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Integration of Wireless Sensor Networks, Internet of Things, Artificial Intelligence, and Deep Learning in Smart Agriculture: A Comprehensive Survey

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Abstract

This survey explores the synergistic integration of Wireless Sensor Networks (WSNs), Internet of Things (IoT), Artificial Intelligence (AI), and Deep Learning (DL) in the realm of smart agriculture (SA). The agricultural sector is undergoing a transformative paradigm shift, leveraging advanced technologies to enhance efficiency, productivity, and sustainability. WSNs serve as the backbone, facilitating real-time data acquisition from various sensors deployed in the field. IoT seamlessly connects these sensor nodes, creating a dynamic and interconnected agricultural ecosystem.
The survey delves into the application of AI and DL techniques to process the vast datasets generated by WSNs and IoT devices. Machine Learning (ML) algorithms enable predictive analytics for crop management, disease detection, and optimal resource utilization. DL models, with their ability to extract intricate patterns from data, play a pivotal role in image recognition for crop monitoring and yield prediction.
Furthermore, the survey outlines the key challenges and opportunities in deploying these technologies in SA, including energy efficiency, scalability, and data security. It discusses current trends, emerging technologies, and potential future developments in this interdisciplinary field.
In conclusion, this comprehensive survey provides a holistic overview of the integration of WSNs, IoT, AI, and DL in SA, highlighting the transformative impact on farming practices. The synthesis of these technologies holds the promise of ushering in a new era of precision agriculture, fostering sustainable practices and ensuring food security for a growing global population.

1. Introduction

In an agricultural domain, significant technological advancements have ushered in a new era, incorporating cutting-edge novelties like IoT, WSNs, Wireless Network Protocols, Unmanned Aerial Vehicles (UAVs), AI, Agricultural Robotics, Big Data Analytics, ML and Blockchain systems. This amalgamation of technologies represents a transformative shift, redefining traditional farming practices [1].
The widespread adoption of IoT systems on a global scale signals a shift towards innovative methodologies that leverage data generated by devices to enhance overall agricultural productivity. IoT facilitates seamless connections between machines and humans, enabling extensive real-time information exchange across disparate networks. In this

context, the deployment of intelligent computational sensors captures real-time data, effortlessly transmitting valuable insights to individuals worldwide via the internet, irrespective of time or geographical constraints. This interconnected framework not only augments the efficiency of agricultural processes but also opens up new possibilities for informed decision-making and resource optimization in the farming ecosystem [2].

The agricultural landscape is undergoing a profound transformation propelled by the integration of cutting-edge technologies, namely WSNs, IoT, AI, and DL. This amalgamation marks a paradigm shift in traditional farming practices, ushering in an era of precision agriculture where data-driven insights and intelligent decision-making converge to optimize productivity, resource utilization, and sustainability [3].

WSNs form the foundational infrastructure of this revolution, acting as the sensory nerve system of SA. These networks consist of spatially distributed sensors strategically deployed across fields to capture real-time data on environmental conditions, soil quality, and crop health. The seamless connectivity facilitated by the IoT interlinks these sensor nodes, creating a dynamic network that transcends the limitations of conventional farming approaches [4].

AI, with its ability to process vast datasets and discern complex patterns, emerges as a key enabler in this transformative landscape. ML algorithms analyze the data generated by WSNs and IoT devices, providing actionable insights for crop management, disease detection, and precision irrigation. DL, a subset of AI, further enhances the capabilities through sophisticated techniques like image recognition for crop monitoring and yield prediction [5].

This comprehensive survey navigates through the intricate integration of these technologies in SA, offering a panoramic view of their collective impact. By examining current applications, challenges, and emerging trends, the survey sheds light on the potential of this interdisciplinary approach to revolutionize farming practices. In essence, the synthesis of WSNs, IoT, AI, and DL not only propels agriculture towards unprecedented efficiency but also contributes to global efforts for sustainable and resilient food production systems [6].

WSNs incorporated with IoT, AI, ML, and DL play a pivotal role in revolutionizing SA by supplying crucial information tailored to definite systems and applications. Here's the compressed outline of their key contributions [7]:

Irrigation Systems: With the ability to closely monitor water usage, WSNs enable farmers to effectively manage water resources and avoid over-irrigation. The detection of regions with drainage problems or inadequate irrigation distribution is made possible by real-time soil moisture content monitoring.

Soil Moisture Monitoring Systems: Continuous measurement and transmission of soil moisture data at countless pits by WSNs empower farmers to optimize irrigation practices. This helps in addressing challenges related to under and over-watering.

Fertilizer Optimization and Control: WSNs are useful instruments for tracking soil nutrient levels and providing current data on the nutritional state of the soil. WSNs help refine fertilizer applications by precisely recommending amounts and ideal timings based on thorough study of soil data.

Early Stage Control of Pest and Crop Diseases: WSNs gather vital information about temperature, humidity, and other elements that affect the growth of pests and diseases. This information helps farmers prevent or minimize crop loss by enabling early diagnosis and intervention.

Energy Saving and Power Consumption: WSNs make it easier to keep an eye on how much energy is used in irrigation systems and other agricultural operations. With the help of this capability, farmers may pinpoint places where they could save energy and optimize power use for more sustainable and productive farming methods.

In essence, the integration of WSNs with IoT, AI, ML, and DL technologies enhances the precision, efficiency, and sustainability of agricultural practices. The real-time data and insights provided by these systems empower farmers to make informed decisions, leading to improved resource management and increased productivity in SA [8].

The research contributes to the field in the following ways:

I. The study extensively reviews existing literature related to SA, with a primary focus on IoT, WSNs, and wireless communication technologies. This entails a careful examination, grouping publications according to the year of publication starting in 2019 and focusing on network protocols and IoT-WSN application domains. The analysis sheds light on the IoT-WSN architectures and related network protocols for SA systems.

II. Wireless communication protocols for SA, such as ZigBee, Wi-Fi, SigFox, and LoRa WAN, are examined in detail. The emphasis is on understanding their features and useful applications [10].
III. A comprehensive survey discusses five key applications within SA: irrigation systems, energy optimisation, insect and crop disease control, fertilizer optimisation, and soil moisture monitoring. The report also looks at how these applications have been integrated with wireless communication technologies since 2019.
IV. The paper explores the current problems and unresolved concerns in SA technology. IoT-WSN scalability and reliability, data privacy and confidentiality, network security, intrusion detection, data integrity and authenticity, user privacy and consent, resilience to failures and attacks, location privacy, power consumption, cost and standardization are all included in these concerns. Possible remedies for these issues are also carefully considered. [11].
V. Moreover, the study offers a wide range of future recommendations covering sophisticated architectures, such as blockchain technology, 5G and 6G networks, agri-robotics, artificial intelligence (AI) and artificial general intelligence (AGI) systems, and renewable energy. Future farmers stand to gain from these developments if they open up new possibilities for economical, sustainable, and user-friendly agricultural systems [9].

1.1 Paper Structure

The structure of this paper unfolds as follows. In Section II, a comprehensive exploration of relevant study is undertaken through a thorough review and analysis of prior research. Moving to Section III, a detailed discussion about SA parameters and studies that have employed various technologies to scrutinize these metrics. Section IV is dedicated to an in-depth discussion of the issues and challenges faced during course of a research, accompanied by suggestions for potential avenues to extend this project in the future. Section V shows Future Directions, ultimately Section VI encapsulates the report, drawing together the findings and insights gleaned throughout the paper, culminating in a coherent and conclusive summary.

2. Literature Review

The authors in [12] presented a multi-objective intelligent agriculture system. They prepared a hardware prototype to test the system. The overall system is developed in conjunction with automated processes and systems operating on IoT through a remotely operated portable gadget and an Internet-connected computer. A robotic machine with different actuators and sensor systems (camera, object detector, sprayer, alarm, and cutter) is remotely controlled through GPS location data. These monitors are used to keep a watch on the crop and ensure that animals or birds do not harm it. Another strategy involves greenhouse management. Its purpose is to sense temperature, humidity, and motion and to operate the light, water pump, and heater. The final mechanism is an intelligent wireless humidity sensor node that transmits gathered data to the greenhouse control unit for the water reservoir to be actuated working on real-time data collected. The projects are based on the device types named as follows: Raspberry Pi, ZigBee modules, and the AVR AT Mega microcontroller.
The authors of the study [13] presented a system that functioned on IoT for assessing the quality of water. The presented hardware model meets WHO standards for water quality parameters. The gathered data is transferred to a cloud server for storage in real-time and analysis. The primary factor of this study concerns the prediction, using a ML model to approximate metrics for water quality through the cloud system. Sughapriya et al. [15] planned a system for analyzing water quality using IoT and multiple sensor modules. This system monitors water quality by detecting pH, conductivity, temperature, and turbidity using different sensors. Information from the sensors is then retrieved by the Arduino controller. The acquired data is evaluated using IoT, and water pollution can be examined using a stringent mechanism. Furthermore, the proposed system provides messages and alerts to concerned municipalities and specialists regarding the quality of water. The presented model is comprised of many sensors that analyze water quality data in real-time for quick deployment. Furthermore, the presented model is accurate, cost-effective, and requires fewer workforces. In another research by Krishnan et al. [14] different approaches involving DL methods are discussed and their importance in the field of water management techniques.
Jerom B. et al. [15] suggested an Intelligent Water Quality Evaluating System that operated on IoT that integrates DL and Cloud techniques to examine the water quality of different water resources. Existing monitoring methods are capable of manually collecting water samples from various water resources, followed by monitoring and evaluation in a laboratory. This procedure is often ineffective because it is tough, requires a long time, and does not produce results in real time. Consistent evaluation of water quality is required to ensure the safe delivery of water to consumers from any water resources or supplies. Thus, manufacturing and implementing a cost-

efficient method for real-time analysis of water quality parameters implementing IoT is now required. The prototype developed for this study detects a variety of intoxicants in the water. Different sensing devices are used to analyse several different factors to determine the water quality from water resources. The collected data is stored in the Cloud, and DL algorithms are applied to analyse if the water under test is safe to drink or not.

Anuradha et al. [16] used IoT to develop an affordable system that monitored the quality of water in real-time. The strategy describes a Water Quality Testing approach based on sensors that analyse the chemical and physical metrics of water. Water properties are monitored using sensors and interpreted using a controller, in this case, Raspberry Pi. Lastly, the acquired measurement from the sensing device is visible on the internet using the Thing Speak API. The water monitoring system devised in this project has numerous returns, including good mobility, high frequency, and minimal power consumption. Quality factors such as hardness, conductivity, ammonia, iron, fluoride, and chloride content can also be tested for quality of water, and the values obtained are used to test the purity of the water for several different purposes like every day needs for industrial sectors and water consumption by humans for drinking.

Demetillo et al. [17] offered a low-cost, real-time water quality assessment method for distant rivers, ponds, and other natural water resources. The main components of the system are a microcontroller, basic sensors operating on an electrochemical approach, a purposely built buoy, and a system of wireless communication technology. The designed structure can monitor pH, water temperature, and dissolved oxygen at pre-set periods. To best serve the authorized customers, the suggested system sends the gathered data in charts and graphs styles to a tailored web-based server and authorized mobile phones. To assess the performance of the system, the buoy's durability in unfavourable environmental conditions, the power usage of the overall system, efficiency in data transmission, and information display in a web-based software tool were carefully analyzed. The outcome of the research demonstrated that the designed method had better prediction and could be used for practical management of the environment by providing the users with important and timely statistics for improved action plans.

In [18], a practical monitoring method for surface water quality is presented employing an affordable seawater sensor capable of sensing water conductivity, temperature, and turbidity. Another strategy based on IoT is described in [19], which uses drone machinery in combination with sensors operable in water to check quality. The measured values of the real-time metrics collected by the sensors are transmitted to the main drone over the RF transceivers, and the IoT device transfers them to the server for analysis of the water pollutant emissions. In a study [20], a system working on IoT for monitoring the quality of water is presented in which sensors are utilized to determine the pH and temperature levels of water to assess the parametric aspects of the water.

In a paper presented by Wai et al. [21], a review was conducted to discuss the DL methods application in the field of water management. This paper helps the authorities in decision-making regarding a sustainable approach in the field of agriculture. According to [22], the proposed system is composed of water quality testing of pH, Turbidity, and Temperature sensors, an Arduino controller data processing unit, an information-provided module, a monitoring centre, and other equipment. Throughout the day, turbidity, pH, water, and temperature are automatically sensed by an individual microcontroller. The data is collected by a single chip, which then functions and analyses it. If the water quality is not up to the standards, the data is transferred to the monitoring center, and the users are alerted instantly. This makes it easier for supervisors to take appropriate steps on time and to monitor real-time water quality conditions remotely. Similarly, [23] proposes the system of an IoT-based water quality analysis that examines water quality on a real-time basis. This system includes sensors that detect water quality constraints like pH, dissolved oxygen, turbidity, conductivity, and temperature. The obtained data collected by the sensors are processed by the microcontroller to make them Zigbee module compliant. This computed data is remotely delivered to the call controller through the Zigbee network. Finally, by using cloud computing, sensor data can be accessed on an internet browser application.

ML models are currently being employed all over the world to make devices smart by executing predictive analysis. A study [24], presents a drinking water predictive study in which the quality of water is assessed using pH, dissolved solids, and turbidity. To calculate the correlation between calculated parameters, a linear regression model is implemented for the measured model metrics. Similarly, in [25], a Fuzzy Neural Network is deployed to a three-year dataset to estimate water quality utilizing water quality metrics.

In another approach, Tace et al. [26] present a technique based on ML for smart irrigation that can be implemented in different regions. They made sure the system was cost-effective and had good power consumption.

In 2019, Mohammad Rezapour et al. evaluated evapotranspiration (ET) by analyzing and contrasting three different models: SVM, and adaptive neuro-fuzzy inference system (ANFIS). The effective evapotranspiration for semi-arid areas was estimated by all three models [27]. ET simulations were executed on data spanning 1970 to 2010, with input values from five various combinations in southern Iran. The SVM, an ML-based model outperformed the other two methods, with daylight hours, average air temperature, relative humidity, and air pressure as input data for the model.

Rokade et.al [28], presented an innovative approach for the smart farming industry. This paper has outlined an efficient smart informatics system of farming with predictive information analytics on measuring characteristics in an intelligent farming system using a supervised ML method.

Nikoo and Mahjouri [29], used a Probabilistic Support Vector Machines (PSVMs) model in combination with a GIS approach to manage the categorization and circulation of shallow and underground water in Iran. They claimed using these two methodologies would deliver reliable data for effective research into water-conserving initiatives. In many case studies, Heddam [30] used artificial neural networks (ANN) to assess water quality components. He claimed that AI methodologies are capable of modeling and forecasting the integrated relationship between water quality parameters and exhibiting their periods.

3. Few Parameters used in Smart Agriculture

3.1 Temperature

Temperature sensors, akin to pH sensors, are integral components in a variety of multi-parametric sensing devices. This prevalence arises from the pivotal role that temperature plays in determining water quality, given that numerous parameters are intricately linked to temperature variations (e.g., bioactivity, pH, conductivity, and dissolved oxygen). Moreover, the ease of monitoring temperature is underscored by its strong linear relationship with resistivity and electromotive force. This makes temperature a key factor in ensuring the accuracy and reliability of water quality assessments, as it significantly influences various critical parameters. The inclusion of temperature sensors in sensing devices thus becomes imperative, not only due to the interdependence of multiple water quality indicators on temperature but also owing to the practical advantages offered by its straightforward and linear monitoring capabilities.

Water temperature can be determined by using range of technologies, consisting thermal expansion of medium, thermoelectric reactions, optical fiber, semiconductors, electrical resistance, and capacitance [31]. The application of thermoelectric tools and/or resistive sensors, on the other hand, is the most typical less costly temperature measurement technique. These techniques are popular due to their accuracy, affordable price for the required range of temperatures for water monitoring, stability, and ease of use [32].

The resistive technique is the most widely used method for determining temperature. The reason is that thermoelectric sensing equipment, particularly thermistors, generally uses resistive sensor nodes to estimate the average heat required for this process. This is in addition to the sensors' convenience of manufacture. Alam, Clyne, and Deen [33] deployed Wheatstone bridge sensors to provide high-precision temperature readings with minimum variability ranging between 0 and 50 C. There are four connecting terminals of which two are made of Silicon wafers of P-type, which offers increased Coefficient Resistance of Temperature (TCR). This is the computation of comparative variation in resistance as each degree of temperature shift takes place. The remaining two terminals are made up of polystyrene.

According to the authors, the sensor was also integrated into the Arduino framework using Android platforms integrating programs. A sensor connected to resistive devices, Wu et al. designed for analysis of heat utilizing platinum (Pt) film, which is a great conductor and offers features that support the measurement of heat factor. Finally, Simic et al. [34] proposed another approach for resistive temperature sensor measurement, this time employing a budget-friendly and commonly available sensor (LM35). They calibrated the gadget in the research laboratory and achieved a precision of 0.23 C.

Lastly, Huang et al. [35] observed temperature using optical fiber. Despite its high price, this approach is typically adopted to monitor temperature when the optical fiber is also utilized to determine other factors. Two insulated optical fiber terminals were deployed since the characteristics the researchers were monitoring are highly sensitive to temperature changes. Thus, by varying the various central wavelengths, a linear relationship with temperature was discovered, enabling the device to be calibrated.

3.2 pH

Due to the vital role of pH in guaranteeing optimal water quality, it is regularly assessed and incorporated into nearly all multiparameter tools. Various techniques, including visual inspection, potentiometric, and photometric methods, are employed to determine the pH of a water sample. The visual method, utilizing specific materials like litmus paper and relying on color changes as a pH indicator, is characterized by lower accuracy levels and provides only approximate pH value estimations.

Nernst equation is the basis of the potentiometric approach, which estimates the variation in hydrogen ion levels resulting from chemical experiments. Spectrophotometry is the fundamental core of the photometric approach that offers data on the varying pH samples as the shifts in wavelength absorption occur.

PH sensors were designed in various ways by Deen, Alam, and Clyne [36], Wu et al. [37], and Simic et al. [38]. In a polyimide substrate, Alam et al. [39] employed a specific palladium (Pd) ink with silver-chloride diodes (AgCl) that worked as a baseline. Wu et al. measured pH using ruthenium (Ru) redox; in comparison to Pd, Ru has less impurity risk, is simple to prepare, and has better chemical resistance. The researchers were able to assess pH with an accuracy of 1.02% between 4.01 and 10.87. Finally, Simic et al. [39] designed a pH sensor by applying titanium dioxide (TiO_2) as the core component linked to a digital communication electronic circuit (using an AD5933 adapter).

Hossain et al. [40] deployed a multi-parametric device to examine water quality parameters in their work. For the analysis of the pH of water, a Photo-Induced Electron Transfer (PET) technique using 4-aminonapthlimide was used as a color agent. Dutta, Nath, and Sarma [41] attempted to implement photometric evaluation on transparent fluids, that is, without the need for color agents for testing. The sensor captures the visual spectrum and conducts the pH measurement by optical pre-processing and subsequent exchange into intensity and wavelength scattering.

To calculate the pH of the samples, Silva et al. [42] utilized a colorimetric-based device that paired the camera of a smartphone with a microfluidic gadget based on paper. For the approach, 3d printing supports were designed to assure the device's durability, and the system was capable of determining pH in the 4.7-12 range.

3.3 Turbidity

Water turbidity is a measure of the extent to which incident light is intercepted when passing through water, primarily caused by the presence of dissolved particles like inorganic and organic compounds that lead to a cloudy appearance. Consequently, turbidity serves as a fundamental indicator for evaluating water quality, helping ascertain its suitability for consumption and, in turn, acting as a preventive measure against waterborne infections.

Considering the significance of turbidity, various turbidity sensors widely available in the market can be coupled with other water quality indicators to create IoT-based online systems for analysis, as implemented and addressed in extensive research. To optimize and reduce the costs related to monitoring turbidity, a recent study, such as that by Azman et al. [43], has devised a cost-effective technique that works on a turbidity sensor that is nephelometric for consistent measurement of the quality of water. The experimenters claim that the functionality of electrical sensing devices relies on the density of reflected light by light dispersing in fluids and solids employing an LDR (Light Dependent Resistor) as receiver, LED (Light Emitting Diode) as a transmitter, and RS232 device for linkage between sensing device and desktop. Arifin et al. [44] explored construction of a sensing device for measuring water turbidity employing an LED, a photodetectors a polymer optical fiber as major materials, and, promising sensitivity values.

Wang et al. also experimented with cost-effective device for measuring turbidity and a web-based water quality assessment project that incorporated an 850 nm infrared LED, a customized IoT platform for communication, and dual orthogonal photodetectors. The study found that the device could measure turbidity with good precision and reliability equal to existing sensors. In another experiment, Rahman et al. [45] used a device that worked with LED for water measurement of turbidity and also observed how it responded to different visible light colors used for the task and determined the best photo detector in terms of power fluctuation in the ON/OFF state. The writers demonstrated that the white light offers the greatest efficiency with lower than 8% experimental errors in most measures, after which follows a UV LED, however, both beams were appropriate for measuring the turbidity of water fluctuating between 0 to 1000 NTU. In another study, Schima et al. [46] designed a photosensitive method for real-time evaluation of turbidity that used sensors in the ultraviolet band of the electromagnetic field and showed significant precision when compared to laboratory criteria. Furthermore, the Python script running on a Raspberry Pi controller was liable for communicating with a detector, demonstrating that open-source technology can be vital to robust and reliable systems even in the laboratory phase.

3.4 Total Dissolved Solids (TDS)

"Dissolved solids" refers to minerals, saline compounds, or metals that are in a dissolved state within water. Total Dissolved Solids (TDS) encompass organic compounds, predominantly consisting of calcium, potassium, magnesium, bicarbonate, sodium, chlorides, and sulphates, along with trace amounts of organic compounds dispersed in the water.

The TDS sensor module is plug-and-play, user-friendly, and compatible with IoT devices. Figure 5 shows this sensor. We can easily construct a TDS detector to determine the TDS value of water.

The concentrations of TDS can increase as a result of wash-off from salted roads in the winter season. Increasing amounts of nitrate or phosphate ions may be produced by wastewater treatment projects that use organic content. When TDS intensity increases, especially when dissolved salts are involved, many species of aquatic life suffer. The dissolved compounds dehydrate animal hides. TDS concentrations in rivers and streams are frequently found to range between 50 and 250 mg/L. In areas with mostly hard water or incredibly high salinity, its amounts can extend up to 500 mg/L. It is a water quality metric derived from the total suspended particle loss on ignition. It is vital in the treatment of water and wastewater.

As per Sibal and Espino [49], most commonly used lab-based methods for analyzing TDS in water are atomic emission spectrometry (AES), atomic absorption spectrometry (AAS), inductively coupled plasma MS (ICP-MS), mass spectrometry (MS), X-ray fluorescence (XRF), and optical technologies. According to Garciá-Miranda Ferrari et al.[47], these procedures are complex and costly and may involve the usage of preconcentration and extraction procedures for high-analysis enactment. Methods using electrochemical sensors, on the other hand, may be more effective, due to their small size, low cost, simple installation, and simple to use. Phyllis et al. [51]presents a review of the effects that total dissolved solids have on marine life and which species are more sensitive and affected by the TDS intensity are different life stages.

3.5 Salinity

Salinity is the measurement of the dissolved salt content in water, typically expressed in units such as parts per thousand (ppt) or percentage (%). For freshwater sourced from rivers, the salinity level is generally 0.5 ppt or lower.

The salinity of the oceans differs, but the relative quantities of the most essential dissolved elements remain almost steady, regardless of the existence of lower percentages of other salt compounds in seawater, sodium (Na^+) and chloride (Cl^-) ions makeup approximately 91% of all seawater ions. Freshwater has far fewer salt ions. Electrical conductivity (EC) testing is frequently used to calculate salinity. EC is calculated by flowing an electric current through a water sample between two metallic plates or electrodes and observing how quickly current flows between the plates.

Two types of sensors are used as salinity sensors: Interferometers and fiber gratings. Cong et al. [47] and Liu et al. [48] modeled the salinity sensor with a fiber grating, with a salinity sensitivity of 10.4 pm/%. Gentleman and Booksh [49] used surface plasmon resonance to determine the salinity of a liquid deploying a multimode optical fiber. Sensitivity of the optical fiber increased to 200 pm/% compared to the standard prism refractive index approach. Hussain et al. [47] proposed two techniques for measuring salinity of water using smartphones, the possibility was proven, and the mobility of the salinity sensor was enhanced.

In the research [52], a sample of saline wastewater from different sources was collected that contained different kinds of salt contents, pollutants, organic and inorganic compounds, and many others. Keeping in view the damage these cause to the environmental system and their contribution to land degradation, various methods of treatment of saline water were proposed in this paper. The most commonly used techniques to desalinate the wastewater into the freshwater discussed in this research are reverse osmosis, membrane distillation, freezing process, electro dialysis, and desalination process.

3.6 Color

Prior to technological advancements and the introduction of remote monitoring tools, color of water, defined by reflection of light in minute particles from organic or mineral sources, served as a longstanding indicator for water quality analysis. However, with the progression of technology in society, increased research attention has been directed toward understanding and characterizing water color. Edwards constructed sensor to assess color and turbidity of water sources through four-beam frequency benefit method for precise assessment. At the time, this prototype, which was utilized in water treatment unit, was considered to be very innovative research.

Studies like Murphy et al. [54] planned cost-effective optical sensor that helps in evaluating the water quality based on a multi-wavelength source of light and has two photodiode sensors that can measure light transmission and sideways scattering at the top of the detector to determine the metrics of color and turbidity. Procedure was carried out in a research center, but research team wishes to employ sensor in long run as the real-time major water contamination evaluation technique.

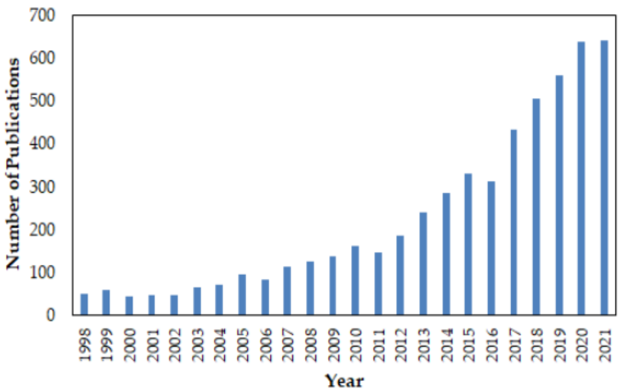

Figure 1. Number of studies reported each year on the topic [53]

Considering the significance of gaining knowledge of the connection between color and other metrics used in water quality assessment, Yang [55] devised a multisensory approach for assessing water quality factors (pH value, temperature, ammonia, nitrogen, and color) for fish farming using algorithmically improved sensing devices, with the evaluation of color constraint in water sent in real-time through Zigbee Network communication standards. In addition, Saravanan et al. [56] discussed an IoT-based monitoring system for the quality of water that involves color as one of the factors to be monitored in real-time.

3.7 Nitrogen

Nitrogen is prevalent in various environmental sources, including decomposed plants, wildlife, human excrement, manure, and pesticides. Monitoring nitrogen levels can be accomplished through diverse techniques like chromatography, electrochemistry, and spectroscopy techniques.

Chromatography is utmost effective approach when there is organic material in testers as it does not undergo involvement from other composites; however, it is considered an expensive and complicated strategy of use because it requires unique methods and specific components in the procedure [43]. Spectroscopy can also encounter intervention, but it is more convenient to utilize than the other two techniques and generates results faster. Electrochemistry monitoring has a significant potential for inexpensive applications, but it can be affected by organic and ion compounds in trials.

An evolution of inexpensive sensors for the real-time identification of nitrogen has attracted consideration in the paper because it is a key factor from an evaluating point of view. For example, Akhter et al. [57] designed a sensor system in which the substrate used is poly dimethyl siloxane, and the conductive medium is tough outer carbon nanotubes. Grapheme has good electrical characteristics, but large-scale manufacture is complicated, which may adversely impact the predictive ability of the designed sensor.

4. Issues and challenges in WSN IoT AI ML and DL in smart agriculture

An addition of WSNs, IoT, AI, ML, and DL in SA introduce a myriad of opportunities, but it is not without its share of challenges. This section explores the key issues and hurdles faced in deploying these advanced technologies in the agricultural landscape.

1. Scalability and Network Coverage: One of the primary challenges in WSNs and IoT deployment is ensuring scalability and adequate network coverage. Large agricultural areas may pose difficulties in maintaining a reliable and expansive network, leading to gaps in data collection and communication.
2. Data Privacy and Security: The vast amount of data generated by WSNs, IoT devices, and AI systems in SA raises significant concerns about data privacy and security. Protecting sensitive information related to crop yields, soil conditions, and farm practices is crucial to prevent unauthorized access and potential misuse.
3. Energy Efficiency: Many WSNs and IoT devices in agriculture operate in remote or challenging environments. Ensuring energy efficiency for these devices, especially those reliant on batteries or renewable sources, is crucial for maintaining uninterrupted data collection and communication.
4. Integration Complexity: Integrating diverse technologies like WSNs, IoT, AI, ML, and DL can be complex. Achieving seamless interoperability and effective communication between these components poses a substantial challenge, requiring standardized protocols and robust integration frameworks.
5. Lack of Standardization: The absence of standardized protocols across different devices and platforms hampers the seamless integration of technologies in SA. Standardization is essential for ensuring compatibility, data consistency, and the interoperability of various solutions.
6. Skill Gaps and Education: The effective deployment of advanced technologies in agriculture requires a skilled workforce. There is a notable gap in agricultural education and training programs that cover WSNs, IoT, AI, ML, and DL. Bridging this gap is essential for farmers and agricultural professionals to harness the full potential of these technologies.
7. Cost Considerations: The initial investment and ongoing costs associated with deploying and maintaining WSNs, IoT devices, and AI systems can be a significant barrier, especially for smaller or resource-constrained farms. Achieving cost-effectiveness without compromising functionality is a persistent challenge.
8. Environmental Impact: While SA aims to enhance sustainability, the environmental impact of deploying technology-intensive solutions should be carefully considered. Issues such as electronic waste, energy consumption, and the ecological footprint of technology implementations need attention.
9. Ethical Considerations: The use of AI and ML in decision-making processes for agriculture raises ethical concerns. Issues related to transparency, accountability, and biases in algorithmic decision-making must be addressed to *ensure fair and responsible use of technology in farming practices.*
10. Connectivity in Remote Areas: In agricultural regions with limited connectivity, ensuring reliable network access for WSNs and IoT devices becomes challenging. This is particularly relevant in remote rural areas where agriculture is a primary economic activity.

In conclusion, addressing these challenges is crucial for the successful and sustainable implementation of WSNs, IoT, AI, ML, and DL in SA. Collaborative efforts from technology developers, policymakers, and the agricultural community are essential to overwhelmed these hurdles and expose occupied prospective of SA for a more efficient and sustainable future.

5. Future Directions

Cutting-edge digital technologies have made remarkable advancements, seamlessly integrating with Internet of Things and Wireless Sensor Networks (IoT-WSNs) to enhance the sustainability of applications in SA. This integration brings about substantial optimization across whole spectrum of agricultural procedures, spanning from cultivation to harvest and revolutionizing whole agricultural sector. These forward-thinking enterprises mark a pivotal moment in reshaping an agricultural background.

Tailoring of digitization to meet specific requirements demands considerable financial investment to align with individual necessities of farmers. To fortify consistency of this digitization, it is imperative to embrace government-backed initiatives, leverage grants, foster strategic public-private partnerships, and implement open data policies. Such initiatives should be complemented by research efforts tailored to regional nuances, strengthening their impact and effectiveness.

Achieving precision in tailoring digitization to unique requirements demands substantial financial commitment that caters to the specific demands of individual farmers. Equally crucial is the establishment of transparent data policies, ensuring reinforcement by local research activities. An organized tactic involves particular implementation of well-structured roadmap for development of SA systems. This journey commences with inaugurating initial architecture that comprises vital constituents and streamlined functionalities, setting the stage for a comprehensive transformation in agricultural practices.

I. DL in Smart agriculture

DL, an advanced technique within the realm of ML, employs multi-layered neural networks to mimic complex structure of human brain. DL algorithms play an indispensable role in context of Internet of Things and Wireless Sensor Networks (IoT-WSNs) specifically tailored for SA. These algorithms excel in cultured data analysis, particularly in areas such as image recognition and Natural Language Processing (NLP), contributing significantly to profound understanding of agricultural procedures.

In this regard, computer vision becomes a crucial component, enabling machines to decode and understand visual data taken from pictures or movies. By carefully analyzing imagery data, its incorporation into IoT-WSNs for agricultural applications increases the potential for monitoring crop health, quickly identifying illnesses, and precisely estimating growth stages. This integration makes it easier to make educated, timely adjustments to agricultural methods, which eventually increases productivity and promotes efficiency.

Modern AI technologies combined with wireless sensor networks (WSNs) have emerged in recent years as a promising new direction for the agriculture industry. This integration offers a once-in-a-lifetime chance to improve resource efficiency, optimize farming methods, and dramatically increase agricultural yield. The sections that follow provide a thorough analysis of the several AI-based tools that can be used to advance sustainable agriculture. These discussions delve into the potential impact and contributions these technologies can make to reshape and advance the agricultural landscape.

II. ML in Smart Agriculture

As a component of AI, ML is specifically dedicated to fostering the development of computer systems that possess the ability to learn and adapt through experiences. When employed in the context of Internet of Things and Wireless Sensor Networks (IoT-WSNs) within agriculture, ML algorithms undertake a thorough analysis of historical and real-time data. Primary goal is to refine irrigation patterns, anticipate and proactively manage crop diseases, and automate diverse agricultural processes. This integration plays a pivotal role in substantially augmenting competence and total output within an agricultural domain.

Artificial General Intelligence (AGI) stands at forefront, showcasing significant prospective to exert profound impact across diverse sectors, with agriculture prominently featured. AGI, particularly in domains such as Natural Language Processing (NLP) and Agri-Robotics, holds the capability to improve crop yields, minimize wastage, and advance sustainable farming practices. This distinctive capability uniquely positions AGI as likely solution to complex contests encountered by an agricultural division.

III. Agri-ROBOTS

Agri-robotics entails incorporating robotic systems and automation technologies into agricultural operations. When coupled with IoT-WSNs, these robotic systems gain additional capabilities through the integration of sensor data, optimizing tasks like accurate planting, monitoring, and harvesting. This integration leads to improved efficiency and productivity in agriculture.

The precision of these robots stems from their specialized sensing and actuation capabilities, potentially reducing the need for labor while enhancing various agricultural processes. Drones play a vital role in tasks such as pesticide spraying, irrigation, crop harvesting, seed sowing, and soil cultivation, playing a pivotal role in transforming conventional farming practices.

IV. 5G and 6G in smart agriculture

The evolution of 5G technologies and the anticipated revolution ushered in by 6G within the context of IoT-WSNs holds significant consequences for an agricultural region. 5G, marking 5^{th} generation of wireless technology, signifies the substantial advancement; introducing key improvements likewise accelerated data speeds, reduced latency, and enhanced connectivity. These enhancements translate into heightened real-time monitoring capabilities and faster transmission of sensor data, ultimately refining coordination among devices in agricultural solicitations.

Looking towards the future, the developmental phase of 6G technology holds a potential to revolutionize data collection and analysis, potentially achieving speeds in terabits-per-second choice. This ensures exceptionally timely and precise insights for farmers. The integration of 5G and an intended capability of 6G within IoT-WSNs for agriculture present massive potential. This combination facilitates real-time monitoring of critical factors, including soil conditions, crop health, weather patterns, and equipment performance, empowering optimized decision-making.

Current generation of intelligent agricultural applications, trusting on the relatively limited number of wireless sensors, demands improved accuracy and effectiveness. Conversely, an ongoing development of 6G communication technologies lays foundation for forthcoming of intelligent and sustainable agriculture. 6G technology initiates to allow an interconnection of general sensors, granting farmers capacity to gather intricate, plant-specific information. This transformative potential fueled by 6G technology is poised to revolutionize SA, ensuring precise data collection, advanced robotics, and precision agriculture in remote locations, thereby making agriculture considerably more efficient, ecological, and economical.

V. Block chain Systems in Smart Agriculture

The integration of blockchain technology in SA represents a significant advancement with far-reaching implications. Blockchain, originally devised as a decentralized and secure ledger for crypto currencies, has found applications in various industries, including agriculture. In the context of SA, blockchain serves as a transparent and tamper-resistant system for managing, recording, and verifying data across the agricultural supply chain.

Blockchain in SA offers a decentralized and distributed ledger that records transactions and information at each stage of the agricultural process. This ledger, comprised of blocks linked in a secure chain, ensures data integrity and transparency. Each block contains a time stamped record of transactions, making it virtually impossible to alter historical data without consensus from whole network.

One notable application of blockchain in SA is supply chain management. It allows for traceability of agricultural products from farm to consumer, providing a secure and unalterable record of each step in the production and distribution process. This transparency enhances food safety by quickly identifying and isolating the source of contamination or other issues.

Smart contracts, self-executing contracts with terms of an agreement directly written into code, further enhance functionality of blockchain in agriculture. These contracts automate and enforce predefined rules, facilitating seamless and trustless transactions. For instance, smart contracts can be employed to automate payments between farmers and suppliers based on predefined conditions, streamlining financial transactions and reducing the risk of disputes.

Moreover, blockchain technology enhances data security and privacy in SA. Farmers can securely store and share sensitive data, such as crop yields or soil quality, with authorized parties without compromising the integrity of the information. This decentralized approach mitigates the risks associated with centralized data storage systems, reducing the likelihood of data breaches or unauthorized access.

In conclusion, the integration of blockchain technology in SA brings forth a paradigm shift by introducing transparency, security, and efficiency across the agricultural supply chain. This innovative approach not only enhances traceability and food safety but also streamlines transactions and ensures the integrity of sensitive agricultural data. As an agricultural industry continues to hold digital transformation, blockchain stands as a robust and promising solution to address key challenges and propel SA into a more secure and transparent future.

6. Conclusion

In conclusion, the comprehensive survey on the integration of WSNs, IoT, AI, and DL in SA reveals a transformative landscape for the agricultural sector. The amalgamation of these cutting-edge technologies offers a holistic and data-driven approach to farming practices, bringing about significant advancements in efficiency, productivity, and sustainability.

The synergy of WSNs and IoT provides real-time monitoring and data acquisition capabilities, enabling farmers to make informed decisions based on accurate and timely information. AI, with its ability to analyze vast datasets, optimizes various agricultural processes such as irrigation, soil management, and pest control, contributing to resource efficiency and yield improvement.

The incorporation of DL, particularly in image recognition and data analysis, enhances the precision of monitoring and decision-making within SA. This holds promising implications for crop health assessment, disease detection, and overall crop management. The survey underscores the potential of these technologies to revolutionize traditional farming methods, paving the way for more intelligent, data-driven, and sustainable agricultural practices.

However, amidst the promises, challenges such as scalability, data security, and standardization need attention for the seamless integration of these technologies. Collaborative efforts from researchers, policymakers, and industry stakeholders are essential to address these challenges and unlock full potential of SA.

In essence, the survey illuminates the transformative power of integrating WSNs, IoT, AI, and DL in agriculture. The synergy of these technologies has the potential to usher in a new era of precision farming, where data-driven insights contribute to more efficient resource utilization, reduced environmental impact, and increased resilience in the face of evolving agricultural challenges. As SA continues to evolve, the integration of these technologies remains a cornerstone in shaping the future of sustainable and intelligent farming practices.

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