flow relative rate sensors, stem flux relative rate sensors, auxanometers, and trunk dendrometer, are used for this purpose [60]. Environmental factors such as atmospheric pressure, solar radiation, wind speed, rainfall, temperature, and humidity can also be measured by wind speed and direction sensors, ambient seismic energy sensors, precipitation sensors, etc. [61]. Global navigation satellite systems (GNSS) can help increase efficiency in smart dairy farming. Smart collars can be worn by cows and can be used to collect data on the health and well-being of livestock [29]. Farmers can program GPS collar trackers to keep cattle in a certain area. The cattle can then be sent to autonomous milking robots when their udders are full. The amount and quality of milk is then analyzed by the robots. Virtual fences can also prevent cattle from getting hurt on electric fencing and allow for rotational grazing [62].

3.2. IoT Platforms

IoT can enable devices and sensors to collect data about physical parameters of a farm. The functionalities provided by IoT, such as smart processing of data and real-time communication between devices, enable it to optimize agricultural practices [63]. IoT blends the usage of physical devices such as actuators and sensors with a WSN to allow for seamless communication [26]. Sensors can serve as the peripheral devices that can gather information over a WSN which can then be analyzed with an IoT platform. There are currently several commercially available IoT platforms that aim to greatly reduce manual labor. They are utilized in various functions of crop monitoring. Zhang et al. [31] propose a monitoring system for wheat diseases, pests, and weed. The system collects data from IoT terminals and attempts real-time monitoring and management of crops. Lee et al. [64] implement a predictive system for effective pest control and proper utilization of pesticides and fungicides. Correlation is calculated between the pests and weather data relevant to the control of pests. Chiochan et al. [32] implement IoT sensors to monitor the humidity of a mushroom farm. The system controls sprinklers and fog pumps and provides push notifications to the user. Benaissa et al. [33] implement Wireless Body Area Networks (WBANs) in conjunction with IoT to monitor the health of dairy cows. Timely detection of health issues in the cattle is a costly and challenging task that was automated in the study through the use of a Long-Range (LoRa) off-body wireless channel and IoT. Garcia et al. [65] implement WSNs to monitor the presence of pests such as snails. The system is also capable of predictive analysis based on environmental factors such as temperature and humidity.

Giri et al. [34] introduce an automation framework called AgriTech for adequate utilization of water, fertilizer, and pesticides. AgriTech allows the farmer to monitor the field and perform actions such as spraying through the use of a mobile device. Kodali et al. [66] present the model of an IoT-based smart greenhouse that automatically carries out irrigation, temperature and air humidity control, and water management with the help of sensors. In the study done by Na et al. [35], an IoT-based remote monitoring system is implemented to monitor soil characteristics such as pH, temperature, and moisture content using a DS18B20 sensor. Accurate measurement of such parameters can enable better analysis and decisions regarding fertilizer usage and crops sown. Kamilaris et al. [36] introduce Agri-IoT, a framework for analyzing real-time data streams from heterogeneous sensors that also supports decision making. It supports integration for data streams from multiple domains, data analytics, and interoperability for smart farming applications. Akkas et al. [37] implement a prototype of a wireless sensor network made up of MicaZ motes that monitor environmental variables such as temperature, light, pressure, and humidity in a greenhouse. The study highlights the advantages of implementing a WSN

over traditional cabling within an IoT platform, such as costs, vulnerability, and inability to relocate the wiring system. Nayyar and Puri [67] propose the use of an IoT-based agricultural stick integrated with Arduino technology and Solar technology to capture live data on physical factors such as temperature and soil moisture. The system provided accuracy of 98% in live feeds when tested on live agricultural fields.

3.3. Decision Support Systems (DSS)

Decision support systems (DSSs) add value to the smooth functioning of farming practices by providing support to farmers, guiding them to correct information, assisting in decision making, and laying out the best course of action for a given scenario. The farm-wide availability of production rules and expertise can drastically improve efficiency. Canadas et al. [38] propose a real-time decision support system implemented for greenhouse tomatoes that facilitates better decision making by identifying sensor faults, maintaining climate variables, and performing disease identification on crops. The study highlights the effectiveness of the DSS in climate control and minimizing crop wastage due to diseases. Taylor et al. [68] perform a case study on web of things that highlights other useful applications of support systems such as environmental and livestock monitoring. Dos Santons et al. [39] present AgriPrediction, an IoT-based support system that utilizes LoRa wireless network range system and the ARIMA predictive model to better manage crop dysfunctions. The system presents promising results, and is also shown to be applicable in rural areas with sparse connectivity. Kukar et al. [40] present AgroDSS, a novel cloud-based decision support system that allows farmers to perform predictive analysis on their own farm data. The system was implemented to study pest population and provide a better understanding of interdependencies of various parameters in a simulated environment. The study done by Antonopoulou et al. [41] provides an approach for continued sustainability by allowing farmers to select alternate crops for a region. The system can be accessed through mobile devices to increase adoptability amongst farmers, and supports the farmer throughout the cultivation process. Thakare et al. [69] provide a DSS for remote monitoring that integrates smart sensing and smart irrigation systems to monitor parameters such as temperature, moisture content, and efficient water use. The study emphasizes the importance of smart farming with hydroponics, which allows farming in unsuitable soil and water conditions.

3.4. Unmanned Vehicles

The advancement in robotics has led to the development of autonomous vehicles, which are used extensively in farming for mechanical weeding, fertilizer spraying, and harvesting. Unmanned vehicles have shown to decrease human labor, improve productivity, reduce costs, and increase accuracy of measurements. They could be further classified into UAVs and UGVs. UAVs are aircraft embedded with wireless sensors, transmitters, and/or cameras that can function autonomously or be controlled remotely. UGVs, on the other hand, are autonomous machines that operate while in contact with the ground. The use of lightweight cameras with autonomous aerial vehicles can allow for remote monitoring of crops, which can allow for better decision making. Bareth et al. [70] performed a study to examine the usability of UAV-based multi-temporal crop surface models for estimating plant height, estimating the biomass through height measurement, and combining vegetation indices for more accurate estimation. The results obtained from field experiments imply that UAV-based RGB imaging can provide accurate modeling of physical parameters of the plant. The review study done by Roldan et al. [71] highlights the advancement of robots in smart farming for automation of labor-intensive tasks such as planting, harvesting, monitoring, inspection, and treating crops. Unmanned vehicles are able to collect information about the environment and navigate it by using machine vision systems. They implement Global Navigation Satellite System (GNSS) technologies [72] to navigate precisely. UAVs provide an added advantage for remote sensing in the form of timely control and high spatial ground resolution. Remote imaging can capture several

characteristics through different types of cameras, such as multispectral, thermal, and high spatial resolution RGB camera, as demonstrated in the study done by Matese et al. [73] to measure intra-vineyard variability and leaf temperature and to perform analysis of missing plants. UAVs possess the potential to obtain high spatial resolution imagery without being too affected by weather conditions.

Lu et al. [74] perform species classification in tall grassland with the use of high spatial resolution imagery obtained from a UAV, and show that the method obtains higher accuracy than other data from satellites. Tripicchio et al. [75] present a novel implementation of an RGB-D sensor integrated with UAVs to differentiate between different plowing techniques used on a field. The system provides the functionality of computer vision, navigation, and data analysis and was shown to be a feasible technique for determination of soil characteristics. Moribe et al. [76] provide an effective and synchronized technique for measuring leaf temperature. Infrared thermometers attached to drones and sensor nodes integrate seamlessly with the WSN. Lottes et al. [77] propose a system that utilizes a UAV to detect vegetation, such as sugar beets, and performs feature extraction and maps the distribution of weeds and crops. UAVs provide an autonomous solution for monitoring large areas of agricultural land covering crops, livestock, and more. Unmanned vehicles function through the use of technologies such as robotics, IoT, remote sensing, and big data, and can automate labor-intensive tasks such as spraying, data collection, water management, weed mapping, irrigation, fertilization, crop monitoring and management, and field-level phenotyping.

3.5. Cloud/Edge Computing

Given the vast amount of incoming data from various sources, a centralized approach to storing and managing large amounts of data is essential. A cloud-based architecture can allow for the necessary computation power to analyze the plethora of data obtained from the different types of sensors installed on a farm. Cloud computing facilitates flexible storage and availability of data and resources, making them suitable for real-time implementation. Rupanagudi et al. [42] propose a novel solution to pest control in tomatoes by crop monitoring using video processing, cloud computing, and robotics. Zhou et al. [43] present a cloud-computing-enabled spatio-temporal cyber-physical infrastructure (CESCI) to perform comprehensive surface soil moisture monitoring, which can help reduce costs, increase agricultural productivity, and boost farmers' net income. FIWARE is an open-sourced cloud platform that has shown potential in many smart farming applications. Kaloxylou et al. [44] present a cloud-based farm management system that utilizes the FIWARE architecture and was shown to be acceptable by farmers during evaluation. Corista et al. [45] introduce an IoT-based smart farming system built upon FIWARE that aims to control fruit quality during the entire fruit production chain. The system is developed using the vf-OS (virtual factory Operating System) platform, which integrates various applications and allows external producers and consumers to interact.

Another IoT platform based on cloud and edge computing is proposed by Zamora et al. [46] and works in three tiers: the local plane collects data on crops, the edge plane monitors and manages the main precision agriculture (PA) tasks, and the cloud platform maintains records and performs data analytics. Fog computing, also called edge computing, is a decentralized computing architecture between the cloud and connected peripheral devices and aims to enhance speed and performance [78]. Edge computing systems provide a decentralized approach to automation of tasks by using pre-loaded field data from edge locations [79]. Thus, fog computing is a promising architecture for smart farming solutions, since it provides low latency and increased reliability for support systems [80]. In case of real-time operational decision making, time is of the essence. Malik et al. [47] introduce a simulation platform that leverages fog computing to allow users to understand sensor deployment and data collection in a complete farming ecosystem. Thus, a cloud platform is essential if real-time analysis is to be performed. Use of additional data-driven approaches can be invaluable depending on the application. Cloud computing

architecture can be used to manipulate large amounts of heterogeneous data arising from several sources. It can provide the necessary storage and computation resources, making it complementary to big data tools.

3.6. Blockchain

Blockchain technology provides new modes of interaction between parties in a supply chain. It is a distributed, immutable ledger that keeps a record of all transactions of digital assets over a network. It also has the capacity to improve food safety by providing traceability for purchased food products and monitoring for contamination. In order to avoid bias in the data collected from ICT and DT devices, it is important that data manipulation is made difficult or impossible. The addition of a new record in a blockchain requires verification from a peer-to-peer network, ensuring its legitimacy. Similarly, the majority should agree while making changes to records, making it difficult for unauthorized individuals to alter the data. Thus, blockchain-based technologies for smart farming ensure that the data is correct, transparent, and traceable. In conjunction with smart contracts, which are protocols that are activated without human intervention when the terms of an agreement are met, blockchain technology can ensure timely payments [81]. Vangala et al. [48] propose an authenticated key agreement mechanism for smart farming that is based on smart contracts. The system is shown to provide more security and functionality than other authentication protocols. Patil et al. [50] present a security framework that combines blockchain technology with IoT devices and allows sharing of a digital ledger of transactions among the nodes on an IoT network. Lin et al. [51] introduce an ecological food traceability system that incorporates blockchain technology and IoT and aims to improve food safety while also establishing trust between the parties involved. The use of smart contracts is also considered for the timely management of problems in the system. An ICT and DT e-agricultural system with blockchain technology that distributes water quality data over a network is proposed by Lin et al. [49]. They also present an evaluation tool that can be used to determine the specific requirements and suitability of this technology. A simulated model of blockchain technology is proposed by Widi Widayat et al. [82] and can be implemented in a smart farming environment. The parties in a smart farming system, namely farmers, food suppliers, and customers, are connected to a global blockchain network and appear as a node account in the smart contract. Another potential application of blockchain technology is for providing agricultural insurance. Nguyen et al. [83] present a smart contract developed on NEO to provide drought-based crop insurance. This could be invaluable to farmers who work in extreme weather conditions, as it can reduce their damages and vulnerability while also avoiding excess evaluation costs.

3.7. Big Data and Artificial Intelligence

IoT devices and sensors capture various types of data from all over the field that can then be analyzed through big data tools. Big data refers to larger and more complex datasets that consist of a greater variety of data from multiple data sources and can also be mined for opinions and information [84]. Data modeling techniques such as machine learning and deep learning can help enhance the entire food production cycle by performing predictive analysis, providing real-time decision making, and refining the business model of the farm to cut losses. AI is a research sub-field of computer science that utilizes robust datasets to solve problems by performing classification or predictions based on the input data [85]. Machine learning is a sub-field of AI that allows models to learn from experience without being explicitly programmed. Deep learning is a sub-field of machine learning that further eliminates some of the human intervention required in training by automating feature extraction from larger datasets [86]. Currently, there are also several types of state-of-the-art conversational systems being used to assist farmers in agricultural operations [87]. Table 2 summarizes some notable research works in smart farming that have performed image processing using Convolutional Neural Networks (CNNs). CNNs are a class of Artificial Neural Networks (ANNs) that are used to perform classification tasks on images

by adjusting learnable weights and biases [88]. Table 3 provides a summary of various studies that have utilized other AI models in smart farming, along with their respective outcomes.

AI can help reduce resource wastage through monitoring and predictive modeling. Varghese and Sharma [89] propose a hardware-based system that helps monitor factors such as moisture content in soil, humidity, and atmospheric conditions. The system also determines the appropriate crops for given soil and environmental conditions through the use of IoT and machine learning. Arvindan et al. [90] introduce an automated irrigation system that measures moisture content in the soil and provides remote control through an Android smart phone. This can help with the sustainable and automatic farming of certain crops that require different degrees of irrigation depending on their growth stage. Khaki et al. [91] introduce WheatNet, which is a CNN that collects field observational data, such as wheat head counts. The system achieves a Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) of 3.85 and 5.19, respectively, in the wheat head counting task with fewer parameters, implying that the approach is robust and crucial for observation and decision making. Deep learning algorithms are used extensively to reduce crop wastage and optimize crop yield. The development of systems for accurate prediction of crop yield is essential, especially in developing countries, as it can secure food availability, prevent famine, and provide further assistance to the sustainable development of agriculture. Crop yield can depend on several factors, such as genotype, environment, etc. Wang et al. [12] present a deep-learning-based system for predicting soybean crop yields based on data collected from remote sensing. Long Short-Term Memory (LSTM) cells were trained and tested on 4 years of Argentinian soybean harvest data. The model's transferability was then tested by using soybean harvest results from Brazil. Khaki et al. [13] implemented Deep Neural Networks (DNNs) for yield prediction of maize. The dataset consisted of the genotype and yield performance of 2267 maize hybrids. The best-performing model provided an RMSE of 12% of the average yield and 50% of the standard deviation for the validation dataset in imperfect weather conditions.

Alfred et al. [92] provide a survey of the implementation of big data and machine learning on paddy rice production in the Asia-Pacific region. The integration of sensors, satellites, and drones complements machine learning tools in improving productivity. Machine learning tools utilize the big data collected from these devices for estimating rice yield [93,94], monitoring growth [94], and providing a smart irrigation system [95]. Kiruthika et al. [96] propose a system to detect paddy rice crop diseases such as leaf blast disease, brown spot disease, and bacterial blight disease. A Gray-Level Co-occurrence Matrix (GLCM) is used to recognize disease from the input image; two classifiers are used for recognition: ANN and Support Vector Machine (SVM). ANN performs better than SVM, with a precision of 90.60% and accuracy of an 93.33%. Dahane et al. [97] propose a novel EDGE-fog-IoT-cloud-based architecture that utilizes WSNs to support farming activities in three steps: data collection from sensors (soil moisture, temperature, humidity, water level, etc.), data cleaning and storage, and predictive analysis through AI tools. Performance of Gated Recurrent Unit (GRU) and LSTMs on live data from three parameters is compared, with varying results.

Jhuria et al. [9] propose a tool that utilizes ANNs to identify diseases in grapes and apples. Image processing is performed on an image dataset, and an accuracy of 90% is obtained based on color and texture. The study also provides a tool to determine the quality of fruit by weight. Bhange et al. [98] present a web-based tool for identification of fruit diseases trained on images of pomegranate fruit. The system processes an image uploaded by the user for parameters such as color and morphology, and classifies it as infected or non-infected using SVMs. Accuracy of 82% was recorded using the 'morphology' parameter in the experiment. Guo et al. [10] propose a system for identification of plant diseases through the use of deep learning. The model identifies black rot, bacterial plaque and rust diseases by implementing a Region Proposal Network (RPN) for leaf localization, the Chan-Vese algorithm for leaf segmentation, and VGG-13 [99] architecture for disease identification. This method provides an accuracy of 83.57%. In the study by Ferentinos [100], image classification through a VGG

CNN is performed on a database of 87,848 photographs of leaves of healthy and infected plants in a set of 58 distinct classes of [plant, disease] combinations, and a success rate of 99.53% is achieved. Similarly, smartphone-assisted crop disease diagnosis is performed by Mohanty et al. [101] on the PlantVillage dataset consisting of 54,306 images of plant leaves. The GoogleNet architecture performed the best out of all models tested, resulting in an accuracy of 99.35% on 14 crop species and 26 diseases. The prevention of fruit tree diseases can also significantly impact overall agricultural production. Li et al. [102] conducted a study comparing the performance of three ensemble learning classifiers and two deep learning classifiers. The stacking ensemble learning classifier provides the highest validation accuracy of 98.05% and test accuracy of 97.34% on a dataset of 10,000 images of pear black spot, pear rust, apple mosaic, and apple rust. Figure 4 displays a generalized example of plant disease identification through the use of CNNs. The network takes input in the form of segmented images and classifies them as 'Diseased' and 'Not Diseased'.

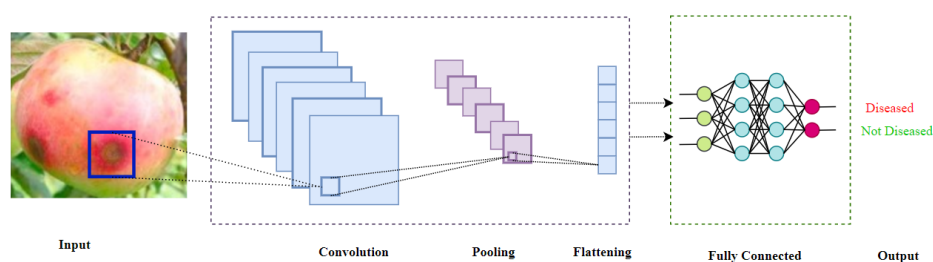


Figure 4. Disease identification through image processing.

Due to the rapid increase in global meat consumption, technologies such as precision livestock farming [103] have become essential to ensure the quality of meat products and reduction of the environmental impact. AI tools can also prove beneficial in livestock management by monitoring cattle health and behavior. Xu et al. [104] propose a system for individual identification of cattle through face detection, performed using the RetinaNet object detection algorithm. Fine-tuning was performed on seven different CNN models, and transfer learning was used for this study. RetinaNet incorporating the ResNet 50 provided the highest average accuracy of 99.8% and an average processing time of 0.0438 s. Gjergji et al. [105] evaluated the following neural networks for the regression task of cattle weight prediction: CNNs, Recurrent Neural Networks (RNN)/CNN networks, recurrent attention models, and recurrent attention models with CNNs. CNNs were shown to provide the best performance with MAE of 23.19 kg, significantly outperforming the top linear regression models, which reached an error of 38.46 kg. Jung et al. [106] present a deep learning-based system for classification of cattle vocals and real-time monitoring of livestock. The voice parameter of cattle can signal valuable information such as gender of cattle, distress, and disorders in the cattle [107]. The voice was converted to Mel-frequency cepstral coefficients (MFCCs) and given as input to a CNN for classification with an accuracy of 91.36%. The accuracy increased to 94.18% when short-time Fourier transform-based noise filtering was used to reduce background noise. In the context of smart farming practices, deep learning has also been shown to be widely beneficial in the field of aquaculture. Fish production contributes to a great portion of the food source in any area. Zhang et al. [108] propose the use of DNNs for fish identification, species classification, analysis of fish behavior, feeding decisions, and water quality prediction. The method provided an accuracy of 96% and recognition rate of 98% when trained on the Fish 4 knowledge dataset, which contains 8487 images of fish with different conditions. The study done by Rohani et al. [109] proposes a model consisting of multi-layer perceptron (MLP) and SVM for classification of rainbow trout as dead or alive. Both classifiers provided an average accuracy of 100% during the training phase and average of 99.45% during the testing phase. Zambrano et al. [110] propose the use of machine learning tools to forecast water quality variables such as dissolved oxygen, pH, and pond temperature. A

comparison is performed between Random Forests (RF), ANNs, and multivariate linear regression, out of which RFs performed the best.

CNNs can also be used to perform object detection and pattern recognition on images collected by aerial vehicles to detect anomalies such as weed clusters, standing water, etc. Chiu et al. [111] introduce ‘Agriculture-Vision’, a large-scale dataset of aerial farmland images, designed for semantic segmentation of agricultural pattern recognition. The dataset consists of 94,986 high-quality aerial images consisting of RGB and near-infrared (NIR) channels. The study proposed a Feature Pyramid Network (FPN)-based model with a ResNet encoder to classify 9 field anomaly patterns. The mean intersection-over-union (mIoU) was 43.40% for the validation set and 43.66% for the test set. The first Agriculture-Vision Challenge [112] encouraged further development of novel algorithms for pattern recognition in agriculture. The challenge dataset consists of 21,061 aerial and multi-spectral farmland images, and six anomaly patterns were to be recognized in the task. The best-performing model, Residual DenseNet with Squeeze-and-Excitation (SE) block, introduced by Team DSCC, achieved a modified mIoU of 63.9%. The study by Kussul et al. [113] performs classification of crops using MLPs, RFs, and CNNs. The dataset consisted of 19 multitemporal scenes acquired by Landsat-8 and Sentinel-1A RS satellites, and the highest classification accuracy of 94.6% was achieved by 2-D CNNs. Another crop vision dataset for species classification and detection is the CropDeep [114] dataset, which consists of 31,147 images and at least 1500 samples for each of the 30 classes. A baseline study showed the best performing model was ResNet50, with an accuracy of 99.81%. The study further suggests the YOLOv3 network with modification to achieve higher accuracy on the dataset. Anand et al. [115] present ‘AgriSegNet’, which is a multi-scale hierarchical attention network for semantic segmentation using UAV-acquired aerial images for IoT-assisted precision agriculture. The mIoU on the test set of the Agriculture-Vision dataset for the six anomaly classes are: Background: 78.10%; Double Plant: 46.40%; Planter Skip: 8.60%; Standing Water: 61.20%; Waterway: 44.90%; Weed Cluster: 50.20%.

Table 2. Summary of applications of CNNs in smart farming.

Applications	Results
Plant disease detection through CNN [100]	99.53% success rate
Plant disease detection by CNN trained on 14 crop species and 26 diseases [101]	99.35% accuracy
CNN for identification of 6 diseases in tomato leaves [116]	AlexNet accuracy: 97.49%; VGG16 net accuracy: 97.23%
Plant disease detection by CNN trained on 13 crop species and 26 diseases [117]	MobileNet accuracy: 99.62%; InceptionV3 accuracy: 99.74%
Cattle face detection through CNN: Object detection algorithm RetinaNet incorporating ResNet 50 [104]	Average precision score: 99.8%; Average processing time: 0.0438 s
Beef cattle body weight prediction through CNN [105]	Mean absolute error: 21.64 kg
Holstein Friesian cattle detection and individual identification through CNN [118]	99.3% accuracy
Species classification and detection on the CropDeep crop vision dataset done by CNNs [114]	Baseline study: ResNet50 average accuracy of 99.81%
Classification of crop types (maize, soybeans, etc.) done by MLPs, RFs, and CNNs [113]	Highest accuracy of 94.6% by ensemble of 2-D CNNs
FPN-based model for semantic segmentation of agricultural land on the Agriculture-Vision dataset [111]	mean intersection-over-union (mIoU) was 43.40% for the validation set and 43.66% for the test set.
Residual DenseNet with squeeze-and-excitation (SE) block on the Agriculture-Vision challenge dataset [112]	modified mIoU of 63.9%.

In this subsection, we emphasize several points regarding the opportunities provided by AI in the field of smart farming. Image processing is of great importance to the agricultural sector. Images captured by UAVs, UGVs, satellites, and sensors need to be analyzed so that relevant insight can be extracted from them to assist in farm operations. Depending on the requirements, different types of cameras, such as visible spectrum, NIR, hyperspectral, or multispectral may be used. In conjunction with several ICTs, AI can efficiently perform functions such as crop monitoring, livestock monitoring, disease detection, pest detection, etc. Predictive modeling can help farmers to prepare for extreme weather conditions and market fluctuations, thereby lowering their vulnerability. Current state-of-the-art models have provided promising results, implying that further research in the area with more advanced AI tools can help to bridge the gap in food production.

Table 3. Summary of applications of Artificial Intelligence in Smart Farming.

Applications	Results
K-means for clustering; SVM for classification of pomegranate diseases [98]	82% accuracy (morphology)
ANN for disease detection in grapes and apples [9]	90% accuracy (morphology)
RPN for localization of leaves; ChanVese algorithm for segmentation; transfer learning model for disease identification [10]	83.57% accuracy
ANN for paddy crop disease detection [96]	93.33% accuracy
Fruit disease identification by stacking ensemble learning classifier trained on apple and pear diseases [102]	Accuracy of 98.05% on validation dataset and 97.34% on test dataset
UAV-based plant/weed classification with Random Forests [77]	Crop vs. weed classification accuracy of 96% and 90% recall
Soybean crop yields in Argentina using LSTMs; Transfer learning approach for Brazil soybean harvests [12]	RMSE of 0.54 for Argentina and 0.38 for Brazil (transfer learning from Brazil)
Deep neural network (DNN) for yield prediction of maize hybrids [13]	Yield prediction: training RMSE = 10.55, validation RMSE: 12.79 for DNN
Classification of fish in aquatic fish farms through DNN [108]	Accuracy = 96%, recognition rate = 98%
Random Forests for forecasting water quality variables such as dissolved oxygen, pond temperature, etc. [110]	RMSE for pond temperature = 0.5971, RMSE for dissolved oxygen = 1.616.
Recognition and classification of dead and alive rainbow trout eggs done by MLP and SVM [109]	Training accuracy = 100%; average testing accuracy = 99.45%

4. Initiatives Worldwide

This section includes the various research initiatives that have been undertaken in smart farming in the European Union [119] and across the world. The initiatives usually employ several of the ICTs and DTs discussed in Section 3. The European Union has funded many projects to allow for the integration of ICTs and DTs into the agricultural sector. Crop monitoring is one of the major functions performed in farms that utilize smart farming tools. Table 4 provides an overview of the recent projects concerning the implementation of SF tools for crop monitoring that have been undertaken in the European Union. Table 5 lists the projects that perform other functions such as harvesting, water management, satellite imagery, and more. The corresponding technologies for each project have also been listed along with their application. The Echord++ [120] project, which lasted from 1 October 2013 to 30 September 2018, involved various field operations such as monitoring, harvesting, and grafting for crops such as tomatoes, asparagus, and peppers. Cloud computing is utilized by many projects that require monitoring operations. These

include Vinbot [121] (crop monitoring and yield prediction in a vineyard), Ermes [122] (crop monitoring for rice), Fractals [123] (monitoring, disease detection, and fertilization of olive trees), and more. The importance of UAVs and UGVs is apparent, as they have been utilized in several projects. Implementations of UGVs include Vinerobot [124] for a vineyard, Sweeper [125] for harvesting peppers, Flourish [126] for monitoring and spraying sugar beets and sunflowers, PANtHEOn [127] for monitoring hazelnuts and water management, and Romi [128] for crop monitoring and weed management. UAVs are utilized for crop monitoring of rice in Ermes [122], potatoes and vineyard in Mistrale [129], and more. Seamless communication between different technologies has been executed through the use of WSNs, such as Water-Bee [130] and Figaro [131], for the purpose of water management.

Table 4. Smart Farming projects in EU for crop monitoring.

Project Name	Technologies	Operations
Echord ++ [120]	Cloud computing; Image processing; Machine learning; UAV; UGV	Crop monitoring; Harvesting; Weed management
Vinerobot [124]	Image processing; Machine learning ; UGV	Crop monitoring; Disease detection; Water management
Vinbot [121]	Cloud computing; Image processing; UGV	Crop monitoring; Yield prediction
Flourish [126]	Image processing; UAV; UGV	Crop monitoring; Spraying
PANtHEOn [127]	Big data; UAV; UGV; WSN	Crop monitoring; Water management
Ermes [122]	Big data; Cloud computing; UAV; WSN	Crop monitoring
Fractals [123]	Cloud Computing; WSN	Crop monitoring; Disease detection
Mistrale [129]	Image processing; UAV	Crop monitoring; Water management
Romi [128]	UAV; UGV	Crop monitoring; Weed management
Apollo [132]	Aerospace sensing	Crop monitoring
AgriCloud P2 [133]	Cloud computing; Edge computing; Information systems; Terrestrial sensing	Crop monitoring
Sensagri [134]	UGV; Terrestrial sensing; Aerospace sensing	Crop monitoring
IoF2020 [135]	Cloud computing; UAV; UGV; Big data; Aerospace and terrestrial sensing; Information systems	Crop monitoring; Livestock farming; Dairy monitoring
DataBio [136]	Machine learning; Big data; Aerospace and terrestrial sensing; Cloud computing	Crop monitoring; Forestry; Fishery
Apmav [137]	Big data; Machine learning; UAV; Terrestrial sensing; Cloud computing	Crop monitoring
AfarCloud [138]	Big data; Terrestrial sensing; UGV	Crop monitoring; Livestock farming
BigDataGrapes [139]	Machine learning; Big data; UAV; Terrestrial sensing; Cloud computing; Information systems	Crop monitoring
Dragon [140]	Machine learning; Big data; UAV; UGV; Aerospace and terrestrial sensing; Information systems	Crop monitoring

There have been several research projects on smart farming taken up all over the world, in part inspired by the positive outcomes of the EU projects. Table 6 provides a summary of government projects and start-ups that focus on the development of innovative solutions for smart farming. Some projects, such as the Villages of Excellence (VoE), have been launched in collaboration between two governments to ensure the sharing of technology and expertise and provide better outcomes for both. Smart irrigation plays an important role in ensuring crop sustainability in dry areas. Startups such as Madar Farms [141] and Responsive drip irrigation [142] aim to provide smart irrigation solutions to tackle water challenges and food security in the United Arab Emirates and the United

States respectively. SunCulture [143] is a Kenyan AgriTech company that provides solar-powered irrigation systems for smallholder farms, and also provides the option of a drip irrigation system. In Morocco, the government introduced the Green Generation 2020–2030 strategy [144], which focuses on the digitization of agriculture through initiatives such as the installation of solar pumps for irrigation. Food security and sustainability are of great concern worldwide. Startups such as AbyFarm [145] in Singapore aim to implement urban farming by employing ICT and DT tools such as IoT and blockchain. Lack of resources in rural areas could be a hindering factor in crop yield. Ossian Agro Automation [146] is an Indian company working towards rural automation and the development of wireless automation systems. All year round production of crops can be achieved by vertical farming, which is the practice of growing crops in many layers in a controlled environment. Ground vertical farming [147] in Lebanon implements vertical farming and aims to reduce water wastage by re-circulation. Figure 5 displays the various smart farming projects taken up across the world, classified according to their primary function.

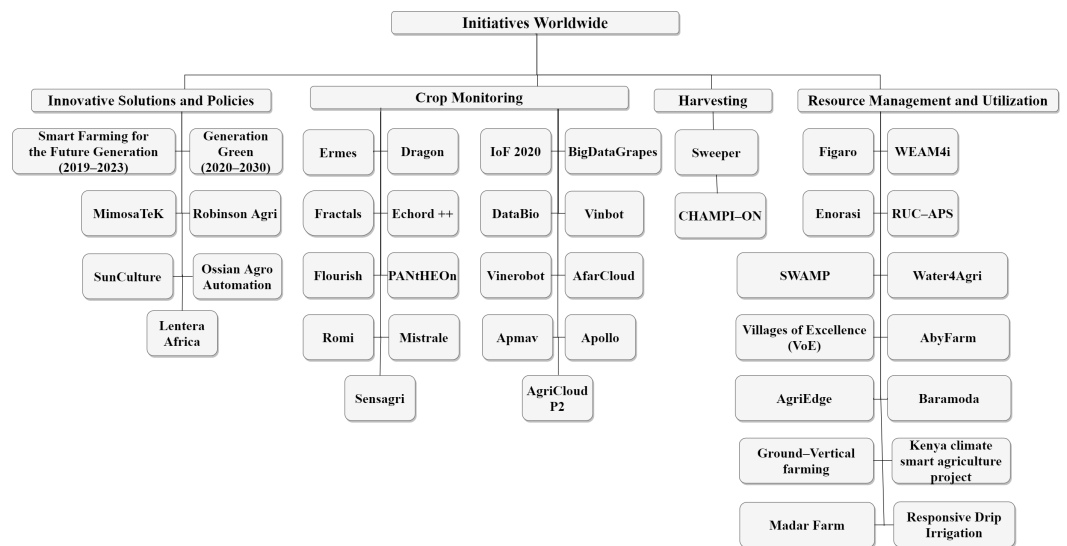


Figure 5. Smart Farming initiatives worldwide

In several developing countries, there is a lack of government-funded projects. The initiative is rather taken up by individual startups, with the goal to provide assistance to farmers, conduct further research, and educate farmers and learners about the potential of agricultural technology. There is an increased interest amongst consumers, who want to ensure that the end product they receive is unadulterated. Public opinion in Europe skews in favor of healthy products grown with minimum pesticides. Consideration of the socio-economic impact of smart farming projects is also necessary. Certain participating farms have reported average cost savings of over €5000 and reduction of climate impact by 10% [148]. Thus, these initiatives have been greatly beneficial to farming operations by decreasing costs, reducing greenhouse emissions, and improving soil conditions. The projects contributed significantly to their objectives of reducing resource wastage, environmental impact, and energy consumption, and demonstrated measures to mitigate issues resulting from climate change and the shortage of skilled labor.

Table 5. Smart Farming projects in EU.

Project Name	Technologies	Operations
Sweeper [125]	Image processing; UGV	Harvesting
Figaro [131]	WSN	Water management
Enorasis [149]	WSN	Water management
WEAM4i [150]	Cloud computing; WSN	Water management
CHAMPI-ON [151]	Image processing; Machine learning	Harvesting
Auditor [152]	Aerospace sensing	Satellite imagery
RUC-APS [153]	Cloud computing; Edge computing; Information systems	Management; Optimization
AfriCultuReS [154]	Big data; Aerospace and terrestrial sensing; Cloud computing; Information systems	Food security
SWAMP [155]	Big data; UAV; Terrestrial sensing; Cloud computing; Information systems	Water Use
Water4Agri [156]	Aerospace sensing	Water Use

Table 6. Smart Farming initiatives worldwide.

Project/Company	Country or Countries	Objectives
Villages of Excellence (VoE) (2021–2023) [157]	India and Isreal	Improve the productivity and quality of horticulture; Increase income of farmers
Nosho Navi 1000 (2014–2016) [158]	Japan	Large-scale smart rice farming
AbyFarm [145]	Singapore	IoT, blockchain and machine learning for urban farming to ensure sufficiency of crops
Smart Farming for the Future Generation (2019–2023) [159]	Vietnam and Uzbekistan	Development of policies, enhancement of skills and knowledge. Support farmers through post-harvest handling and markets
AgriEdge [160]	Morocco	Precision agriculture platform for practices such as efficient use of water and fertilizer, monitoring weather data, and satellite imaging.
Generation Green 2020–2030 [144]	Morocco	Introduction of new technologies for sustainable agriculture; Installation of over 100,000 solar pumps for irrigation
Baramoda [161]	Egypt	Sustainable agriculture; Maximize the efficiency of agri-waste management
Ground–Vertical farming [147]	Lebanon	Improve efficiency of agricultural yield; Reduce water consumption and costs.
Robinson Agri [162]	Lebanon	Greenhouse technology; Distribution of agricultural resources
Kenya Climate Smart Agriculture Project (KCSAP) [163]	Kenya	Improve productivity in case of climate change risks and provide response in emergencies
MimosaTek [164]	Vietnam	IoT platforms for precision farming solutions
Ossian Agro Automation [146]	India	Wireless automation systems (Nano Ganesh) for irrigation in rural areas
SunCulture [143]	Kenya	Solar-powered irrigation systems (RainMaker2)
Madar Farm [141]	United Arab Emirates	Ensure food and water security
Responsive Drip Irrigation [142]	United States of America	Smart irrigation
Lentera Africa [165]	Kenya	Technology enabled farmer advisory services; Farm inputs and equipment

5. Sentiment Analysis

In order to ensure successful integration of new tools and technologies available for smart farming, it is necessary to understand how knowledgeable the general public is about the topics and how the innovations are perceived. Public sentiment can be a strong determinant of whether or not a project is approved for implementation in an area [166]. It can also be indicative of the various socio-economic, behavioral, and cultural issues that arise by the advancement and implementation of such technology [28,167]. In light of this, we performed sentiment analysis on the comments of YouTube videos pertaining to smart farming technologies. This section provides details about the dataset, experimental methodology, and the results and analysis of the experiment.

5.1. Dataset

The dataset was constructed by scraping YouTube comments left by users on 16 YouTube videos that were relevant to our study [168–172]. The videos were selected by searching the relevant keywords, such as ‘smart farming IoT’, and then filtering the ones with most views and comments. Table 7 provides a list of the video titles, the channels, upload date, and the total number of likes and views on each video. For this study, only comments in English were considered. A total of 7311 comments were included in the dataset from videos about smart farming.

5.2. Experiment

Two approaches were used for performing sentiment analysis. In the first approach, two annotators assigned one of the following six labels to the comments: ‘Praising’, ‘Queries’, ‘Suggestions’, ‘Undefined’, ‘Hybrid’, and ‘Opinion’. Cohen’s kappa coefficient, which is a measure of inter-rater agreement, was calculated on the ratings of the two annotators. The value of the kappa statistic ranges from 0 to 1, with 0 implying only a chance agreement and 1 implying perfect agreement between the two annotators. The formula to calculate Cohen’s kappa for two raters is:

$$\kappa = \frac{p_o - p_e}{1 - p_e} = 1 - \frac{1 - p_o}{1 - p_e} \quad (1)$$

where: p_o = the relative observed agreement among raters, and p_e = the hypothetical probability of chance agreement.

A brief description of these labels is given in Table 8, along with the total number of comments for each label, and an example of the label from the dataset. Table 9 gives the total counts of each of the six labels that were assigned to the comments collected from the videos.

Table 7. Videos selected for sentiment analysis.

Video Serial No.	Video Title	Channel	Total Likes (Accessed on—14 April 2022)	Uploaded On	No. of Views
1.	How Japan Is Reshaping Its Agriculture By Harnessing Smart-Farming Technology	Science Insider	1100	8 March 2021	35,000
2.	Europe has the best regenerative farmers in the world	Richard Perkins	543	8 October 2020	16,000
3.	The Futuristic Farms That Will Feed the World	Freethink	22,000	19 August 2019	805,000
4.	Vertical farms could take over the world	Freethink	26,000	22 May 2021	753,000
5.	India’s largest Precision Farm—Simply Fresh	Discover Agriculture	2500	12 March 2021	70,000
6.	Solar Panels Plus Farming? Agrivoltaics Explained	Undecided with Matt Ferrell	59,000	5 October 2021	1.9 million
7.	7 Israeli Agriculture Technologies	Israel	35,000	21 January 2019	2 million

Table 7. Cont.

Video Serial No.	Video Title	Channel	Total Likes (Accessed on—14 April 2022)	Uploaded On	No. of Views
8.	The CNH Industrial Autonomous Tractor Concept (Full Version)	CNH Industrial	17,000	30 August 2016	2.7 million
9.	IoT Smart Plant Monitoring System	Viral Science—the home of creativity	6800	20 December 2020	341,000
10.	Singapore’s Bold Plan to Build the Farms of the Future	Tomorrow’s Build	30,000	13 July 2021	1.8 million
11.	Smart Vertical Farms in Sharjah	Episode Up	1200	17 September 2020	59,000
12.	Drones, robots, and super sperm—the future of farming	DW Documentary	6700	7 February 2019	919,000
13.	Simply Fresh—India’s Largest State Of The Art Precision Farm	Simply Fresh	7100	10 October 2020	314,000
14.	RIPPA The Farm Robot Exterminates Pests And Weeds	ABC Science	8800	14 May 2018	813,000
15.	Top 10 Agritech Startups Empowering Indian Farmers	Backstage With Millionaires	11,000	9 June 2020	325,000
16.	This Farm of the Future Uses No Soil and 95% Less Water	Stories	152,000	5 July 2016	152,000

The second approach was to apply transfer learning to perform surface level sentiment analysis using the pre-trained Pattern library for Python. Pattern library can be used to perform various natural language processing tasks such as parsing, N-gram generation, and more. Polarity of a given text ranges from 1 to -1 , with 1 representing a highly positive sentiment and -1 representing a highly negative sentiment. The subjectivity ranges from 0 (Objective) to 1 (Subjective). It provides a measure of factual information or personal opinion in the comments, with 1 being subjective and 0 being objective. For example, for the following comment in our dataset: ‘Fantastic. We need a lot of that here in Australia; suffering from drought; really bad water management by those in authority etc.’, the polarity was calculated as -0.1499 and subjectivity was 0.7833 . The negative value of polarity indicates that the sentiment expressed by the comment was negative, whereas the value of subjectivity is closer to 1 suggesting that the comment was mostly subjective.

Table 8. Label description.

Label Serial No.	Label	Description	Example
1	Praising	Simple positive response	This is amazing! Everyone is a winner when we chose sustainability!
2	Suggestion	Any concrete suggestion relevant to the topic	technology is really spectacular, now just assess its viability.
3	Opinion	Positive, negative, or combined sentiment	Technology is taking over farming, I like having to do it the way they do it now
4	Undefined	Could not be determined or isn’t relevant	that would be like playing farming simulator in real life!
5	Hybrid	More than one of the categories	best part of farming is driving tractor. now get a robot to shovel manure, do chores like that would be sweet. why does the robot need lights at night?
6	Queries	Any concrete queries relevant to the topic	i wonder how much this thing costs

Table 9. Number of comments of each label type.

Video Serial No.	Praising	Suggestion	Opinion	Undefined	Hybrid	Queries
1.	14	5	3	5	0	2
2.	8	2	10	2	2	4
3.	33	7	83	14	20	21
4.	98	33	504	176	81	149
5.	8	0	5	3	0	4
6.	31	15	70	25	47	11
7.	61	1	17	50	12	16
8.	31	9	351	233	17	54
9.	39	4	5	29	15	110
10.	129	39	399	225	29	57
11.	26	2	4	2	4	3
12.	36	4	113	36	9	9
13.	94	0	24	4	24	32
14.	23	14	155	126	8	33
15.	54	14	45	23	13	15
16.	273	85	1455	438	218	466

5.3. Results and Analysis

In this section, we detail the results of our experiment and analyze our findings. Evaluation has been conducted separately for the two approaches through user-based analysis and transfer-learning-based analysis. Table 10 records the number of comments under a video and the results obtained from sentiment analysis. The value of mean polarity, mean subjectivity, and Cohen's kappa coefficient is listed for each corresponding video serial number.

5.3.1. User-Based Analysis

In user-based analysis, the mean Cohen's kappa was calculated to be 0.9617, which shows high inter-rater reliability. Figure 6 displays the Cohen's kappa coefficient for each video with respect to the mean value. The value is highest at 1 for videos no. 5, 9, and 12, indicating perfect agreement between the labels assigned by both annotators. The value is lowest at 0.8141 for video no. 2 titled 'Europe has the best regenerative farmers in the world', implying a slight disagreement between the assigned labels. The high value of kappa coefficient implies that the categories assigned by the annotators are correct.

Figure 7 plots the correlation matrix between the frequency of the six labels. We can see the highest degree of correlation is 0.96 between the following labels: 'Opinion' and 'Suggestion', and 'Queries' and 'Hybrid', indicating that the frequency of one increases with the other. The lowest degree of correlation is 0.81 between 'Hybrid' and 'Undefined', suggesting that all labels show a relatively positive correlation amongst each other.

Table 10. Results of Sentiment Analysis

Video Serial No.	No. of Comments	Mean Polarity	Mean Subjectivity	Kappa Coeff.
1	29	0.2143	0.3124	0.9061
2	28	0.2546	0.4956	0.8141
3	178	0.2262	0.4809	0.9609
4	1041	0.1420	0.4197	0.9890
5	20	0.3104	0.4197	1.0
6	199	0.2140	0.4942	0.9220
7	157	0.3404	0.4710	0.9467
8	695	0.0919	0.3838	0.9526
9	202	0.1743	0.2915	1.0
10	878	0.1417	0.4087	0.9698
11	41	0.3849	0.5369	0.9571
12	207	0.1172	0.4116	1.0
13	178	0.4360	0.5480	0.9827
14	359	0.1186	0.3734	0.9958
15	164	0.2736	0.4614	0.9921
16	2935	0.1942	0.4546	0.9995
Average Score		0.2092	0.4352	0.9617

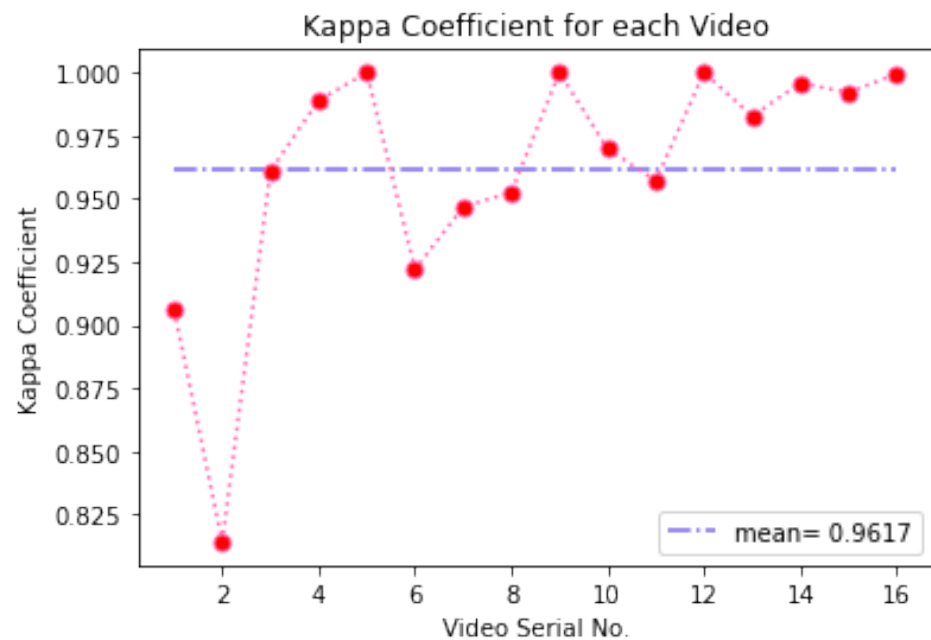


Figure 6. Cohen’s Kappa Coefficient plotted against mean value of 0.9617.

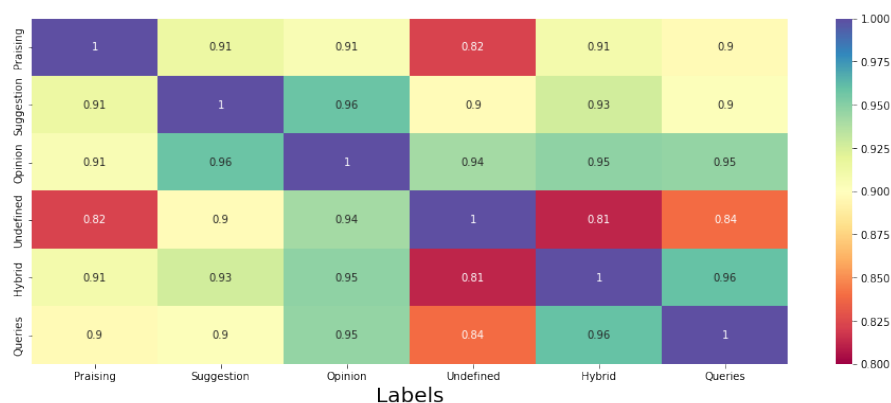


Figure 7. Correlation heatmap between assigned labels.

A word cloud is a data visualization technique used for representing text data where the frequency or importance of each word is indicated by its size. It can help us highlight and analyze significant textual data points. Pre-processing of the comments was performed to remove stop words and punctuation from the text. Figure 8 displays the word clouds for the comments collected from videos of serial number 1–8. We can see that on the word cloud in Figure 8a, which is for the video titled ‘How Japan Is Reshaping Its Agriculture By Harnessing Smart- Farming Technology’, ‘Japan’ is one of the most frequent and important words in the text. Similarly, for Figure 8g for video no. 7 on the bottom left titled ‘7 Israeli Agriculture Technologies’, the most significant word is ‘Israel’. Figure 9 displays the word clouds for the comments collected from videos of serial number 9–16. The word 9b on the top left for the video titled ‘Singapore’s Bold Plan to Build the Farms of the Future’ has ‘Singapore’ as the most prominent word. This indicates that several comments for these videos included some text about the country in which the technology was implemented. For videos demonstrating a particular technology, such as No. 7: ‘Solar Panels Plus Farming? Agrivoltaics Explained’; No. 8: ‘The CNH Industrial Autonomous Tractor Concept (Full Version)’; and No. 14: ‘RIPPA The Farm Robot Exterminates Pests And Weeds’, the name of the technology (solar, tractor, robot, respectively) is of great prominence. Table 11 provides a list of the top five most-relevant words in the comments dataset for each video, along with their respective frequencies.

5.3.2. Transfer-Learning-Based Analysis

The results of sentiment analysis using the Pattern library are discussed in this subsection. Mean polarity and mean subjectivity are plotted opposite each other in Figure 10. The overall polarity for all 7311 comments is 0.2092, suggesting that the overall sentiment is slightly positive. The overall subjectivity of all comments is 0.4352, implying that the comments were close to being neutral. Subjective statements generally contain personal opinion, emotion, or judgment, whereas objective comments are factual information. Polarity determines the degree of positive or negative sentiment in the text. The highest mean subjectivity score was 0.5480 for video no. 13 titled ‘Simply Fresh—India’s Largest State Of The Art Precision Farm’, followed by 0.5369 for video no. 11 titled ‘Smart Vertical Farms in Sharjah’. This shows that the comments were of a more opinionated nature, rather than being factual. The lowest mean subjectivity score was 0.2915 for video no. 9 titled ‘IOT Smart Plant Monitoring System’, indicating that mostly facts were discussed in the comments for this video. The score suggesting higher objectivity could be because the video is discussing technical details about an IoT platform rather than explaining widespread innovative concepts such as precision farms and vertical farms. The comments collected from video no. 8 titled ‘The CNH Industrial Autonomous Tractor Concept (Full Version)’ resulted in the lowest mean polarity of 0.0919, indicating that the user sentiment was generally neutral. The highest mean polarity of 0.4460 was achieved for video no. 13 titled

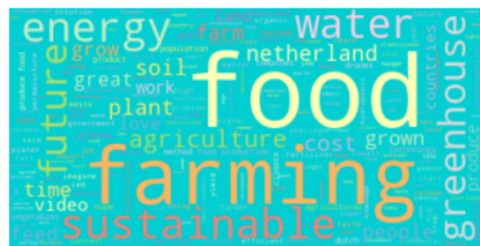
‘Simply Fresh—India’s Largest State Of The Art Precision Farm’, showing that user attitude was generally positive towards the state-of-the-art precision farm highlighted in the video.



(a)



(b)



(c)



(d)



(e)



(f)



(g)



(h)

Figure 8. Word clouds for videos serial no. 1–8 corresponding (a–h) respectively.



Figure 9. Word clouds for videos no. 9–16 corresponding (a–h) respectively.

In the investigation of user sentiment towards smart farming and precision agriculture, the main objective was to analyze user opinion, which is the voice of masses. During compilation of the dataset, it was observed that videos providing more in-depth and case-study-based information about smart farming tools did not receive many views and comments. This could be because the general public is not well-informed about novel technology in the farming sector, as asserted in Section 6. The majority of the comments were collected from videos about broader topics. The Cohen’s kappa coefficient indicated that the labels assigned by the two annotators were mostly in agreement and valid. The mean values of polarity and subjectivity in the comments was calculated through the Pattern library, and the results suggest that there is a varying degree of subjectivity amongst the comments. The polarity suggests that user opinion was mostly positive in the comments analyzed. Thus, it can be safely inferred that training and education programs can increase the visibility of innovations in smart farming, allowing the general population to form a

well-informed opinion on the risks and benefits. Positive user sentiment can then serve as a catalyst towards faster adoption of such tools.

Table 11. List of five most frequent words for each video with respective frequencies.

Video Serial No.	Most Common	2nd	3rd	4th	5th
1.	technology (6)	japanese (5)	japan (5)	video (4)	good (4)
2.	richard (5)	regenerative (4)	love (4)	farming (3)	start (3)
3.	food (66)	farming (29)	sustainable (21)	energy (21)	water (20)
4.	farming (183)	food (157)	vertical (151)	grow (109)	people (97)
5.	hands (2)	environment (2)	farmer (2)	corporate (2)	awesome (2)
6.	solar (129)	panels (101)	energy (56)	water (51)	land (41)
7.	israel (42)	love (35)	india (21)	agriculture (13)	technology (13)
8.	tractor (109)	farming (104)	farm (61)	farmer (57)	work (56)
9.	project (39)	code (26)	software (24)	sir (24)	error (22)
10.	singapore (201)	food (145)	farming (88)	people (83)	firms (70)
11.	great (9)	video (8)	good (7)	farm (5)	food (5)
12.	farming (30)	future (24)	people (22)	cow (18)	nature (18)
13.	great (36)	farming (26)	work (24)	sir (24)	farm (22)
14.	robot (42)	robots (30)	people (27)	farm (22)	good (19)
15.	video (36)	great (25)	farmers (24)	india (24)	good (19)
16.	plants (430)	food (429)	farming (355)	water (332)	soil (319)

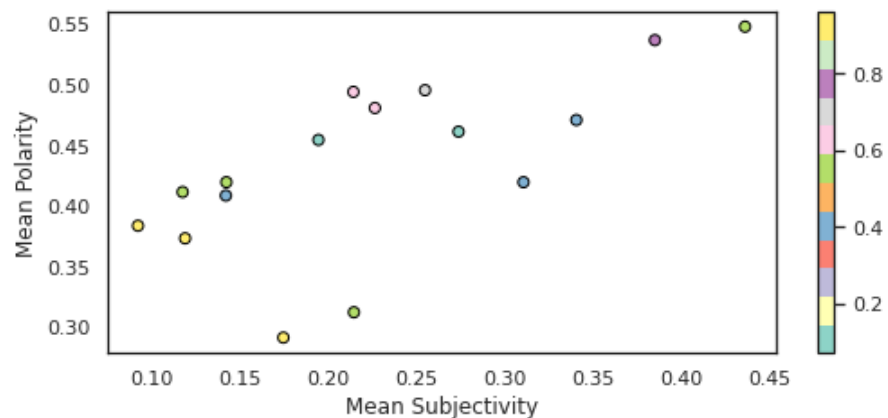


Figure 10. Mean polarity vs. mean subjectivity.

6. Challenges

There has been a significant increase in the number of smart farming initiatives being taken up around the world, with promising results. However, with the advent of new, innovative technologies there are always some unseen risks and associated challenges. The agricultural sector has greatly impacted the environment by taking up about 40% of the world’s available land [173] and consuming approximately 70% of the water [174]. Climate change and the growing population further exacerbate food and water scarcity, making sustainable food production a challenging task. Thus, it is critical that current agricultural practices need to evolve to ensure the efficient use of land and water resources. To elaborate further on Research Question 2, we discuss the various challenges that hamper the adoption of smart farming in the following bullet points:

1. **Training and awareness:** Lack of technical expertise by the farmers implementing new technology is a major setback to smart farming. Das et al. [28] conducted a study to understand the views of Irish farmers towards adoption of cloud computing and smart farming technologies. Surveys and interviews conducted with 32 farmers revealed that the rate of adoption was higher among younger farmers and lower amongst older farmers, who were hesitant to use new technology and preferred traditional farming. The digital divide has to be reduced by providing guidance and training to the farmers [175]. Lack of knowledge about the technology results in greater skepticism towards its adoption amongst farmers, who may not realize the value of the tool or consider it an unsuitable fit for their farm. In this current study, we formed a dataset of YouTube comments related to smart farming operations and performed surface level sentiment analysis of them. During the data collection process, it was observed that very few comments were left under videos that provided a technical and detailed framework for a smart farming project. Comments were mostly collected from videos explaining broader topics, such as ‘Vertical Farming’. This indicates that there is a general lack of awareness about these technologies and their applicability to farming.
2. **Technical considerations:** Fixed and moving sensing technologies require further improvements to be able to withstand extreme weather conditions in order to remain fully functional [176,177]. Edge node devices may be battery dependent and run out of power during operation [178,179]. Data is collected from various sensors and can be analyzed through IoT platforms. There is a requirement for data storage, as there is a huge amount of data being generated from IoT devices. IoT has improved connectivity of all operations by leaps and bounds, but it does come with the added concern of data privacy and security [180]. It also exposes the smart farming environment to cybersecurity threats, which could result in significant losses [181]. Data encrypting in the Industrial Internet of Things (IIoT) also presents a significant challenge for farmers [182].
3. **Costs:** The costs associated with sensors need to be reduced so that they can be implemented in small-scale farms as well. The solution needs to be designed specifically for the project in question, and also needs regular updates and management. Farmers may hesitate in implementing such technologies as they could create issues and cause further losses instead of providing benefits. Research and development costs for the implementation of such tools are also steep. There is also a significant amount of cost associated with data transmission within a smart farm [183]. Market uncertainty adds substantial risk to ensuring a sustainable income for farmers, as profit margins are getting increasingly smaller. Farmers in small-scale agricultural fields are hesitant to use upgraded technology because of the high initial costs, perceived risks, and complexity of the system.
4. **Government support:** The laws and regulations in the area where smart farming is being considered for implementation play a huge role in its eventual success or failure. The local governments are responsible for taking initiatives and providing funding and support training programs for the adoption of such tools [184]. Several successful initiatives taken up in the European Union [119] and across the world [144] have highlighted the importance of the effort taken up by regulatory bodies.
5. **Ethical considerations:** Human safety is also a concern in the operation of unmanned vehicles [185]. Collisions with the ground or other objects may also cause damage to the vehicle. It is also essential that the UAVs be flown in unrestricted areas. Currently, it is not clear where the accountability for the actions taken by autonomous vehicles lies. Data need to be uploaded to cloud systems in a secure manner, keeping regulations in mind. It is necessary for smart farming operations to be transparent so that they are more trusted and accepted. The ownership of agricultural data is a huge liability that needs to be kept in mind. There are also legal and ethical considerations with the potential mishandling and misuse of these data [186]. Animal welfare is

- also a concern while making use of autonomous robots to perform functions such as milking [187].
6. Regional considerations: Lack of proper infrastructure, such as roads, can be a major hurdle towards the advancement of smart farms, as the necessary resources and technology will not be successfully transported. There is limited availability of internet in rural areas, where smart farming could be of greater significance. Standard protocols and frameworks for wireless communication cannot be defined, as the requirements rely heavily on the specific use case [188]. Further, communication protocols implemented within the smart farm may only provide coverage over small areas [189].

7. Discussion

This review study was conducted to assess the challenges and opportunities in smart farming by exploring current state-of-the-art ICTs and DTs, analyzing global projects, and understanding the perception of the general public towards such innovative practices. The two hypothesis stated at the beginning of the study have been supported by the findings of the research questions, which have been answered as follows:

Hypothesis 3. *ICTs and DTs can be used in the agricultural sector to make significant improvements in several farming applications.*

The following research question were crafted to accept or reject the hypothesis:

1. What are the state-of-the-art ICTs and DTs currently used in smart farming?
Over the last decade, several smart farming projects have been launched across the world that were powered by technologies such as IoT, wireless sensor networks, unmanned vehicles, etc., as detailed in Section 3. The potential use cases for each technology are discussed in Section 4, although several projects utilize more than one. Several research projects in the European Union [18] and worldwide have also been discussed. The development of precise sensors enables the capture of data with higher accuracy, thus enabling better quality analysis and decision making [14]. Decision support systems can guide the farmer with operational decisions about choice of crop, frequency of fertilizer use, better utilization of resources, and more [69]. Autonomous vehicles take care of labor-intensive tasks, thus freeing up farmers for other important tasks [77]. Communication between various IoT devices through a WSN can allow for effective monitoring of the farm throughout the day, making it easier for the farmer to make operational decisions [36]. Blockchain technology can ensure that the supply and raw materials purchased are of good quality and there is no adulteration taking place [48]. DTs such as artificial intelligence also have an array of potential applications in smart farming, building upon the availability of massive amounts of heterogeneous data from sensors [20]. We have discussed the use of machine learning and deep learning for disease identification in crops, fruits, and cattle in Section 3.7. AI has also shown great potential in optimizing resource utilization by automating timely irrigation, performing preemptive actions if a certain parameter crosses a threshold, and predictive analysis of weather and crop conditions [188]. AI can also be used to identify optimal conditions for growing crops and preventing crop wastage. Image processing is of great relevance in smart farming, as there have been several studies that implement CNNs [98]. Image processing can be used for livestock management, guiding the decision-making processes of harvesting robots and pest and weed elimination drones. It can also enable precision farming by collecting data from sensors and deploying resources accordingly [9].

Hypothesis 4. *There are certain significant challenges to the widespread adoption of smart farming tools, such as lack of awareness about the topic amongst the general population.*

The following research questions are explored in this context:

1. What are the challenges associated with the widespread adoption of smart farming tools?
Despite the increasing number of smart farming projects being launched all over the world, there still exist many factors that hinder the widespread implementation of such tools [6,188]. As we have discussed in Section 6, the limitations can be broadly categorized as lack of training and awareness, technical considerations, costs, government support, ethical considerations, and regional considerations. Technical difficulties arise due to the inability of current systems to withstand extreme weather and atmospheric conditions, being too bulky and costly to implement, and not providing up-to-the-mark accurate data [176]. Another challenge is the proper infrastructure required for storing and processing large amounts of data collected from sensors [181]. The privacy and security of this data is of great importance. Regional limitations could be the lack of infrastructure and connectivity. Smaller farms in rural areas could benefit greatly from the use of smart farming tools. However, most smart farming practices require the use of internet connectivity, which is sparse in rural areas. Other factors that hamper the development of smart farming may include lack of technical expertise by farmers, insufficient incentives provided by the government for the implementation of such practices, and skepticism of farmers towards the benefits of smart farming [28]. General awareness amongst farmers is generally low and can be increased through training programs. Although smart farming tools are generally black-box techniques, farmers making use of them still need to understand their operations so that they can consider the process reliable. Cost considerations could also make farmers skeptical towards installing new tools, as the upfront expenditure may be too much [183].
2. What are the current opinions and expectations of the digital user with regard to smart farming?
In order to better understand user perception of smart farming technologies [166], we performed sentiment analysis on relevant English comments collected from YouTube [168], as detailed in Section 5. The comments were collected from 16 different videos that detailed innovative farming solutions. Then, two different approaches to observe user sentiment were utilized. In the first approach, comments were manually labeled by two annotators into one of the following six categories: Praising, Queries, Suggestions, Undefined, Hybrid and Opinion. Cohen's Kappa coefficient, which is the measure of inter-rater reliability, was calculated as 0.9617. This shows a high rate of agreement between the labels assigned by both annotators. The labels also show high positive correlation with each other, as depicted in Figure 10. Word clouds created for each video in Figures 8 and 9 highlight significant words, such as 'technology', 'farming', 'solar', etc. In the second approach, polarity and subjectivity were calculated for each comment using Pattern library for Python. The polarity score ranges from -1 (negative) to 1 (positive) and indicates whether the sentiment is positive or negative. The overall polarity was calculated as 0.2092, indicating a slightly positive sentiment. The subjectivity score ranges from 0 (objective) to 1 (subjective) and indicates the degree of factual information or opinion in the statement. The overall subjectivity was calculated as 0.4352, suggesting that the comments were slightly objective. This implies that the comments discussed were fact-based rather than opinionated. However, only a rudimentary study was performed to determine user sentiment, and better results can be achieved using state-of-the-art models for sentiment analysis. In the brief overview of user sentiment conducted in the study, we noticed lack of user comments on informative and technical videos about smart farming platforms, indicating that a knowledge gap and a digital divide exists for such technologies [175], which can be detrimental to their widespread adoption. The general attitude of users towards smart farming technologies is superficial, as the public is not well-informed about these topics.

8. Conclusions

Ensuring a sustainable food supply for the ever-increasing global population has become a necessity due to the unprecedented changes in the environment. The agricultural sector must update its practices in light of the worsening strain on land and water resources, and data-driven approaches provide such an opportunity to ensure sustainability. This study provided an overview of ICTs and DTs in automating and streamlining farming operations, and demonstrated how smart farming can improve crop yields by monitoring, disease prevention, automation of sowing and harvesting, etc. Examples of primary technological tools available for smart farming are IoT, unmanned vehicles, remote sensing, predictive analysis through big data, and so on. This shift towards data-driven approaches enables farming facilities to utilize available resources for maximum yield. The study also presents various challenges that are associated with large-scale implementation of smart farming practices, such as poor connectivity in rural areas, insufficient funds and skilled labor, skepticism from farmers, concerns with data privacy, and more. To analyze the attitude of the public towards implementation of smart farming, we performed sentiment analysis on comments from YouTube channels related to smart farming. Preliminary findings in both user-based and transfer-learning based opinion mining suggest that a better understanding of smart farming tools would help the public in forming an informed opinion. Further advances are required to improve precision, cost, and efficiency of robots, sensors, and unmanned vehicles before they are readily adopted. Keeping the barriers to adoption for smart farming techniques in mind, the future scope of research would be to develop techniques that provide greater adaptability, ensure food sustainability, reduce cost, and counter the harmful affects of climate change on agriculture. Greater connectivity in rural areas could accelerate the integration of ICTs in smallholder farms, allowing them to prepare for unprecedented changes in farming conditions. Further research and investigation of the possible uses of DTs and ICTs is necessary to understand the challenges and opportunities in smart farming. A detailed sentiment analysis using advanced language models and inclusion of non-English comments can also provide greater insight into the expectations and opinions of digital users towards innovative farming solutions. Multidisciplinary research also needs to be conducted to elucidate other socio-economic, environmental, and technical factors that impede development and adoption of such innovations.

Author Contributions: Conceptualization, A.K. and S.S.; methodology, S.Y.; Computing, S.Y.; validation, M.S., S.Y. and A.K.; formal analysis, M.S.; investigation, S.Y.; resources, A.K.; data curation, S.Y. and M.S.; writing—original draft preparation, S.Y.; writing—review and editing, A.K. and S.S.; visualization, S.Y.; supervision, A.K. and S.S.; project administration, A.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: For data, please contact the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. UN Population. Available online: <https://www.un.org/development/desa/en/news/population/world-population-prospects-2019.html> (accessed on 2 March 2022).
2. Hunter, M.C.; Smith, R.G.; Schipanski, M.E.; Atwood, L.W.; Mortensen, D.A. Agriculture in 2050: Recalibrating targets for sustainable intensification. *Bioscience* **2017**, *67*, 386–391. [[CrossRef](#)]
3. Samir, K.; Lutz, W. The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Glob. Environ. Chang.* **2017**, *42*, 181–192.
4. De Clercq, M.; Vats, A.; Biel, A. Agriculture 4.0: The future of farming technology. In Proceedings of the World Government Summit, Dubai, United Arab Emirates, 11–13 February 2018; pp. 11–13.
5. Walter, A.; Finger, R.; Huber, R.; Buchmann, N. Opinion: Smart farming is key to developing sustainable agriculture. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 6148–6150. [[CrossRef](#)] [[PubMed](#)]

6. Bacco, M.; Barsocchi, P.; Ferro, E.; Gotta, A.; Ruggeri, M. The digitisation of agriculture: A survey of research activities on smart farming. *Array* **2019**, *3*, 100009. [CrossRef]
7. Ju, C.; Son, H.I. Discrete event systems based modeling for agricultural multiple unmanned aerial vehicles: Automata theory approach. In Proceedings of the 2018 18th International Conference on Control, Automation and Systems (ICCAS), PyeongChang, Korea, 17–20 October 2018; pp. 258–260.
8. Muchiri, N.; Kimathi, S. A review of applications and potential applications of UAV. In Proceedings of the Sustainable Research and Innovation Conference, New York, NY, USA, 21–22 September 2016; pp. 280–283.
9. Jhuria, M.; Kumar, A.; Borse, R. Image processing for smart farming: Detection of disease and fruit grading. In Proceedings of the 2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013), Shimla, India, 9–11 December 2013; pp. 521–526.
10. Guo, Y.; Zhang, J.; Yin, C.; Hu, X.; Zou, Y.; Xue, Z.; Wang, W. Plant disease identification based on deep learning algorithm in smart farming. *Discret. Dyn. Nat. Soc.* **2020**, *2020*, 2479172. [CrossRef]
11. Blackmore, S. Precision farming: An introduction. *Outlook Agric.* **1994**, *23*, 275–280. [CrossRef]
12. Wang, A.X.; Tran, C.; Desai, N.; Lobell, D.; Ermon, S. Deep transfer learning for crop yield prediction with remote sensing data. In Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, San Jose, CA, USA, 20–22 June 2018; pp. 1–5.
13. Khaki, S.; Wang, L. Crop yield prediction using deep neural networks. *Front. Plant Sci.* **2019**, *10*, 621. [CrossRef]
14. Chetan Dwarkani, M.; Ganesh Ram, R.; Jagannathan, S.; Priyatharshini, R. Smart farming system using sensors for agricultural task automation. In Proceedings of the 2015 IEEE Technological Innovation in ICT for Agriculture and Rural Development (TIAR), Chennai, India, 10–12 July 2015; pp. 49–53.
15. Skobelev, P.O.; Simonova, E.V.; Smirnov, S.; Budaev, D.S.; Voshchuk, G.Y.; Morokov, A. Development of a knowledge base in the “smart farming” system for agricultural enterprise management. *Procedia Comput. Sci.* **2019**, *150*, 154–161. [CrossRef]
16. Mohamed, E.S.; Belal, A.; Abd-Elmabod, S.K.; El-Shirbeny, M.A.; Gad, A.; Zahran, M.B. Smart farming for improving agricultural management. *Egypt. J. Remote Sens. Space Sci.* **2021**, *24*, 971–981. [CrossRef]
17. 2021’s Weather Disasters Brought Home the Reality of Climate Change. Available online: <https://www.nationalgeographic.com/environment/article/this-year-extreme-weather-brought-home-reality-of-climate-change> (accessed on 7 April 2022).
18. Moysiadis, V.; Sarigiannidis, P.; Vitsas, V.; Khelifi, A. Smart farming in Europe. *Comput. Sci. Rev.* **2021**, *39*, 100345. [CrossRef]
19. Harvey, C.A.; Rakotobe, Z.L.; Rao, N.S.; Dave, R.; Razafimahatratra, H.; Rabarijohn, R.H.; Rajaofara, H.; MacKinnon, J.L. Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. *Philos. Trans. R. Soc. B Biol. Sci.* **2014**, *369*, 20130089. [CrossRef] [PubMed]
20. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.J. Big data in smart farming—A review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
21. Mogili, U.R.; Deepak, B. Review on application of drone systems in precision agriculture. *Procedia Comput. Sci.* **2018**, *133*, 502–509. [CrossRef]
22. Shamshiri, R.R.; Weltzien, C.; Hameed, I.A.; Yule, I.J.; Grift, T.E.; Balasundram, S.K.; Pitonakova, L.; Ahmad, D.; Chowdhary, G. Research and development in agricultural robotics: A perspective of digital farming. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 1–14. [CrossRef]
23. Migdall, S.; Klug, P.; Denis, A.; Bach, H. The additional value of hyperspectral data for smart farming. In Proceedings of the 2012 IEEE International Geoscience and Remote Sensing Symposium, Munich, Germany, 22–27 July 2012; pp. 7329–7332.
24. Uddin, M.A.; Ayaz, M.; Mansour, A.; Le Jeune, D.; Aggoune, E. Wireless sensors for modern agriculture in KSA: A survey. In Proceedings of the 2016 7th International Conference on Computer Science and Information Technology (CSIT), Amman, Jordan, 13–14 July 2016; pp. 1–7.
25. Sona, G.; Passoni, D.; Pinto, L.; Pagliari, D.; Masseroni, D.; Ortuani, B.; Facchi, A. UAV multispectral survey to map soil and crop for precision farming applications. In Proceedings of the Remote Sensing and Spatial Information Sciences Congress: International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences Congress, Prague, Czech Republic, 12–19 July 2016; International Society for Photogrammetry and Remote Sensing (ISPRS): Nice, France, 2016; Volume 41, pp. 1023–1029.
26. Boursianis, A.D.; Papadopoulou, M.S.; Diamantoulakis, P.; Liopa-Tsakalidi, A.; Barouchas, P.; Salahas, G.; Karagiannidis, G.; Wan, S.; Goudos, S.K. Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. *Internet Things* **2020**, *18*, 100187. [CrossRef]
27. Despommier, D. Farming up the city: The rise of urban vertical farms. *Trends Biotechnol.* **2013**, *31*, 388–389. [CrossRef]
28. Das, V.J.; Sharma, S.; Kaushik, A. Views of Irish farmers on smart farming technologies: An observational study. *AgriEngineering* **2019**, *1*, 164–187.
29. Akbar, M.O.; Ali, M.J.; Hussain, A.; Qaiser, G.; Pasha, M.; Pasha, U.; Missen, M.S.; Akhtar, N. IoT for development of smart dairy farming. *J. Food Qual.* **2020**, *2020*, 4242805. [CrossRef]
30. Gang, L.L.L. Design of greenhouse environment monitoring and controlling system based on bluetooth technology. *Trans. Chin. Soc. Agric. Mach.* **2006**, *10*, 97–100.
31. Zhang, S.; Chen, X.; Wang, S. Research on the monitoring system of wheat diseases, pests and weeds based on IOT. In Proceedings of the 2014 9th International Conference on Computer Science & Education, Vancouver, BC, Canada, 22–24 August 2014; pp. 981–985.

32. Chieochan, O.; Saokaew, A.; Boonchieng, E. IOT for smart farm: A case study of the Lingzhi mushroom farm at Maejo University. In Proceedings of the 2017 14th International Joint Conference on Computer Science and Software Engineering (JCSSE), NakhonSiThammarat, Thailand, 12–14 July 2017; pp. 1–6.
33. Benaissa, S.; Plets, D.; Tanghe, E.; Trogh, J.; Martens, L.; Vandaele, L.; Verloock, L.; Tuytens, F.; Sonck, B.; Joseph, W. Internet of animals: Characterisation of LoRa sub-GHz off-body wireless channel in dairy barns. *Electron. Lett.* **2017**, *53*, 1281–1283. [[CrossRef](#)]
34. Giri, A.; Dutta, S.; Neogy, S. Enabling agricultural automation to optimize utilization of water, fertilizer and insecticides by implementing Internet of Things (IoT). In Proceedings of the 2016 International Conference on Information Technology (InCITE)-The Next Generation IT Summit on the Theme-Internet of Things: Connect your Worlds, Noida, India, 6–7 October 2016; pp. 125–131.
35. Na, A.; Isaac, W.; Varshney, S.; Khan, E. An IoT based system for remote monitoring of soil characteristics. In Proceedings of the 2016 International Conference on Information Technology (InCITE)-The Next Generation IT Summit on the Theme-Internet of Things: Connect your Worlds, Noida, India, 6–7 October 2016; pp. 316–320.
36. Kamilaris, A.; Gao, F.; Prenafeta-Boldu, F.X.; Ali, M.I. Agri-IoT: A semantic framework for Internet of Things-enabled smart farming applications. In Proceedings of the 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT), Reston, VA, USA, 12–14 December 2016; pp. 442–447.
37. Akkaş, M.A.; Sokullu, R. An IoT-based greenhouse monitoring system with Micaz nodes. *Procedia Comput. Sci.* **2017**, *113*, 603–608. [[CrossRef](#)]
38. Cañadas, J.; Sánchez-Molina, J.A.; Rodríguez, F.; del Águila, I.M. Improving automatic climate control with decision support techniques to minimize disease effects in greenhouse tomatoes. *Inf. Process. Agric.* **2017**, *4*, 50–63. [[CrossRef](#)]
39. dos Santos, U.J.L.; Pessin, G.; da Costa, C.A.; da Rosa Righi, R. AgriPrediction: A proactive internet of things model to anticipate problems and improve production in agricultural crops. *Comput. Electron. Agric.* **2019**, *161*, 202–213. [[CrossRef](#)]
40. Kukar, M.; Vračar, P.; Košir, D.; Pevec, D.; Bosnić, Z. AgroDSS: A decision support system for agriculture and farming. *Comput. Electron. Agric.* **2019**, *161*, 260–271.
41. Antonopoulou, E.; Karetos, S.; Maliappis, M.; Sideridis, A. Web and mobile technologies in a prototype DSS for major field crops. *Comput. Electron. Agric.* **2010**, *70*, 292–301. [[CrossRef](#)]
42. Rupanagudi, S.R.; Ranjani, B.; Nagaraj, P.; Bhat, V.G.; Thippeswamy, G. A novel cloud computing based smart farming system for early detection of borer insects in tomatoes. In Proceedings of the 2015 International Conference on Communication, Information & Computing Technology (ICCICT), Mumbai, India, 15–17 January 2015; pp. 1–6.
43. Zhou, L.; Chen, N.; Chen, Z. A cloud computing-enabled spatio-temporal cyber-physical information infrastructure for efficient soil moisture monitoring. *ISPRS Int. J.-Geo-Inf.* **2016**, *5*, 81. [[CrossRef](#)]
44. Kaloxylou, A.; Groumas, A.; Sarris, V.; Katsikas, L.; Magdalinos, P.; Antoniou, E.; Politopoulou, Z.; Wolfert, S.; Brewster, C.; Eigenmann, R.; et al. A cloud-based Farm Management System: Architecture and implementation. *Comput. Electron. Agric.* **2014**, *100*, 168–179. [[CrossRef](#)]
45. Corista, P.; Ferreira, D.; Gião, J.; Sarraipa, J.; Gonçalves, R.J. An IoT agriculture system using FIWARE. In Proceedings of the 2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Stuttgart, Germany, 17–20 June 2018; pp. 1–6.
46. Zamora-Izquierdo, M.A.; Santa, J.; Martínez, J.A.; Martínez, V.; Skarmeta, A.F. Smart farming IoT platform based on edge and cloud computing. *Biosyst. Eng.* **2019**, *177*, 4–17. [[CrossRef](#)]
47. Malik, A.W.; Rahman, A.U.; Qayyum, T.; Ravana, S.D. Leveraging fog computing for sustainable smart farming using distributed simulation. *IEEE Internet Things J.* **2020**, *7*, 3300–3309. [[CrossRef](#)]
48. Vangala, A.; Sutrala, A.K.; Das, A.K.; Jo, M. Smart Contract-Based Blockchain-Envisioned Authentication Scheme for Smart Farming. *IEEE Internet Things J.* **2021**, *8*, 10792–10806. [[CrossRef](#)]
49. Lin, Y.P.; Petway, J.R.; Anthony, J.; Mukhtar, H.; Liao, S.W.; Chou, C.F.; Ho, Y.F. Blockchain: The evolutionary next step for ICT e-agriculture. *Environments* **2017**, *4*, 50. [[CrossRef](#)]
50. Patil, A.S.; Tama, B.A.; Park, Y.; Rhee, K.H. A framework for blockchain based secure smart green house farming. In *Advances in Computer Science and Ubiquitous Computing*; Springer: Singapore, 2017; pp. 1162–1167.
51. Lin, J.; Shen, Z.; Zhang, A.; Chai, Y. Blockchain and IoT based food traceability for smart agriculture. In Proceedings of the 3rd International Conference on Crowd Science and Engineering, Singapore, 28–31 July 2018; pp. 1–6.
52. Nikodem, M. Bluetooth Low Energy Livestock Positioning for Smart Farming Applications. In *International Conference on Computational Science*; Springer: Singapore, 2021; pp. 55–67.
53. Sukhadeve, V.; Roy, S. Advance agro farm design with smart farming, irrigation and rain water harvesting using internet of things. *Int. J. Adv. Eng. Manag.* **2016**, *1*, 33–45. [[CrossRef](#)]
54. Chung, W.Y.; Luo, R.H.; Chen, C.L.; Heythem, S.; Chang, C.F.; Po, C.C.; Li, Y. Solar powered monitoring system development for smart farming and Internet of Thing applications. *Meet. Abstr. Electrochem. Soc.* **2019**, *28*, 1371–1375. [[CrossRef](#)]
55. Bedord, L. Sensors Protect Crops from Insect Damage. 2015. Available online: https://www.agriculture.com/technology/crop-management/fieldwork/senss-protect-crops-from-insect-damage_590-ar47778 (accessed on 7 April 2022).
56. Schmidt, F. Agricultural Sensors: Improving Crop Farming to Help Us Feed the World. Available online: <https://www.dw.com/en/agricultural-sensors-improving-crop-farming-to-help-us-feed-the-world/a-17733350> (accessed on 7 April 2022).

57. López, O.; Rach, M.M.; Migallon, H.; Malumbres, M.P.; Bonastre, A.; Serrano, J.J. Monitoring pest insect traps by means of low-power image sensor technologies. *Sensors* **2012**, *12*, 15801–15819. [CrossRef]
58. Rach, M.M.; Gomis, H.M.; Granado, O.L.; Malumbres, M.P.; Campoy, A.M.; Martín, J.J.S. On the design of a bioacoustic sensor for the early detection of the red palm weevil. *Sensors* **2013**, *13*, 1706–1729. [CrossRef]
59. Stoner, R. The Rev 3 Leaf Sensor. 2014. Available online: <https://leafsensor.wordpress.com/> (accessed on 7 April 2022).
60. Hydraulic Conductivity in Plant Stems. Available online: www.ictinternational.com/casestudies/hydraulic-conductivity-in-plant-stems/ (accessed on 7 April 2022).
61. Karlen, D.L.; Mausbach, M.; Doran, J.W.; Cline, R.; Harris, R.; Schuman, G. Soil quality: A concept, definition, and framework for evaluation (a guest editorial). *Soil Sci. Soc. Am. J.* **1997**, *61*, 4–10. [CrossRef]
62. Butler, Z.; Corke, P.; Peterson, R.; Rus, D. Virtual fences for controlling cows. In Proceedings of the IEEE International Conference on Robotics and Automation, New Orleans, LA, USA, 26 April–1 May 2004; Volume 5, pp. 4429–4436.
63. Nukala, R.; Panduru, K.; Shields, A.; Riordan, D.; Doody, P.; Walsh, J. Internet of Things: A review from ‘Farm to Fork’. In Proceedings of the 2016 27th Irish Signals and Systems Conference (ISSC), Londonderry, UK, 21–22 June 2016; pp. 1–6.
64. Lee, H.; Moon, A.; Moon, K.; Lee, Y. Disease and pest prediction IoT system in orchard: A preliminary study. In Proceedings of the 2017 Ninth International Conference on Ubiquitous and Future Networks (ICUFN), Milan, Italy, 4–7 July 2017; pp. 525–527.
65. Garcia-Lesta, D.; Cabello, D.; Ferro, E.; Lopez, P.; Brea, V.M. Wireless sensor network with perpetual motes for terrestrial snail activity monitoring. *IEEE Sensors J.* **2017**, *17*, 5008–5015. [CrossRef]
66. Kodali, R.K.; Jain, V.; Karagwal, S. IoT based smart greenhouse. In Proceedings of the 2016 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), Agra, India, 21–23 December 2016; pp. 1–6.
67. Nayyar, A.; Puri, V. Smart farming: IoT based smart sensors agriculture stick for live temperature and moisture monitoring using Arduino, cloud computing & solar technology. In Proceedings of the International Conference on Communication and Computing Systems (ICCCS-2016), Gurgaon, India, 9–11 September 2016; CRC Press: London, UK, 2017; ISBN 9781315364094.
68. Taylor, K.; Griffith, C.; Lefort, L.; Gaire, R.; Compton, M.; Wark, T.; Lamb, D.; Falzon, G.; Trotter, M. Farming the web of things. *IEEE Intell. Syst.* **2013**, *28*, 12–19. [CrossRef]
69. Thakare, A.; Belhekar, P.; Budhe, P.; Shinde, U.; Waghmode, V. Decision support system for smart farming with hydroponic style. *Int. J. Adv. Res. Comput. Sci.* **2018**, *9*, 427–431.
70. Bareth, G.; Aasen, H.; Bendig, J.; Gnyp, M.L.; Bolten, A.; Jung, A.; Michels, R.; Soukkamäki, J. 7 Low-Weight and UAV-based Hyperspectral Full-frame Cameras for Monitor-ing Crops: Spectral Comparison with Portable Spectroradiometer Measurements. *Photogramm. Fernerkund. Geoinf.* **2015**, *69*–80. [CrossRef]
71. Roldán, J.J.; del Cerro, J.; Garzón-Ramos, D.; Garcia-Aunon, P.; Garzón, M.; de León, J.; Barrientos, A. Robots in agriculture: State of art and practical experiences. In *Service Robots*; IntechOpen: London, UK, 2018; pp. 67–90.
72. Groves, P.D. Principles of GNSS, inertial, and multisensor integrated navigation systems, [Book review]. *IEEE Aerosp. Electron. Syst. Mag.* **2015**, *30*, 26–27. [CrossRef]
73. Matese, A.; Toscano, P.; Di Gennaro, S.F.; Genesio, L.; Vaccari, F.P.; Primicerio, J.; Belli, C.; Zaldei, A.; Bianconi, R.; Gioli, B. Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. *Remote Sens.* **2015**, *7*, 2971–2990. [CrossRef]
74. Lu, B.; He, Y. Species classification using Unmanned Aerial Vehicle (UAV)-acquired high spatial resolution imagery in a heterogeneous grassland. *ISPRS J. Photogramm. Remote Sens.* **2017**, *128*, 73–85. [CrossRef]
75. Tripicchio, P.; Satler, M.; Dabisias, G.; Ruffaldi, E.; Avizzano, C.A. Towards smart farming and sustainable agriculture with drones. In Proceedings of the 2015 International Conference on Intelligent Environments, Prague, Czech Republic, 15–17 July 2015; pp. 140–143.
76. Moribe, T.; Okada, H.; Kobayashl, K.; Katayama, M. Combination of a wireless sensor network and drone using infrared thermometers for smart agriculture. In Proceedings of the 2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC), Las Vegas, NV, USA, 12–15 January 2018; pp. 1–2.
77. Lottes, P.; Khanna, R.; Pfeifer, J.; Siegwart, R.; Stachniss, C. UAV-based crop and weed classification for smart farming. In Proceedings of the 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, 29 May–3 June 2017; pp. 3024–3031.
78. Yi, S.; Li, C.; Li, Q. A survey of fog computing: Concepts, applications and issues. In Proceedings of the 2015 Workshop on Mobile Big Data, Hangzhou, China, 21 June 2015; pp. 37–42.
79. Sittón-Candanedo, I.; Alonso, R.S.; Rodríguez-González, S.; Coria, J.A.G.; De La Prieta, F. Edge computing architectures in industry 4.0: A general survey and comparison. In *International Workshop on Soft Computing Models in Industrial and Environmental Applications*; Springer: Cham, Switzerland, 2019; pp. 121–131.
80. Moysiadis, V.; Sarigiannidis, P.; Moscholios, I. Towards distributed data management in fog computing. *Wirel. Commun. Mob. Comput.* **2018**, *2018*, 7597686. [CrossRef]
81. Zheng, Z.; Xie, S.; Dai, H.N.; Chen, W.; Chen, X.; Weng, J.; Imran, M. An overview on smart contracts: Challenges, advances and platforms. *Future Gener. Comput. Syst.* **2020**, *105*, 475–491. [CrossRef]
82. Widi Widayat, I.; Köppen, M. Blockchain Simulation Environment on Multi-image Encryption for Smart Farming Application. In *International Conference on Intelligent Networking and Collaborative Systems*; Springer: Cham, Switzerland, 2021; pp. 316–326.

83. Nguyen, T.; Das, A.; Tran, L. NEO smart contract for drought-based insurance. In Proceedings of the 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE), Edmonton, AB, Canada, 5–8 May 2019; pp. 1–4.
84. Hurwitz, J.; Nugent, A.; Halper, F.; Kaufman, M. *Big Data for Dummies*; John Wiley & Sons: Hoboken, NJ, USA; New York, NY, USA, 2013.
85. Dick, S. Artificial Intelligence. *Harv. Data Sci. Rev.* **2019**, *1*. [[CrossRef](#)]
86. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016.
87. Yadav, S.; Kaushik, A. Do You Ever Get Off Track in a Conversation? The Conversational System’s Anatomy and Evaluation Metrics. *Knowledge* **2022**, *2*, 55–87. [[CrossRef](#)]
88. O’Shea, K.; Nash, R. An introduction to convolutional neural networks. *arXiv* **2015**, arXiv:1511.08458.
89. Varghese, R.; Sharma, S. Affordable smart farming using IoT and machine learning. In Proceedings of the 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 14–15 June 2018; pp. 645–650.
90. Arvindan, A.; Keerthika, D. Experimental investigation of remote control via Android smart phone of arduino-based automated irrigation system using moisture sensor. In Proceedings of the 2016 3rd International Conference on Electrical Energy Systems (ICEES), Chennai, India, 17–19 March 2016; pp. 168–175.
91. Khaki, S.; Safaei, N.; Pham, H.; Wang, L. Wheatnet: A lightweight convolutional neural network for high-throughput image-based wheat head detection and counting. *arXiv* **2021**, arXiv:2103.09408.
92. Alfred, R.; Obbit, J.H.; Yee, C.C.P.; Haviluddin, H.; Lim, Y. Towards Paddy Rice Smart Farming: A Review on Big Data, Machine Learning and Rice Production Tasks. *IEEE Access* **2021**, *9*, 50358–50380. [[CrossRef](#)]
93. Rahmat, R.F.; Lini, T.Z.; Pujiarti; Hizriadi, A. Implementation of Real-Time Monitoring on Agricultural Land of Rice Plants Using Smart Sensor. In Proceedings of the 2019 3rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM), Medan, Indonesia, 16–17 September 2019; pp. 40–43. [[CrossRef](#)]
94. Alifah, S.; Gunawan, G.; Taufik, M. Smart Monitoring of Rice Logistic Employing Internet of Things Network. In Proceedings of the 2018 2nd Borneo International Conference on Applied Mathematics and Engineering (BICAME), Balikpapan, Indonesia, 10–11 December 2018; pp. 199–202. [[CrossRef](#)]
95. Tiglao, N.M.; Alipio, M.; Balanay, J.V.; Saldivar, E.; Tiston, J.L. Agrinex: A low-cost wireless mesh-based smart irrigation system. *Measurement* **2020**, *161*, 107874. [[CrossRef](#)]
96. Kiruthika, S.U.; Raja, S.K.S.; Jaichandran, R.; Priyadharshini, C. Detection and Classification of Paddy Crop Disease using Deep Learning Techniques. *Int. J. Recent Technol. Eng.* **2019**, *8*, 2277–3878. [[CrossRef](#)]
97. Dahane, A.; Benameur, R.; Kechar, B.; Benyamina, A. An IoT Based Smart Farming System Using Machine Learning. In Proceedings of the 2020 International Symposium on Networks, Computers and Communications (ISNCC), Montreal, QC, Canada, 20–22 October 2020; pp. 1–6.
98. Bhange, M.; Hingoliwala, H. Smart farming: Pomegranate disease detection using image processing. *Procedia Comput. Sci.* **2015**, *58*, 280–288. [[CrossRef](#)]
99. Sengupta, A.; Ye, Y.; Wang, R.; Liu, C.; Roy, K. Going deeper in spiking neural networks: VGG and residual architectures. *Front. Neurosci.* **2019**, *13*, 95. [[CrossRef](#)] [[PubMed](#)]
100. Ferentinos, K.P. Deep learning models for plant disease detection and diagnosis. *Comput. Electron. Agric.* **2018**, *145*, 311–318. [[CrossRef](#)]
101. Mohanty, S.P.; Hughes, D.P.; Salathé, M. Using deep learning for image-based plant disease detection. *Front. Plant Sci.* **2016**, *7*, 1419. [[CrossRef](#)] [[PubMed](#)]
102. Li, H.; Jin, Y.; Zhong, J.; Zhao, R. A Fruit Tree Disease Diagnosis Model Based on Stacking Ensemble Learning. *Complexity* **2021**, *2021*, 6868592. [[CrossRef](#)]
103. Banhazi, T.M.; Lehr, H.; Black, J.; Crabtree, H.; Schofield, P.; Tscharke, M.; Berckmans, D. Precision livestock farming: An international review of scientific and commercial aspects. *Int. J. Agric. Biol. Eng.* **2012**, *5*, 1–9.
104. Xu, B.; Wang, W.; Guo, L.; Chen, G.; Wang, Y.; Zhang, W.; Li, Y. Evaluation of Deep Learning for Automatic Multi-View Face Detection in Cattle. *Agriculture* **2021**, *11*, 1062. [[CrossRef](#)]
105. Gjergji, M.; de Moraes Weber, V.; Silva, L.O.C.; da Costa Gomes, R.; De Araújo, T.L.A.C.; Pistori, H.; Alvarez, M. Deep learning techniques for beef cattle body weight prediction. In Proceedings of the 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 19–24 July 2020; pp. 1–8.
106. Jung, D.H.; Kim, N.Y.; Moon, S.H.; Jhin, C.; Kim, H.J.; Yang, J.S.; Kim, H.S.; Lee, T.S.; Lee, J.Y.; Park, S.H. Deep Learning-Based Cattle Vocal Classification Model and Real-Time Livestock Monitoring System with Noise Filtering. *Animals* **2021**, *11*, 357. [[CrossRef](#)]
107. Riede, T.; Tembrock, G.; Herzel, H.; Brunnerberg, L. Vocalization as an Indicator for Disorders in Mammals. Ph.D. Thesis, Acoustical Society of America, Melville, NY, USA, 1997.
108. Zhang, Y.; Zhang, F.; Cheng, J.; Zhao, H. Classification and Recognition of Fish Farming by Extraction New Features to Control the Economic Aquatic Product. *Complexity* **2021**, *2021*, 5530453. [[CrossRef](#)]
109. Rohani, A.; Taki, M.; Bahrami, G. Application of artificial intelligence for separation of live and dead rainbow trout fish eggs. *Artif. Intell. Agric.* **2019**, *1*, 27–34. [[CrossRef](#)]
110. Zambrano, A.F.; Giraldo, L.F.; Quimbayo, J.; Medina, B.; Castillo, E. Machine learning for manually-measured water quality prediction in fish farming. *PLoS ONE* **2021**, *16*, e0256380. [[CrossRef](#)] [[PubMed](#)]

111. Chiu, M.T.; Xu, X.; Wei, Y.; Huang, Z.; Schwing, A.G.; Brunner, R.; Khachatryan, H.; Karapetyan, H.; Dozier, I.; Rose, G.; et al. Agriculture-vision: A large aerial image database for agricultural pattern analysis. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, 13–19 June 2020; pp. 2828–2838.
112. Chiu, M.T.; Xu, X.; Wang, K.; Hobbs, J.; Hovakimyan, N.; Huang, T.S.; Shi, H. The 1st agriculture-vision challenge: Methods and results. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, Seattle, WA, USA, 13–19 June 2020; pp. 48–49.
113. Kussul, N.; Lavreniuk, M.; Skakun, S.; Shelestov, A. Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geosci. Remote Sens. Lett.* **2017**, *14*, 778–782. [[CrossRef](#)]
114. Zheng, Y.Y.; Kong, J.L.; Jin, X.B.; Wang, X.Y.; Su, T.L.; Zuo, M. CropDeep: The crop vision dataset for deep-learning-based classification and detection in precision agriculture. *Sensors* **2019**, *19*, 1058. [[CrossRef](#)]
115. Anand, T.; Sinha, S.; Mandal, M.; Chamola, V.; Yu, F.R. AgriSegNet: Deep aerial semantic segmentation framework for IoT-assisted precision agriculture. *IEEE Sensors J.* **2021**, *21*, 17581–17590. [[CrossRef](#)]
116. Rangarajan, A.K.; Purushothaman, R.; Ramesh, A. Tomato crop disease classification using pre-trained deep learning algorithm. *Procedia Comput. Sci.* **2018**, *133*, 1040–1047. [[CrossRef](#)]
117. Kulkarni, O. Crop disease detection using deep learning. In Proceedings of the 2018 Fourth International Conference on Computing Communication Control and Automation (ICCCBEA), Pune, India, 16–18 August 2018; pp. 1–4.
118. Andrew, W.; Greatwood, C.; Burghardt, T. Visual localisation and individual identification of holstein friesian cattle via deep learning. In Proceedings of the IEEE International Conference on Computer Vision Workshops, Venice, Italy, 22–29 October 2017; pp. 2850–2859.
119. Smart Farming European Union. Available online: <https://cordis.europa.eu/> (accessed on 11 April 2022).
120. Project ECHORD Plus Plus (European Clearing House for Open Robotics Development Plus Plus). 2018. Available online: <https://cordis.europa.eu/project/id/601116> (accessed on 13 December 2021).
121. Project VINBOT (Autonomous Cloud-Computing Vineyard Robot to Optimize Yield Management and Wine Quality). 2017. Available online: <http://vinbot.eu> (accessed on 13 December 2021).
122. Project ERMES (An Earth observation Model Based Rice Information Service). 2017. Available online: <http://www.ermes-fp7.space.eu/en>. (accessed on 14 December 2021).
123. Project FRACTALS (Future Internet Enabled Agricultural Applications). 2016. Available online: <https://www.fractals-fp7.com> (accessed on 14 December 2021).
124. Project VINEROBOT (VINEyardROBOT). 2017. Available online: <http://www.vinerobot.eu> (accessed on 13 December 2021).
125. Project SWEEPER (Sweet Pepper Harvesting Robot). 2018. Available online: <http://www.sweeper-robot.eu> (accessed on 13 December 2021).
126. Project Flourish (Aerial Data Collection and Analysis, and Automated Ground Intervention for Precision Farming). 2018. Available online: <http://flourish-project.eu> (accessed on 13 December 2021).
127. Project PANtHEOn (Precision Farming of Hazelnut Orchards). 2020. Available online: <http://www.project-pantheon.eu> (accessed on 13 December 2021).
128. Project ROMI (RObotics for Microfarms). 2020. Available online: <https://romi-project.eu> (accessed on 14 December 2021).
129. Project MISTRAL (Monitoring of Soil moisture and water-Flooded Areas for agriculture and Environment). 2017. Available online: <http://www.mistrale.eu> (accessed on 14 December 2021).
130. Project WaterBee Smart Irrigation Systems Demonstration Action. Available online: <https://cordis.europa.eu/project/id/283638> (accessed on 14 December 2021).
131. Project FIGARO (Flexible and Precise Irrigation Platform to Improve Farm Scale Water Productivity). 2016. Available online: <http://www.figaro-irrigation.net> (accessed on 13 December 2021).
132. Project Apollo (Advisory Platform for Small Farms Based on Earth Observation). 2016. Available online: <https://cordis.europa.eu/project/id/687412> (accessed on 14 December 2021).
133. Project AgriCloud P2 (Demonstration of a Cloud-Based Precision Farming Management System). 2016. Available online: <https://cordis.europa.eu/project/id/720176> (accessed on 14 December 2021).
134. Project Sensagri (Sentinels Synergy for Agriculture). 2016. Available online: <https://cordis.europa.eu/project/id/730074> (accessed on 14 December 2021).
135. Project IoF2020 (Internet of Food and Farm 2020). 2017. Available online: <https://cordis.europa.eu/project/id/731884> (accessed on 14 December 2021).
136. Project DataBio (Data-Driven Bioeconomy). 2017. Available online: <https://cordis.europa.eu/project/id/732064> (accessed on 14 December 2021).
137. Project Apmav (Innovative Drone-Based Solution for Agriculture). 2017. Available online: <https://cordis.europa.eu/project/id/763132> (accessed on 14 December 2021).
138. Project AfarCloud (Aggregate Farming in the Cloud). 2018. Available online: <https://cordis.europa.eu/project/id/783221> (accessed on 14 December 2021).
139. Project BigDataGrapes (Big Data to Enable Global Disruption of the Grapevine-Powered Industries). 2018. Available online: <https://cordis.europa.eu/project/id/780751> (accessed on 14 December 2021).

140. Project Dragon (Data Driven Precision Agriculture Services and Skill Acquisition). 2018. Available online: <https://cordis.europa.eu/project/id/810775> (accessed on 14 December 2021).
141. Madar Farms (United Arab Emirates). Available online: <https://www.madarfarms.co/> (accessed on 25 December 2021).
142. Responsive Drip Irrigation (United States of America). Available online: <https://www.responsivedrip.com/> (accessed on 26 December 2021).
143. SunCulture (Kenya). Available online: <https://sunculture.com/> (accessed on 25 December 2021).
144. Generation Green 2020–2030. Available online: <https://www.ada.gov.ma/en/news/his-majesty-king-mohammed-vi-launches-new-agricultural-strategy-generation-green-2020-2030> (accessed on 15 December 2021).
145. AbyFarm (Urban Farming in Singapore). Available online: <https://www.abymfarm.com/> (accessed on 15 December 2021).
146. Ossian Agro Automation (India). Available online: <http://nanoganesh.com/> (accessed on 25 December 2021).
147. GROUND-Vertical Farming (Lebanon). Available online: <https://berytech.org/profiles/ground-vertical-farming/> (accessed on 17 December 2021).
148. Smart Farming Identifies €5600 Average Cost Savings on Participating Farms. Available online: <https://smartfarming.ie/> (accessed on 12 April 2022).
149. Project ENORASIS (ENvironmental Optimization of IRrigAtion Management with the Combined uSe and Integration of High PreciSlon Satellite Data). 2014. Available online: <http://www.enorasis.eu> (accessed on 14 December 2021).
150. Project WEAM4i (Water and Energy Advanced Management for Irrigation). 2017. Available online: <http://weam4i.eu> (accessed on 14 December 2021).
151. Project CHAMPI-ON (Fully Automatic System for Picking and Handling Mushrooms for the Fresh Market). 2013. Available online: <http://www.champi-on.eu> (accessed on 14 December 2021).
152. Project Auditor (Advanced Multi-Constellation EGNSS Augmentation and Monitoring Network). 2016. Available online: <https://auditor-project.accorde.com> (accessed on 14 December 2021).
153. Project RUC-APS (Enhancing and Implementing Knowledge Based ICT Solutions within High Risk and Uncertain Conditions for Agriculture Production Systems). 2016. Available online: <https://cordis.europa.eu/project/id/691249> (accessed on 14 December 2021).
154. Project AfriCultuReS (Enhancing Food Security in AFRiCAn AgriCULTUral Systems with the Support of REmote Sensing). 2017. Available online: <https://cordis.europa.eu/project/id/774652> (accessed on 14 December 2021).
155. Project SWAMP (Smart Water Management Platform). 2017. Available online: <https://cordis.europa.eu/project/id/777112> (accessed on 14 December 2021).
156. Project Water4Agri (Securing Water for Food and Safety with the World’s Most Advanced Soil Moisture Information Derived from Satellites). 2017. Available online: <https://cordis.europa.eu/project/id/783989> (accessed on 14 December 2021).
157. VoE (Village of Excellence). 2021. Available online: https://www.business-standard.com/article/economy-policy/india-israel-sign-3-year-work-programme-for-cooperation-in-agri-tomar-121052401072_1.html (accessed on 14 December 2021).
158. Noshonavi (Smart Paddy Agriculture Mode Implemented by Agricultural Production Corporation). 2014. Available online: <http://www.agr.kyushu-u.ac.jp/lab/keiei/Noshonavi/Noshonavi1000/eng/index.html> (accessed on 14 December 2021).
159. Smart farming for the Future Generations (Vietnam and Uzbekistan). Available online: <https://www.fao.org/vietnam/programmes-and-projects/project-list/en/> (accessed on 15 December 2021).
160. AgriEdge (Moroccan-Based Precision Agriculture Services Platform and Digital Marketplace for Agro-Products). Available online: <https://agriedge.um6p.ma/> (accessed on 15 December 2021).
161. Baramoda (Egypt). Available online: <https://baramoda.org/> (accessed on 15 December 2021).
162. Robinson Agri (Lebanon). Available online: <https://www.robinsons-lb.com/> (accessed on 17 December 2021).
163. Kenya Climate Smart Agriculture Project (Kenya). Available online: <https://www.kcsap.go.ke/> (accessed on 25 December 2021).
164. Mimosatek (Vietnam). Available online: <https://mimosatek.com/> (accessed on 25 December 2021).
165. Lentera Africa. Available online: <https://lenterafrica.com/> (accessed on 11 March 2022).
166. Salim, J.N.; Trisnawarman, D.; Imam, M.C. Twitter users opinion classification of smart farming in Indonesia. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *852*, 012165. [CrossRef]
167. Regan, Á. ‘Smart farming’ in Ireland: A risk perception study with key governance actors. *NJAS-Wageningen. J. Life Sci.* **2019**, *90*, 100292. [CrossRef]
168. Kaur, G.; Kaushik, A.; Sharma, S. Cooking is creating emotion: A study on hinglish sentiments of youtube cookery channels using semi-supervised approach. *Big Data Cogn. Comput.* **2019**, *3*, 37. [CrossRef]
169. Shah, S.R.; Kaushik, A. Sentiment analysis on indian indigenous languages: A review on multilingual opinion mining. *arXiv* **2019**, arXiv:1911.12848.
170. Shah, S.R.; Kaushik, A.; Sharma, S.; Shah, J. Opinion-mining on marglish and devanagari comments of youtube cookery channels using parametric and non-parametric learning models. *Big Data Cogn. Comput.* **2020**, *4*, 3. [CrossRef]
171. Venkatakrisnan, S.; Kaushik, A.; Verma, J.K. Sentiment analysis on google play store data using deep learning. In *Applications of Machine Learning*; Springer: Singapore, 2020; pp. 15–30.
172. Kazhuparambil, S.; Kaushik, A. Classification of Malayalam-English Mix-Code Comments using Current State of Art. In Proceedings of the 2020 IEEE International Conference for Innovation in Technology (INOCON), Bangluru, India, 6–8 November 2020; pp. 1–6.

173. Goldewijk, K.; Beusen, A.; Doelman, J.; Stehfest, E. New anthropogenic land use estimates for the Holocene. *J. Earth Syst.Sci. Data Discuss.* **2016**, *10*.
174. FAO. AQUASTAT Database. 2016. Available online: <http://www.fao.org/nr/water/aquastat/data/query/index.html?lang=en> (accessed on 6 April 2022).
175. O'Shaughnessy, S.A.; Kim, M.; Lee, S.; Kim, Y.; Kim, H.; Shekailo, J. Towards Smart Farming Solutions in the US and South Korea: A Comparison of the Current Status. *Geogr. Sustain.* **2021**, *2*, 312–327.
176. Ojha, T.; Misra, S.; Raghuvanshi, N.S. Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. *Comput. Electron. Agric.* **2015**, *118*, 66–84. [[CrossRef](#)]
177. Yue, Y.G.; He, P. A comprehensive survey on the reliability of mobile wireless sensor networks: Taxonomy, challenges, and future directions. *Inf. Fusion* **2018**, *44*, 188–204. [[CrossRef](#)]
178. Føre, M.; Frank, K.; Norton, T.; Svendsen, E.; Alfredsen, J.A.; Dempster, T.; Eguiraun, H.; Watson, W.; Stahl, A.; Sunde, L.M.; et al. Precision fish farming: A new framework to improve production in aquaculture. *Biosyst. Eng.* **2018**, *173*, 176–193. [[CrossRef](#)]
179. Berckmans, D. Precision livestock farming technologies for welfare management in intensive livestock systems. *Rev. Sci. Tech.* **2014**, *33*, 189–196. [[CrossRef](#)]
180. Tzounis, A.; Katsoulas, N.; Bartzanas, T.; Kittas, C. Internet of Things in agriculture, recent advances and future challenges. *Biosyst. Eng.* **2017**, *164*, 31–48. [[CrossRef](#)]
181. Gupta, M.; Abdelsalam, M.; Khorsandroo, S.; Mittal, S. Security and privacy in smart farming: Challenges and opportunities. *IEEE Access* **2020**, *8*, 34564–34584. [[CrossRef](#)]
182. Choo, K.K.R.; Gritzalis, S.; Park, J.H. Cryptographic solutions for industrial Internet-of-Things: Research challenges and opportunities. *IEEE Trans. Ind. Inform.* **2018**, *14*, 3567–3569. [[CrossRef](#)]
183. Alzubi, J.; Nayyar, A.; Kumar, A. Machine learning from theory to algorithms: An overview. *J. Phys. Conf. Ser.* **2018**, *1142*, 012012. [[CrossRef](#)]
184. Soto, I.; Barnes, A.; Eory, V.; Beck, B.; Balafoutis, A.; Sanchez, B.; Vangeyte, J.; Fountas, S.; Van Der Wall, T.; Gomez-Barbero, M. Which factors and incentives influence the intention to adopt precision agricultural technologies? In Proceedings of the 2018 Conference, Vancouver, BC, Canada, 28 July–2 August 2018.
185. Yinka-Banjo, C.; Ajayi, O. Sky-farmers: Applications of unmanned aerial vehicles (UAV) in agriculture. In *Autonomous Vehicles*; IntechOpen: London, UK, 2019; pp. 107–128.
186. Charo, R.A. Yellow lights for emerging technologies. *Science* **2015**, *349*, 384–385. [[CrossRef](#)] [[PubMed](#)]
187. Eastwood, C.; Klerkx, L.; Ayre, M.; Dela Rue, B. Managing socio-ethical challenges in the development of smart farming: From a fragmented to a comprehensive approach for responsible research and innovation. *J. Agric. Environ. Ethics* **2019**, *32*, 741–768. [[CrossRef](#)]
188. Bacco, M.; Berton, A.; Ferro, E.; Gennaro, C.; Gotta, A.; Matteoli, S.; Paonessa, F.; Ruggeri, M.; Virone, G.; Zanella, A. Smart farming: Opportunities, challenges and technology enablers. In Proceedings of the 2018 IoT Vertical and Topical Summit on Agriculture-Tuscany (IOT Tuscany), Tuscany, Italy, 8–9 May 2018; pp. 1–6.
189. Santamaria-Artigas, A.E.; Franch, B.; Guillevic, P.; Roger, J.C.; Vermote, E.F.; Skakun, S. Evaluation of Near-Surface Air Temperature From Reanalysis Over the United States and Ukraine: Application to Winter Wheat Yield Forecasting. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2019**, *12*, 2260–2269. [[CrossRef](#)]