

## Research Article

# Unmanned Aerial Vehicle and Geospatial Analysis in Smart Irrigation and Crop Monitoring on IoT Platform

Wei Zhao,<sup>1</sup> Meini Wang ,<sup>2</sup> and V. T. Pham <sup>3</sup>

<sup>1</sup>School of Digital Art and Design, Dalian Neusoft University of Information, Dalian 116023, Liaoning, China

<sup>2</sup>College of Information Engineering, Dalian Ocean University, Dalian 116023, Liaoning, China

<sup>3</sup>Saigon University, Ho Chi Minh City, Vietnam

Correspondence should be addressed to Meini Wang; [wmn@dloou.edu.cn](mailto:wmn@dloou.edu.cn)

Received 8 September 2022; Revised 22 September 2022; Accepted 29 September 2022; Published 20 February 2023

Academic Editor: R. Mo

Copyright © 2023 Wei Zhao et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The geospatial analysis provides high potential for modeling, understanding, and visualizing artificial and natural ecosystems, utilizing big data analytics and the Internet of things as a pervasive sensing infrastructure. Precision agriculture, weed control, fertilizer distribution, and field management benefit from unmanned ariel vehicles (UAVs). Reduced production costs and improved crop quality are some of the benefits of using this method. Smart farming denotes geographical data utilization to identify field variability, guarantee optimal inputs, and enhance a farm's output. Hence, in this paper, an IoT-assisted Smart Farming Framework (IoT-SFF) with big data analytics has been proposed using geospatial analysis. The use of wireless sensors in IoT devices and communication methods in agricultural applications is thoroughly examined. IoT sensors are available for particular agriculture applications, such as crop status, soil preparation, insect, pest detection, and irrigation scheduled. It is now possible to view our regions in various ways and make accurate agrotechnological decisions, thanks to a computer-generated geographic information system (GIS) for crop irrigation and monitoring. Analytical and monitoring processes that yield timely and accurate decision-making add value to big data, which is a key component for intelligently managing and operating farms. Still, it is constrained by both technical and socioeconomic variables. The simulation findings show that the proposed IoT-SFF model improves the crop yield ratio by 92.4%, prediction ratio by 97.7%, accuracy ratio by 94.5%, the average error by 38.3%, and low-cost rate by 34.4%.

## 1. Introduction of Smart Farming Using IoT and Big Data

As a new term, “smart farming” refers to farm management that incorporates information technology with modern information and communication technologies, which increases production quantity and quality while optimizing the required human labor [1]. The objective of smart research in agriculture is to establish the farm management support decision-making system. Smart farming believes that population growth, climate change, and work must be resolved from planting and watering crops to health and harvesting [2]. This study aims to develop an IoT-based smart farming method for dealing with difficult situations by UAV. High-precision crop control and data collection can be achieved

through the use of smart farming techniques for the optimization of irrigation and monitoring crops. An intelligent agricultural field monitoring system that measures soil moisture and temperature is presented here. The need to efficiently utilize natural resources, the growing use and sophistication of information and communication technologies, and the increasing demands of climate change make smart agriculture increasingly important [3]. Sustainable, smart farming methods lead to a greater diversity of feed, more efficient facilities for water preservation and drought-tolerant crops, and improved animal health. Farmers are leading advocates against climate change risks [4].

Geospatial analytics collect, manipulate, and display data and images, including GPS and satellite photographs, in

geographic information systems (GISs) [5]. They are used to create geographical patterns and visualizations of data for more precise modeling and trend prediction [6]. Geospatial forecasting may help companies, due to shifting space environments or locality-based incidents, predict and plan future changes [7]. To avoid risk and disease using UAV, this smart farming sensor-based technology monitors water, monitors normal and dangerous animals through sensors, and saves and improves the farm's production time, production costs, and health for irrigation and monitoring crops. Site-based testing may help politicians understand why strategies that succeed at one location frequently fail at another [8]. It helps to consider the adequacy of soil for different land-use practices, and it is important to avoid the degradation of the atmosphere in connection with land violence [9]. GIS promotes identifying soil types and the concept of soil borders in a region [10].

The combination of GPS and GIS allows data to be correctly obtained in real-time [11]. This helps farmers use mapping devices to chart the farm's precise use of resources to improve water use and production [12]. Farmers can consider farmers' site-specific needs using remote sensing, GPS, and GIS [13]. They can devise and execute management strategies with this knowledge that ensure the optimum utilization of inputs to optimize production and income [14]. GIS will analyze soil data to assess when and how to manage soil nutrients to support the plants' growth. GIS has the potential to use plants [15]. GIS assists farmers in agriculture in increasing productivity and lowering costs by having better land resource management [16]. GIS encourages farmers in agriculture to boost productivity and cut costs by allowing enhanced land resource management [17]. Using Geomatics Technology Agricultural Geographical Information Systems, crops, precipitation, and temperatures can be mapped and forecasted by farmers [18].

Intelligent farming is a high-technology and capital-intensive, cleanly, and environmentally responsible food processing [19]. With an Internet of Things (IoT) sensors' aid (light, humidity, temperature, and soil humidity) and an automatic irrigation device, a system is developed for IoT-based intelligent agriculture to track crop area [20]. The industry will improve operating efficacy, lower costs, minimize waste, and increase its returns in the latest applications in smart agriculture and precision IoT [21]. In addition to helping farmers conserve energy and water, IoT-based systems for precise cultivation often help make agriculture greener; they greatly reduce pesticide and fertilizer use [22] in contrast to conventional farming practices, obtaining a healthier and more organic end product [23]. Trade-in agricultural and food products can be supported by digital technologies based on UAV for optimizing irrigation, which open up new markets for private sector suppliers and give governments new tools for monitoring and ensuring standard compliance, as well as providing more rapid and efficient border procedures for crop monitoring, which is critical for agricultural foods. Big data can have an important effect on intelligent agriculture and the entire supply chain [24]. Smart capabilities, data ownership and protection, and market models are the major concerns that need to be

addressed in future research in order to harness the vast quantities of data that deliver unparalleled decision-making capabilities.

The major contribution of the paper is as follows:

- (i) IoT-SFF is implemented to collect revenue from developed agricultural fields using UAVs
- (ii) Crop monitoring, irrigation, and agricultural requirements can all be better understood with the help of big data
- (iii) IoT-SFF can better plan out what crops they will be planting and harvesting times

The rest of the paper structure is as follows: Section 1 discusses the introduction of smart farming using UAV for irrigation and crop monitoring process, and Section 2 discusses literature works. In Section 3, IoT-SFF has been proposed for improved smart farming productivity. Finally, Section 4 concludes the research paper.

## 2. Literature Works

Saqib et al. [25] suggest smart farming applications using a low-cost information monitoring system. A low-data and low-cost solution are proposed to meet the necessity to track information on real, large-scale farmers. A small farm can be handled quickly. Measurement of sensor-based soil characteristics plays a central role in designing and delivering fully integrated agricultural farms. Remote sensing, global positioning, and geographic information systems can help farmers better understand the unique characteristics of their land. They can use these data to develop and commit to strategies that maximize their outcome and earnings by making the best use of their resources.

Sarker et al. [26] discussed sustainable farm management and digital agriculture through big data. Although it is a long-term debate on the applicability of the big data technology in agriculture, it seeks to investigate how broad data technology leads to sustainable agriculture. The research shows many available large-scale agricultural technology and methods for addressing existing and potential problems on the ground. The study showed that big data technology, that is increasing in agriculture, is still relatively poor. The study indicates that the comprehensive introduction of agricultural big data technology calls for state programs, public-private collaborations, data transparency, financial commitments, and research work on a regional basis.

Santos et al. [27] introduced a wireless sensor technology for cloud-based smart farming for crop production suitability. Agriculture plays a dominant role in the Philippines' economic growth. With more than 6% of overall exports, a total of 25% is nonconstrained, and about 75% has several problem soils, such as steep slopes, low drainage, ground texture, hard cracking clays, extreme fertility constraints, acidic sulfate soils, featuring soils, mining tailing, and contaminated fields. Integration of the wireless sensor network (WSN) technology is required to measure soil's moisture content, wetness, temperature, and pH, and

evaluate its current geographic positions in 3D and 3,600 satellite views using the Global Position System (GPS). Farmers can use big data to get granular information on precipitation patterns, watercourses, fertilizer criteria, and many more. Knowing UAVs for optimizing irrigation when to plant and harvest certain crops can make more informed decisions about their business. As a result of the right decisions, farm yields will increase over time from crop monitoring.

Munz et al. [28] explored the farm management information systems (FMIS) in Germany, exploring the characteristics and utilization. Agriculture digitization is one of Germany's most ongoing trends today to address rising commercial, social, and ecological needs in the agriculture and food field. UAV for optimizing irrigation has already become a common practice in the agricultural sector, which uses ICT to collect, share, and analyze data from and within the various stakeholders and structures for crop monitoring at various stages. Based on defined characteristics and features, this paper aims to assign two stages of the digital evolution model to the "one-product" model.

Trilles et al. [29] initialized cloud computing for smart farming and a microservices-based IoT platform. This paper suggests an agnostic architecture of IoT, which emphasizes the IoT platform's role in a larger integrated environment to increase scalability, reliability, interoperability, and reusability. This idea is validated in the IoT scenario of intelligent agriculture, which deploys five IoT devices (SEnviro nodes) to improve wine production. A rigorous performance review guarantees a flexible, secure network.

Maimaitijiang et al. [30] discussed smart farming and plant morphological characteristics, as well as grain policy and food production decisions, which can benefit greatly from nondestructive crop management over huge areas with high performance. In this study, the purpose was to assess the possibility of incorporating shade structure spectral data with a tree crown individual system for crop management using unmanned aerial vehicle (UAV) big data and advanced analytics.

Sinha [31] deliberated the enhancing farmers' net benefit and aerial robot for smart farming. The developing, evaluating, and managing essential time and space factors for farming to optimize profitability, productivity, and environmental conservation is a time-consuming process of knowledge and new electronic technical advancement of the agricultural production system. In this respect, it may play an important function for the robot (aerial, land, and underwater). The existing constraints of aerial robot for the management of agricultural production are being discussed, and potential requirements and technology advancement recommendations are expected.

Based on the survey, there are some challenges in the existing model. This paper proposes the IoT-SFF model to implement smart farming and improve productivity with geospatial analysis and big data to overcome these issues using UAVs for irrigation and crop monitoring process. Section 3 discusses the proposed model briefly which is as follows.

### 3. IoT-Assisted Smart Farming Framework (IoT-SFF)

This paper discussed the IoT-SFF model to enhance crop yield. Intelligent agricultural research aims to develop an agricultural management decision support system [32–35]. Smart agriculture finds it appropriate to solve the population's concerns, climate change, and labor from seed planting and watering to health and harvesting, which has attracted significant interest. Based on UAV applications for optimizing irrigation, chemicals and fertilizers are commonly used to increase the yield of genetically modified crops in conventional farming. Management levels are a key difference between precision farming and traditional farming. Small areas within fields are managed rather than the entire field as a whole. This increased management level highlights the need for crop monitoring practices. Geographic information system (GIS) [36, 37] is a technology that promotes current agricultural precision methods that ensure the agricultural analytics degree and GIS implementations. This research considers GIS applications such as land adaptability, site search, discovery, allocation of services, impact measurement, land allocation, and information systems. The Internet of things (IoT) gathers geographical information from multiple sources and thus creates connectivity through the Internet to the entire world. It has been reported that a UAV-enabled process for irrigation and crop monitoring for a wide range of salinity assessment methods have been utilized, including modern electrostatic EM38, electro-optic section, and particle micrograph techniques. The knowledge would help manage the land using the appropriate quantity of fertilizers at the correct place.

Figure 1 shows the application of GIS in smart farming. Food producers compete for land, water, and energy supplies and limit food production's detrimental environmental effects. The modification moved manufacturers from conventional farming (CA) to precision farming (PA). PA is introduced to adapt the tractors and machines with GPS sensors for knowledge management [38–40]. In the process of crop irrigation for UAV based on least squares, regression's loss function is the MSE. RMSE, the squared loss function, from which MSE is derived, penalizes larger errors more severely because it is formulated for monitoring crops. The PA extension is the major driving force in big data analysis (BDA) agriculture. The key priority of PA is to collect, handle, and use data for decision-making. PA requires a range of synchronizing technology to capture and interpret data. Although Figure 1 shows the Geographic Positioning System (GPS), remote sensor (RS), and geospatial sensors, the environmental geography division studies the geographical distribution of agriculture and its influences and laws. The geographical distribution of agriculture is subject to a set of laws indicative of its life support system. From the process of crop irrigation for UAV and crop monitoring, the measurement of erosion can be done in one of four ways: (1) modification in mass, (2) modification in the atmospheric boundary layer, (3) transformation in channel flow, and (4) depositional collection from corrosion

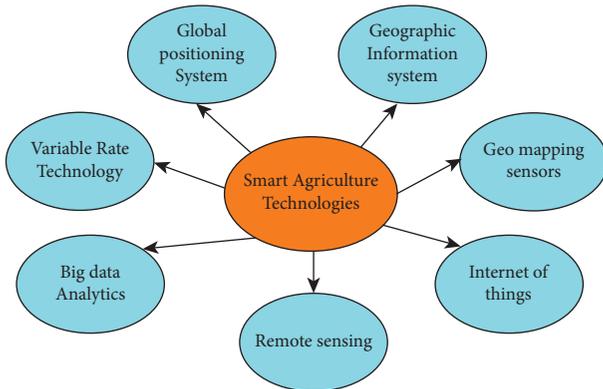


FIGURE 1: Application of GIS in smart farming.

plot lines and water sources. Agricultural geography is a field of physical science that focuses on the spatial interactions between agriculture and humans. In other words, the study of the phenomena and results in various areas contribute to creating the planet's top surface. Agricultural geographical maps reflect the distinction of the soil. They represent the ties between farming, nature, and economic conditions. Remote sensing provides soil humidity data, which helps measure soil moisture. Water resource mapping: remote sensing is important in mapping water supplies and can be used on a given piece of land for agriculture. The IoT is used in an agricultural environment to translate all elements and activities involved in agriculture into data through sensors, cameras, and other technologies. Big data provide farmers with granular data on precipitation levels, water cycles, and nutrient needs. This encourages them to make intelligent choices, such as cultivating and harvesting plants for better profitability. Ultimately the right choices raise agricultural yields. The production and execution of correct agriculture or site-specific agricultural practices have been enabled by integrating the Global Positioning System (GPS) and GIS. Millimeters (mm) per hour is the unit of measure for evapotranspiration. Water loss from a cropped area is measured using water depth units. Time can be measured in terms of an hour, a day, a decade, a month, or even an entire growing year in UAV for optimization and crop monitoring. In poor visibility field conditions, GPS helps farmers operate, for example, in mud, gravel, fog, and darkness. The VRT technology permits the application of fertilizers, pesticides, calcium, rinsing water, drainage, and other agricultural inputs at varying rates around the field without increasing the rate on machines manually or making multiple crossings [41, 42].

**3.1. Case 1: Big Data-Based Smart Farming.** Figure 2 shows the big data and GIS-based smart farming. Due to its unique capacity to visually reflect data, descriptive GIS analytics, tools, and applications can execute effective research with elaborated knowledge and transparency. Data filtering methods increase productivity. As of now, it is assisting in the analysis of decades' worth of climate and crop data, looking for trends that will allow farmers to forecast better crop yields and use UAV-enabled processes

for irrigation and crop monitoring. Data extraction in farming operations can now benefit from the predictive capabilities generated by large datasets, as well as the proper operating decisions and process redesigns that these datasets allow, all thanks to the development of game-changing marketing strategies. Increased farm productivity, commercial viability, and stronger economic ties are part of agricultural development. There are a few key areas where agricultural change needs to be prioritized under transformation. The GIS analytics deals with internal device problems daily using spatial online analytical processing or surface-down approaches to assess soil and water consistency by implementing surface energy balance applications for soil and digital image processing. The economic and environmental efficiency of precision farming is assessed using pattern analysis to estimate the evapotranspiration rate needed for soil salination assessment. RS data are used for long-term acquisition, validation, and calculation of parameters to explain land cover change and measure soil erosion using unmanned area vehicles for optimization and crop monitoring. The topographic shuttle radar mission data serve as a baseline for testing the landscape characteristics. Agricultural greenhouse gas emissions are studied using economic and environmental models. GIS analytics uses hardware and programming to identify graphic and predictive trends within data and is primarily used to model future events. Various predictive analytics have been used, such as database mining, text mining, and forecasting. An adequate prediction approach is developed for the risks and uncertainty of supply chains for agriculture [43–45]. The crop monitoring uses spatial online analytical processing or surface-down approaches to assess soil and water consistency by implementing surface energy balance applications for soil and digital image processing in the GIS. UAV for optimizing irrigation is used to estimate the evapotranspiration rate required for soil salinity assessment in precision farming. The cost is minimized, and farmers and other interested parties are likely to obtain highly accurate knowledge of climate prediction and take advantage of favorable weather. In this analysis, we categorize GIS analyses' particular applications. The predictive GIS analytics applications is categorized into water/irrigation, soil, plant/agricultural, and fertilization systems.

Further experiments in water/irrigation and crops and agricultural systems have been carried out. Predictive GIS analytics are used when the data are forwarded to the spatially complex event processing engine after filtering and reprocessing.

Figure 3 shows the average error. The typical day of data gathered from different sensors is processed as part of the data preprocessing in the cloud network. The mean of the data is considered since it may include missing and noisy values. Since the data include multiple measuring units (categorical and numerical), standardization is carried out before using the proposed model. In addition to the aforementioned micromeasures and macromeasures, the resulting method defines the error as root mean squared error (RMSE) and mean squared error (MSE). GIS, or

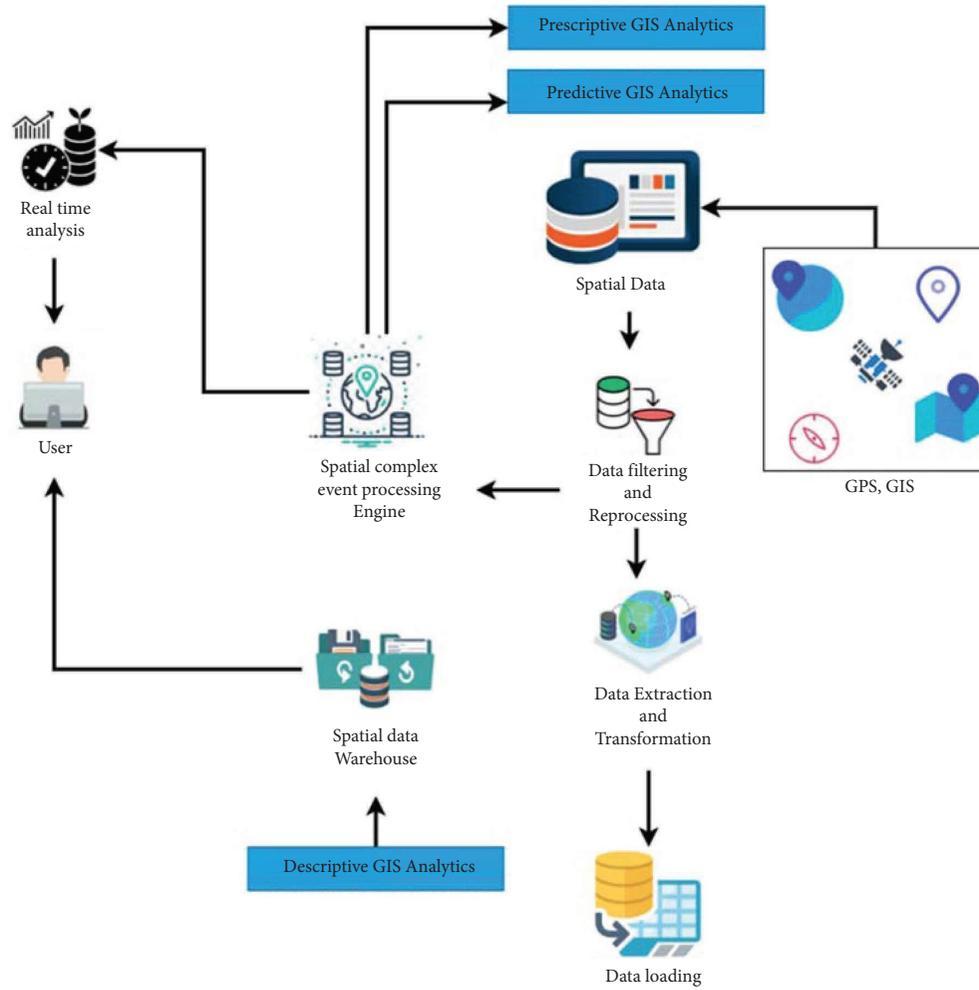


FIGURE 2: Big data and GIS-based smart farming.

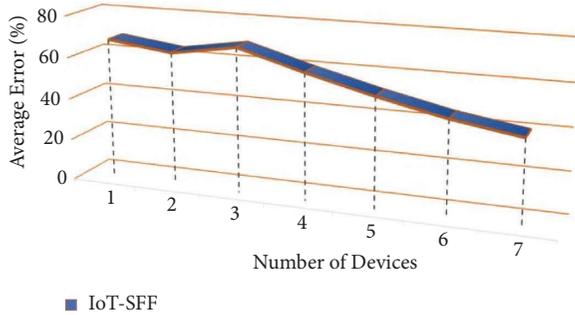


FIGURE 3: Average error.

geographic information systems, is a relatively new field of study in the information technology in unmanned area vehicles for optimization and crop monitoring. Natural resources used in food production, such as land, weather, hydrogeology, and a wide range of socioeconomic factors, can now be examined and analyzed with greater ease. To transmit data to GPS receivers on the ground, satellites in orbit around the Earth are used. Geographic information systems (GIS) are computer programs that make it possible to use data collected by GPS satellites.

Nevertheless, it should be noted that during testing, the stochastic descent of gradients does not require MSE or RMSE. Rather, the error term is expected between an altered sample and its prediction for big data nodes' weights. MSE and RMSE determine the average model absorption error as

$$MSE = \frac{1}{n} \sum_{j=1}^n (X_j - X'_j)^2. \quad (1)$$

Here,  $n$  is the overall number of data samples,  $X_j$  is the target and  $j$  th instance, and  $X'_j$  is the output or product of the learning model's  $j$  th data instance.

Figure 4 shows the ratio for prediction. Decision-making calls for accurate information from sensor results. The big data from the sensor provide learning opportunities in a continuously evolving climate. Such decision-making can be short-term, medium-term, or long-term. When those requirements are met, automatic decisions from big data may be taken that require little to no human involvement. These automatic decisions could vary from temperature management to water supply control irrigation systems. Geospatial analysis and the agriculture stick are combined in this paper. It can be accessed electronically via a mobile phone and combined with various sensors and live data

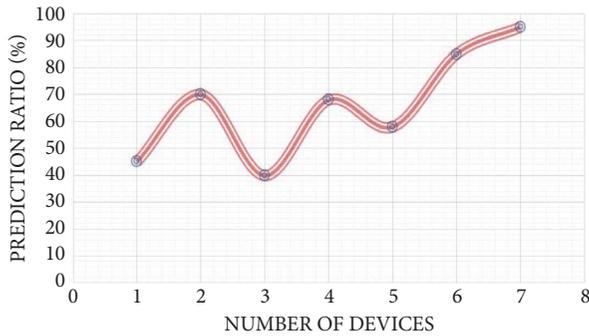


FIGURE 4: Ratio for prediction.

streams in unmanned area vehicles for optimization and crop monitoring. Testing on actual farmland ensures that the data feeds are accurate in various soil conditions. The use of big data in greenhouses will lead to the identification of ideal conditions for crop cultivation by observing data from the sensors on nutrients, yield, growth, perspiration, color, taste, transplantation, levels of light pest temperatures, and air quality. The precision, conciseness, completeness, and timeliness of data are critical. Several programs have been developed to enable farmers to decide on farms and animals in a cultivated way.

**3.2. Case 2: IoT-Based Smart Farming.** Figure 5 shows the IoT-based effective communication in agriculture. Smart agriculture based on IoT sensors monitors the environmental state of fields, soil, and crop development for professionals and growers. Sensors, drones, satellite systems, GPS systems, actuators, gateways, cloud servers, the Internet, and android cell phones are all part of the smart farming system. The actuator provides the central coordinator's response to an order, which powers the driving systems in smart farming in crop irrigation for UAV and crop monitoring. A central coordinator measures ground moisture and the actuators based on agricultural field sensor readings. The presented software and hardware led to the progress of these innovations in crop production. Big data, practical guidance, and recommendations from online expert guidance systems for farmers, pests, and disease management are described in [46, 47].

Figure 6 shows the crop yield level. The IoT-enabled precision farming technology ensures that farm efficiency increases and demand grows to satisfy the growing population's food requirements. Surface-down approaches to assess soil and water consistency by implementing surface energy balance applications for soil and digital image processing are two ways GIS analytics which are used daily to solve internal device issues. To prevent soil salinization, farmers use UAVs to monitor crops and analyze irrigation patterns to determine the evapotranspiration rate. Using IoT to boost weather consistency influences crop yields greatly, and one-way IoT has a positive effect on yield. The higher the precision it achieves, the less likely the crop will be damaged by unexpected circumstances, thus improving productivity. A connected farm IoT network has been conducted and

found to increase yields by decreasing energy costs per acre for the average farm with IoT-enabled technology and water usage for irrigation. Food farmers drench their crops, limiting growth and yield and increasing the probability that fungal diseases emerge in the soil. Water can be processed, and overwatering challenges are avoided when the farmer has access to the data. It may indicate whether irrigation is inadequate and needs to be increased to optimize cultivation output. There are two types of formats stored: organized and curated. These are based on the smart farming analytics (SFA) data model. Here, the analytical system finds its reference point for reality in UAVs for optimization and crop monitoring. Files in the raw zones must be removed until new data is placed here to avoid undesirable outcomes. There are two types of zones: those containing raw data and those containing processed data.

Figure 7 shows the water management system based on big data and IoT. In several areas of agriculture, IoT is now a feasible database. A study has been conducted to use big data to tackle the large volume of data in many agriculture fields. The formats are stored based on the smart farming analytics (SFA) data model and include organized and curated data. This region becomes the analytical system's center of reality. The files placed under the raw zones should be removed until data are brought into this zone to avoid results. Based on unmanned aerial vehicles for irrigation and crop monitoring, the six steps of multicriteria decision-making include the following: (1) formulation of the problem, (2) identifying the necessities, (3) setting goals, (4) identifying various alternatives, and (5) developing criteria. Verifications of QC and "farming" laws are made at the tables. We provide a single source of truth/access to all main key performance indicators (KPI) for agricultural research. Data are saved in a format that data scientists and data visualization software can process. Promoting healthy water-based relations between biophysical and human processes and maintaining water control to minimize water leakage and recommend emergency measures. The water pressure is within acceptable bounds based on the analysis and simulation of water use patterns. They gather this knowledge, called historical usage data, and offer other data that can be used to predict the potential consumption of water. Multicriteria decision analyses are used in the prescriptive GIS analysis to gather knowledge about large and complex datasets in crop irrigation for UAV and crop monitoring. The MCDA method has been the method of choice for most researchers in their quest to identify the most important factors affecting agricultural productivity. Smart water dripping for farmers can help the automatic and productive use of soil-based irrigation methods based on soil temperature. The approach includes integrating smart farming big data technology into the next granularity stage, offering an infrastructure tailored to fulfill the SFA criteria for smart farm analytics.

GIS analytics are used daily to solve internal device issues using spatial online analytical processing or surface-down approaches to assess soil and water consistency by implementing surface energy balance applications for soil and digital image processing in Figure 8. Farming with precision is evaluated using UAVs in crop monitoring and irrigation

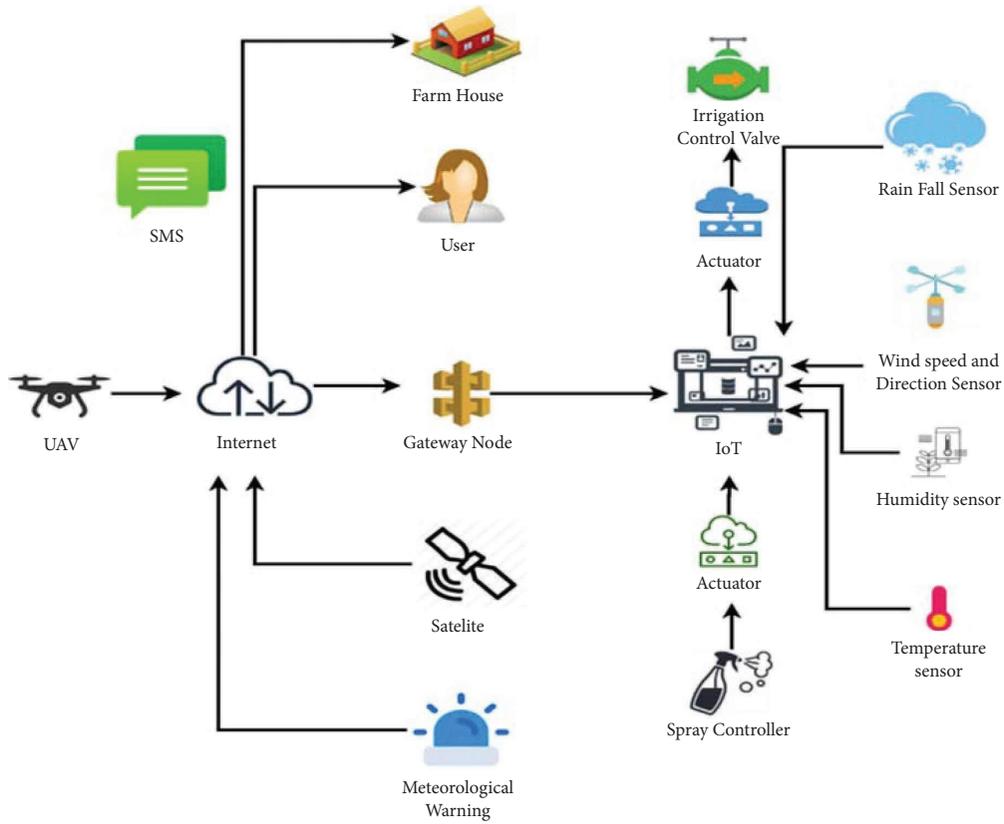


FIGURE 5: IoT-based effective communication in agriculture.

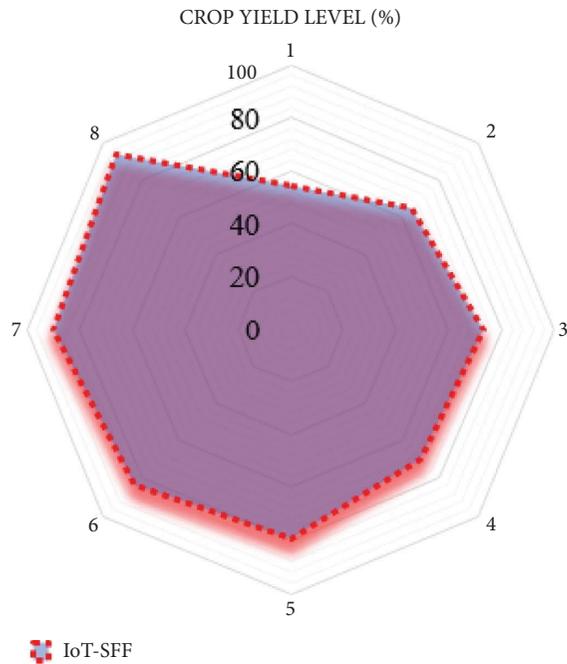


FIGURE 6: Crop yield level.

pattern analysis to determine the evapotranspiration rate required to prevent soil salinization. The suggested approach includes multiple data sources, data modeling, elements of applications, and technological limitations in UAVs. Our proposal for enhancing the efficiency of the work schedule,

mastering the quality of the data from smart farms, and including the irrigation systems to promote agriculture is still being worked on.

Figure 9 shows the IoT-based smart farming. The earliest accuracy relied on satellites to pass seed knowledge to a central hub. Wi-Fi is available to link data directly to a farmer’s smartphone from on-site instruments. Many farms that use precise farming use mesh networks that send Wi-Fi signals over several acres. Agriculture’s key performance indicators (KPIs) stay updated on feed consumption for irrigation and monitoring, production, and costs in the UAV process. Agriculture and its output are impacted by making more money and being more productive. Time is money when it comes to farming programs based on IoT features. In the measurement of gain and loss, computers are used as records for the cost of manufacturing, shipping, farm processing, and details. The Internet allows farmers and traders to connect with experts in agriculture. In the cloud database, the storage of soil and water resources data and the network management of farm data are realized. In the agriculture knowledge system, multilevel decision-making information and climate growth are important. Developers may use this platform to visually determine how APIs function, the quantity and consistency of data, request processing speed, and resources’ availability. The dashboard makes getting actual samples, which IoT offers via our agricultural applications, easier to enlighten rural areas, service water pumps, and run the computer system and telecommunications.

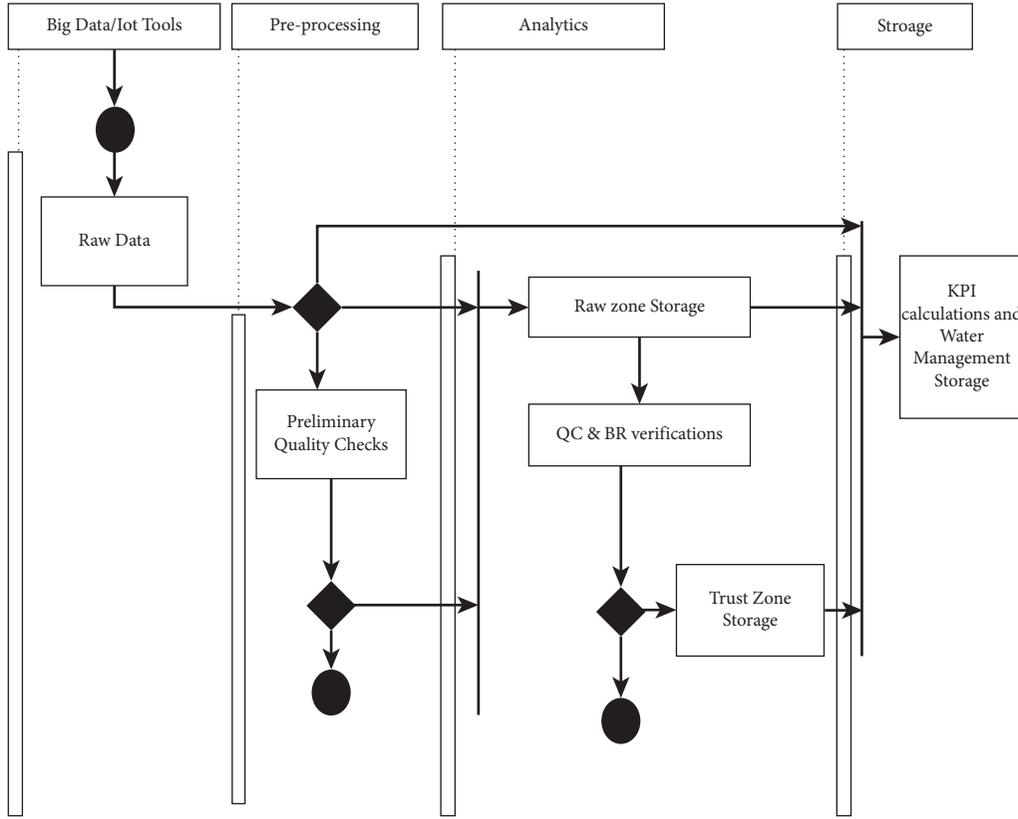


FIGURE 7: Water management system based on big data and IoT.

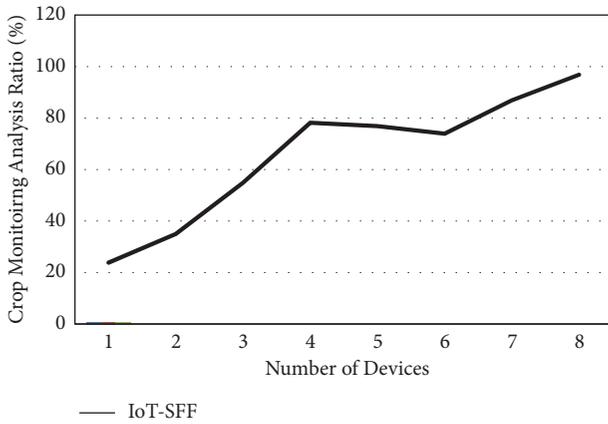


FIGURE 8: Crop monitoring ratio.

Figure 10 shows the accuracy ratio. A lack of awareness of the importance of climate in agriculture can significantly impact crop production and efficiency. However, when it comes to the Internet of things (IoT), it is possible to monitor the situation in real-time accuracy ratio irrigation and monitoring of crops using UAV. In and out of the agricultural sector, sensors have been installed to select the best cultivars for various climates, using environmental data. Environmental sensors, such as those measuring moisture, rainfall, temperature, and other variables in real-time, make up the IoT ecosystem. Many sensors are needed to monitor and optimize all of these parameters to serve the needs of

smart farming. In adverse weather conditions, the need for human intervention increases productivity and yields greater returns on investment for farmers.

Figure 11 shows the cost ratio. The invention of numerous IoT-based devices for intelligent farming transforms every day, leading to crop production by enhancing it, reducing waste, and making it cost-effective. This paper is intended for farmers to generate live data on temperature and soil moisture. Other variables for accurate environmental monitoring are to improve their total production and the quality of products. In utilizing the UAV process for irrigation and monitoring, the robotics in farming GIS can provide accurate maps that include all the necessary information about crops in the field. Task maps and application maps are examples of task maps by precision methods that will use them to maintain the field. This paper combines the agriculture stick with geospatial analysis, and it can be accessed electronically by mobile telephone and combined with different sensors and live data stream. The proposed product is tested on live farming fields to ensure high precision in data feeds in various soil circumstances.

$$f(sa) = s_0 + \sum_{n=1}^{\infty} \left( s_n \cos \frac{n\pi x}{cd} s_n \sin \frac{n\pi x}{cd} \right), \quad (2)$$

$$(1 + x)^n = 1 + \frac{nx}{1!} + \frac{n(n-1)x^2}{2!} + \text{MSE}. \quad (3)$$

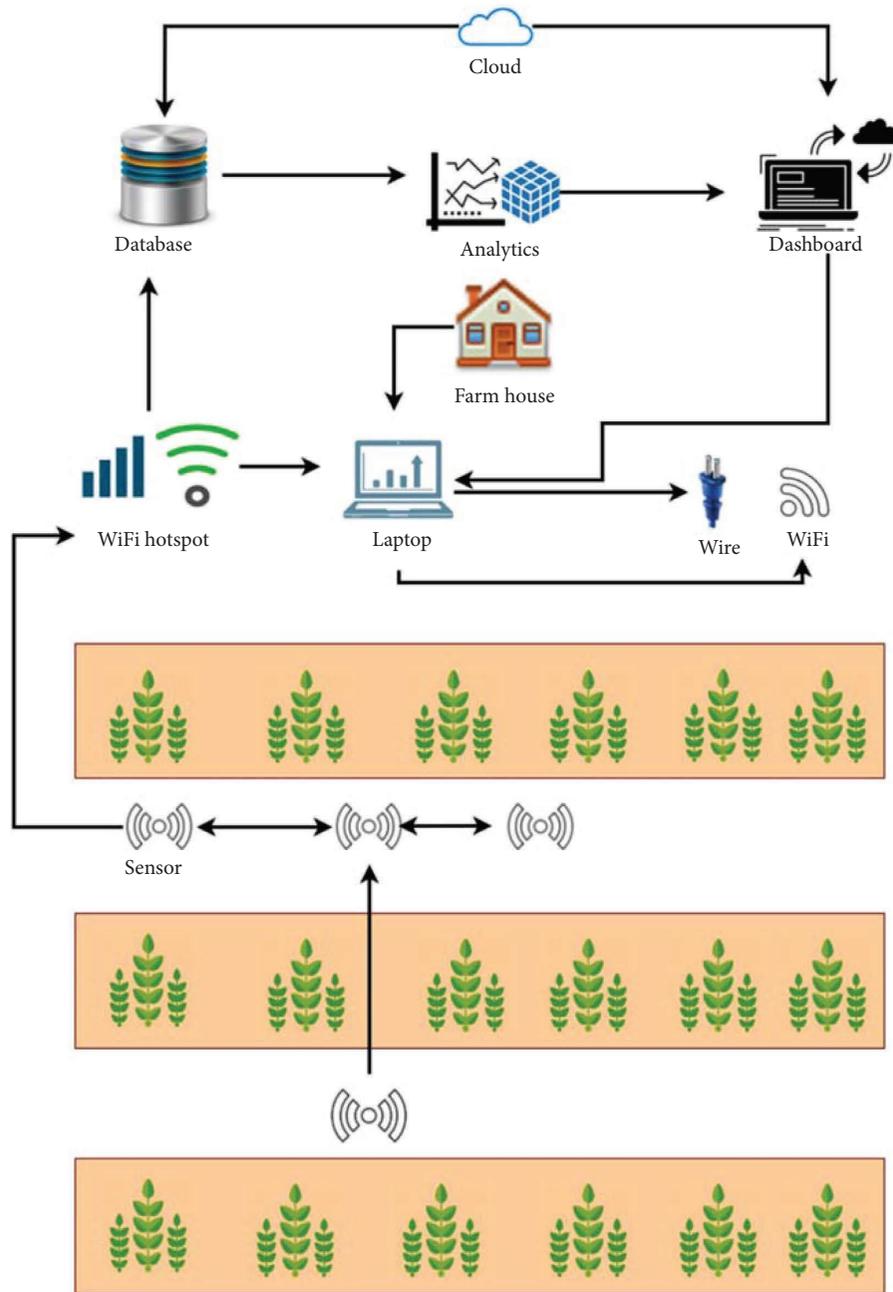


FIGURE 9: IoT-based smart farming.

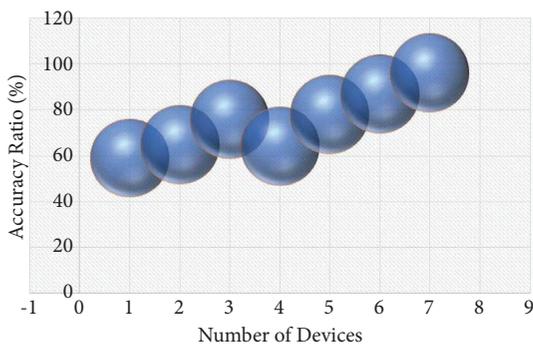


FIGURE 10: Accuracy ratio.

In the prescriptive GIS analysis, statistical algorithms  $f(sa)$ , simulations  $s_0$ , and multipronged decision analyses are used to collect knowledge of high-volume and complex data  $cd$  in crop irrigation for UAVs and crop monitoring with values obtained using binomial equations (2) and (3) with trigonometric values. For the most part, researchers have turned to the MCDA method when attempting to pinpoint critical variables that influence agricultural productivity.

The UAV process in irrigation and crop monitoring can collect operational data and impact operations more than manual practices shown in Figure 12. As a result, the use of robots in manufacturing can be further reduced, and the

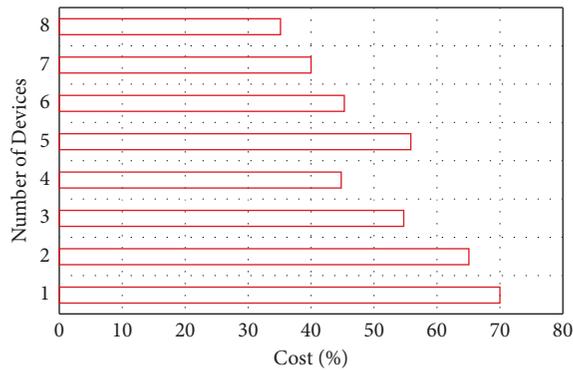


FIGURE 11: Cost ratio.

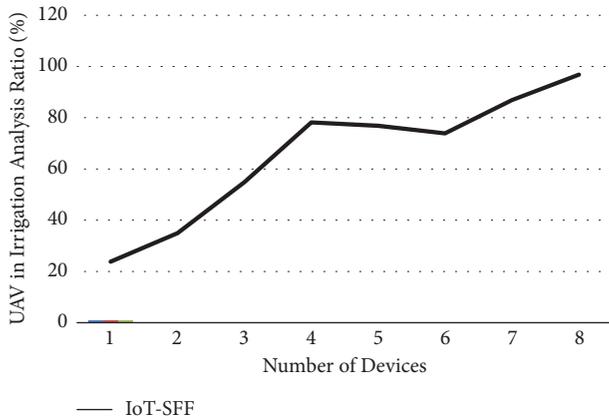


FIGURE 12: UAV in irrigation ratio.

accuracy and effectiveness of the inputs to the operation can increase. Agriculture is transforming with UAV is a term used to describe the ability of physical devices to communicate with each other over the Internet. With an IoT, devices all over a farm can collect data remotely and send it to the farmworker in real-time for crop irrigation and monitoring activities.

The proposed model is analyzed using sample smart farming implementation to measure various parameters and achieve high crop yield, accuracy ratio, prediction ratio, low cost, and average error; automation of greenhouses, crops, cattle, and livestock monitoring and management; farming with precision, smart farming with drones, and predictive analytics; systems for the complete management of a farm are examples of devices used with UAV-enabled processes for irrigation and crop monitoring.

#### 4. Conclusion

This paper discussed the IoT and big data based smart farming technology to improve crop production. Hence, this paper proposed the IoT-SFF with GIS analysis to increase crop yield and fertilize inland smart agriculture. UAV-enabled irrigation and crop monitoring process can get information on soil moisture using remote sensing. This information is then used to determine the crops grown in the area. Farmers can use this information to determine how

much water their soil needs by comparing its moisture content with other soils. The Internet of things (IoT) is illuminating agricultural management in a big way, which is why smart farming is becoming increasingly important. Sensors, power transmission, and feelings all contribute to the generation of enormous amounts of data. Big data tracking, evaluation, and value stream from such big data are crucial for smartly coordinating and managing farms. Even though this research, IoT-SFF, is focused on the existence in agricultural production of big data technology, IoT, and data management in the context of agriculture, these constraints are relevant to this research. This IoT-SFF recognizes large-scale analysis to play a major role in enhancing the efficiency of GIS implementation. In farms, the Internet of things enables the system across a farm to collect and transmit real-time data on a wide range of metrics to the farmer. Moisture content, contaminant application, dam thresholds, livestock wellbeing, irrigation, and monitoring can all be monitored by UAV devices, which can then be used to monitor barricades, automobiles, and snow conditions. They provide researchers, agriculture experts, and officials with recommendations for efficient management of large GIS data to increase farm productivity. The simulation findings show that the proposed IoT-SFF model improves crop yield ratio by 92.4%, prediction ratio by 97.7%, accuracy ratio by 94.5%, average error by 38.3%, and low-cost rate by 34.4%.

#### Data Availability

The dataset used to support the findings of the study is available from the corresponding author upon request.

#### Conflicts of Interest

The authors declare that they have no conflicts of interest.

#### References

- [1] A. Vangala, A. K. Das, N. Kumar, and M. Alazab, "Smart secure sensing for iot-based agriculture: blockchain perspective," *IEEE Sensors Journal*, vol. 21, no. 16, pp. 17591–17607, 2021.
- [2] V. Higgins and M. Bryant, "Framing agri-digital governance: industry stakeholders, technological frames and smart farming implementation," *Sociologia Ruralis*, vol. 60, no. 2, pp. 438–457, 2020.
- [3] P. K. R. Maddikunta, S. Hakak, M. Alazab et al., "Unmanned aerial vehicles in smart agriculture: applications, requirements, and challenges," *IEEE Sensors Journal*, vol. 21, no. 16, p. 1, 2020.
- [4] N. Tantalaki, S. Souravlas, and M. Roumeliotis, "Data-Driven decision making in precision agriculture: the rise of big data in agricultural systems," *Journal of Agricultural & Food Information*, vol. 20, no. 4, pp. 344–380, 2019.
- [5] K. Sekaran, M. N. Meqdad, P. Kumar, S. Rajan, and S. Kadry, "Smart agriculture management system using internet of things," *Telkomnika*, vol. 18, no. 3, pp. 1275–1284, 2020.
- [6] D. S. Bullock, M. Boerngen, H. Tao et al., "The data-intensive farm management project: changing agronomic research through on-farm precision experimentation," *Agronomy Journal*, vol. 111, no. 6, pp. 2736–2746, 2019.

- [7] T. C. Hsu, H. Yang, Y. C. Chung, and C. H. Hsu, "A Creative IoT agriculture platform for cloud fog computing," *Sustainable Computing: Informatics and Systems*, vol. 28, Article ID 100285, 2018.
- [8] A. Anwer and G. Singh, "Geo-spatial technology for plant disease and insect pest management," *Bulletin of Environment, Pharmacology and Life Sciences*, vol. 8, no. 12, pp. 1–12, 2019.
- [9] M. W. Convolbo, J. Chou, C. H. Hsu, and Y. C. Chung, "GEODIS: towards the optimization of data locality-aware job scheduling in geo-distributed data centers," *Computing*, vol. 100, no. 1, pp. 21–46, 2018.
- [10] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A survey on the role of IoT in agriculture for the implementation of smart farming," *IEEE Access*, vol. 7, pp. 156237–156271, 2019.
- [11] K. T. Liu, S. J. Chang, and S. Wu, "Fabrication and characterization of GaN ultraviolet photodetector prepared by growing on geometrical patterned sapphire substrate," in *Proceedings of the 2016 International Conference on Advanced Materials for Science and Engineering (ICAMSE)*, pp. 401–403, IEEE, Tainan, Taiwan, November 2016.
- [12] A. T. Balafoutis, F. K. V. Evert, and S. Fountas, "Smart farming technology trends: economic and environmental effects, labor impact, and adoption readiness," *Agronomy*, vol. 10, no. 5, p. 743, 2020.
- [13] F. Farivar, M. S. Haghighi, A. Jolfaei, and M. Alazab, "Artificial intelligence for detection, estimation, and compensation of malicious attacks in nonlinear cyber-physical systems and industrial IoT," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 4, pp. 2716–2725, 2020.
- [14] P. Paul, P. S. Aithal, A. Bhuimali, and T. Kalishankar, "Environmental informatics vis-à-vis big data analytics: the geo-spatial & sustainable solutions," *International Journal of Applied Engineering and Management Letters (IJAEML)*, vol. 4, no. 2, pp. 31–40, 2020.
- [15] A. Kumari, S. Tanwar, S. Tyagi, N. Kumar, M. Maasberg, and K. K. R. Choo, "Multimedia big data computing and Internet of Things applications: a taxonomy and process model," *Journal of Network and Computer Applications*, vol. 124, pp. 169–195, 2018.
- [16] A. Wąs, P. Sulewski, E. Majewski, and P. Kobus, "Use of big data for assessment of environmental pressures from agricultural production," in *Management in the Era of Big Data*, J. Paliszkiwicz, Ed., pp. 137–152, Auerbach Publications, Boca Raton, Fla., USA, 2020.
- [17] S. Garg, K. Kaur, N. Kumar, G. Kaddoum, A. Y. Zomaya, and R. Ranjan, "A hybrid deep learning-based model for anomaly detection in cloud datacenter networks," *IEEE Transactions on Network and Service Management*, vol. 16, no. 3, pp. 924–935, 2019.
- [18] A. Karkaya, "Smart farming-precision agriculture technologies and practices," *Journal of Scientific Perspectives*, vol. 4, no. 2, pp. 123–136, 2020.
- [19] K. Kaur, S. Garg, G. Kaddoum, F. Gagnon, N. Kumar, and S. H. Ahmed, "An energy-driven network function virtualization for multi-domain software defined networks," in *Proceedings of the IEEE INFOCOM 2019-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 121–126, IEEE, Paris, France, April 2019.
- [20] A. Farouk, J. Batle, M. Elhoseny et al., "Robust general N user authentication scheme in a centralized quantum communication network via generalized GHZ states," *Frontiers of Physics*, vol. 13, no. 2, Article ID 130306, 2018.
- [21] K. G. Orjuela, P. A. Gaona-García, and C. E. M. Marin, "Towards an agriculture solution for product supply chain using blockchain: case study Agro-chain with BigchainDB," *Acta Agriculturae Scandinavica Section B Soil and Plant Science*, vol. 71, pp. 1–16, 2020.
- [22] S. Sankar, P. Srinivasan, A. K. Luhach, R. Somula, and N. Chilamkurti, "Energy-aware-grid-based data aggregation scheme in routing protocol for agricultural internet of things," *Sustainable Computing: Informatics and Systems*, vol. 28, Article ID 100422, 2020.
- [23] P. Hemalatha, K. Dhanalakshmi, S. Matilda, and M. BalaAnand, "Farmbot-a smart agriculture assistant using internet of things," *International Journal of Pure and Applied Mathematics, Special Issue*, vol. 119, no. 10, pp. 557–566, 2018.
- [24] S. Balamurugan, B. A. Muthu, S. L. Peng, and M. H. A. Wahab, "Call for special issue papers: big data analytics for agricultural disaster management: deadline for manuscript submission: december 12, 2020," *Big Data*, vol. 8, no. 5, pp. 450–451, 2020.
- [25] M. Saqib, T. A. Almohamad, and R. M. Mehmood, "A low-cost information monitoring system for smart farming applications," *Sensors*, vol. 20, no. 8, p. 2367, 2020.
- [26] M. N. I. Sarker, M. S. Islam, M. A. Ali, M. S. Islam, M. A. Salam, and S. H. Mahmud, "Promoting digital agriculture through big data for sustainable farm management," *International Journal of Innovation and Applied Studies*, vol. 25, no. 4, pp. 1235–1240, 2019.
- [27] M. D. Santos, L. L. Lacatan, and F. G. Balazon, "Cloudbased smart farming for crop production suitability using wireless sensor technology," *Test Engineering and Management*, vol. 81, no. 11–12, pp. 5043–5052, 2019.
- [28] J. Munz, N. Gindele, and R. Doluschitz, "Exploring the characteristics and utilisation of farm management information systems (FMIS) in Germany," *Computers and Electronics in Agriculture*, vol. 170, Article ID 105246, 2020.
- [29] S. Trilles, A. González-Pérez, and J. Huerta, "An IoT platform based on microservices and serverless paradigms for smart farming purposes," *Sensors*, vol. 20, no. 8, p. 2418, 2020.
- [30] M. Maimaitijiang, V. Sagan, P. Sidike, A. M. Daloye, H. Erkbol, and F. B. Fritsch, "Crop monitoring using satellite/UAV data fusion and machine learning," *Remote Sensing*, vol. 12, no. 9, p. 1357, 2020.
- [31] J. P. Sinha, "Aerial robot for smart farming and enhancing farmers' net benefit," *Indian Journal of Agricultural Sciences*, vol. 90, no. 2, pp. 258–267, 2020.
- [32] T. Qureshi, M. Saeed, K. Ahsan, A. A. Malik, E. S. Muhammad, and N. Touheed, "Smart agriculture for sustainable food security using internet of things (IoT)," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 9608394, 10 pages, 2022.
- [33] K. N.-E.-A. Siddiquee, Md. S. Islam, N. Singh et al., "Development of algorithms for an IoT-based smart agriculture monitoring system," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 7372053, 16 pages, 2022.
- [34] L. H. Li, J. C. Hang, and Y. Gao, "Using an integrated group decision method based on SVM, TFN-RS-AHP, and TOPSIS-CD for cloud service supplier selection," *Mathematical Problems in Engineering*, vol. 2017, Article ID 3143502, 14 pages, 2017.
- [35] Y. Li and L. H. Li, "Enhancing the optimization of the selection of a product service system scheme: a digital twin-driven Framework," *STROJNISKI VESTNIK-JOURNAL OF MECHANICAL ENGINEERING*, vol. 66, no. 9, pp. 534–543, 2020.

- [36] L. H. Li and H. G. Wang, "A VVWBO-BVO-based GM (1,1) and its parameter optimization by GRA-IGSA integration algorithm for annual power load forecasting," *PLoS One*, vol. 13, no. 5, Article ID e0196816, May.
- [37] J. Tian, D. Li, and X. Jia, "IoT smart agriculture and agricultural product income insurance participant behavior based on fuzzy neural network," *Computational Intelligence and Neuroscience*, vol. 2022, Article ID 4778975, 12 pages, 2022.
- [38] E. Ramirez-Asis, A. Bhanot, V. Jagota et al., "Smart logistic system for enhancing the farmer-customer corridor in smart agriculture sector using artificial intelligence," *Journal of Food Quality*, vol. 2022, Article ID 7486974, 8 pages, 2022.
- [39] L. Li, C. Mao, H. Sun, Y. Yuan, and B. Lei, "Digital twin driven green performance evaluation methodology of intelligent manufacturing: hybrid model based on fuzzy rough-sets AHP, multistage weight synthesis, and PROMETHEE II," *Complexity*, vol. 2020, no. 6, Article ID 385392, 24 pages, 2020.
- [40] L. Li, J. Hang, H. Sun, and L. Wang, "A conjunctive multiple-criteria decision-making approach for cloud service supplier selection of manufacturing enterprise," *Advances in Mechanical Engineering*, vol. 9, no. 3, Article ID 168781401668626, 2017.
- [41] K. Phasinam, T. Kassanuk, P. P. Shinde et al., "Application of IoT and cloud computing in automation of agriculture irrigation," *Journal of Food Quality*, vol. 2022, Article ID 8285969, 8 pages, 2022.
- [42] A. H. Adow, M. K. Shrivastava, H. F. Mahdi et al., "Analysis of agriculture and food supply chain through blockchain and IoT with light weight cluster head," *Computational Intelligence and Neuroscience*, vol. 2022, Article ID 1296993, 11 pages, 2022.
- [43] L. Li, B. Lei, and C. Mao, "Digital twin in smart manufacturing," *Journal of Industrial Information Integration*, vol. 26, no. 9, Article ID 100289, 2022.
- [44] R. Sharma, S. Rani, and S. J. Nuagh, "RecIoT: a deep insight into IoT-based smart recommender systems," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 9218907, 15 pages, 2022.
- [45] L. Li, T. Qu, Y. Liu et al., "Sustainability assessment of intelligent manufacturing supported by digital twin," *IEEE Access*, vol. 8, pp. 174988–175008, 2020.
- [46] L. Li and C. Mao, "Big data supported PSS evaluation decision in service-oriented manufacturing," *IEEE Access*, vol. 8, no. 99, pp. 154663–154670, 2020.
- [47] Y. Wang, H. Li, B. S.-X. Teo, A. A. Jaharadak, and A. Adam, "Image detection system based on smart sensor network and ecological economy in the context of fine agriculture," *Journal of Sensors*, vol. 2022, Article ID 8953914, 12 pages, 2022.