Smart irrigation monitoring and commodity price predictor

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Abstract -- This paper proposes an integrated dual module system developed to enhance agricultural resource management as well as economic planning. In this regard, the initial module is primarily focused on smart irrigation systems via IoT technologies, which entail soil moisture sensors, temperature sensors, as well as humidity sensors that monitor environmental conditions in real time. This information regarding environmental conditions is then processed via a microcontroller-based control unit that automates irrigation scheduling via set threshold values. The second module employs Machine Learning methods to predict prices of agricultural commodities. Historical datasets of the agricultural market are processed and analyzed using Machine Learning predictive methods such as Random Forest Regression and Long Short-Term Memory (LSTM). Even though Random Forest Regression offers high accuracy in regression tasks, LSTM methods show promise in handling temporal dependencies in time-series patterns of price fluctuations. Experimental studies show that high reliability in predictions will be achieved, thus helping the farmer take decisions to store crops, transport, and sell them at appropriate times to achieve maximum profit. By integrating intelligent irrigation management with data-driven price predictions, the proposed system will enable the implementation of precision agriculture techniques, thus ensuring sustainable water management

Keywords -- IoT, Smart Irrigation, Machine Learning, Commodity Price Prediction, Random Forest

INTRODUCTION

Agriculture is still considered the mainstay of most economies but the industries are under increasing pressure because of the shrinking resources, global climatic changes and the constraints of the conventional methods of farming. One of the most urgent issues is the problem of water shortage that directly affects the crop production and its sustainability. The traditional irrigation methods normally depend on manual monitoring and predetermined time, which usually leads to either excessive irrigation or inadequate watering. Not only do such methods consume precious water resources, but also lead to a higher dependency on labor and higher operation costs.

Besides production factors, agricultural markets are full of uncertainty to farmers. Unpredictable commodity prices, unavailability of accurate information and accessibility to predictive tools for decision making in determining what crops to grow or when to sell the harvested farming products makes this a hard task. Due to this, financial planning in the agricultural sector has been pretty reactive, and not data-driven, which impacts profitability and economic sustainability in the long-term. Recent innovation in digital agriculture, specifically, the introduction of Internet of Things (IoT) and Artificial Intelligence (AI), has created new opportunities to transform farming activities. The IoT technologies help to monitor the environmental parameters of soil moisture, temperature and humidity continuously via distributed sensor networks. These technologies enable accurate irrigation where water is provided to crops according to their real needs as opposed to guesses when they are used in conjunction with automated control systems. Regression and time-series forecasting are predictive models that help assess the future market based on the previous price trends of a commodity that can be used to grasp the future of the commodity. Such predictive features enable farmers with the actionable market knowledge that can be utilized to make improved crop-making, storage planning and sales decisions. Motivally filling the chasm between these two technological features, this paper presents a combined AI- IoT system that will be used to solve both the agronomic and economic dilemmas in a single structure. The system will be an autonomous decision-support agent, which will keep an eye on field conditions and, at the same time, provide predictions of commodity prices with the use of Machine Learning algorithms. The data of environmental sensors is fed through microcontroller-based platforms to control irrigation, and the historical market data is processed to give quality price forecasts.

I. PROBLEM DEFINITION AND RESEARCH OBJECTIVES

The agricultural sector is now being faced by two coupled problems in lack of efficient use of natural resources and financial instability on the commodity markets. Water is one of the most important inputs in crop production and is often not managed properly in the traditional irrigation methods. Traditional techniques are largely reliant on manual field surveying or on a set irrigation program, neither of which considers dynamic environmental changes. Consequently, crops either receive too much water or they lack moisture and this has a negative impact on the health of plants and the quality of soil and the general yield. Further, these methods lead to the depletion of unnecessary water and the influx of more labor which are not sustainable in the long run. In addition to the cultivation practices, agricultural farmers are experiencing unending economic instability caused by fluctuating agricultural prices. In most of the situations, crop production is done without the availability of good forecasting tools or market intelligence that is organized. Lack of anticipatory knowledge on the movement of commodity prices compels the farmers to make assumptions or latent information. This means that by the time of harvesting, the produce will be sold in the low-price seasons and this decreases the profitability and farmers are at a risk of losing money. Absence of coordinated decision- making between market timing and irrigation planning also increases productivity and income issues even more. The solution to these limitations must be a technology-based framework that will be able to integrate real-time environmental monitoring with predictive economic analytics. A combination of Artificial Intelligence (AI) and Internet of Things (IoT) provides a way to pursue the trend of data-centric farming when the decisions about cultivation and marketing are made not by intuition but by quantifiable information.

1.Research Objectives

The main objective of the study is to develop and introduce a single AI-IoT solution that will increase the level of agricultural output and improve the financial planning of the business. The research paper is designed with reference to the following objectives:

1. Automated Environmental Monitoring

To create an IoT-based sensing infrastructure that will be able to record real-time field parameters such as soil moisture, ambient temperature and relative humidity. The data gathered is the basis of the intelligent irrigation and crop control.

2. Precision Irrigation Control

To introduce an automated irrigation system that controls the delivery of water in accordance with specified moisture level requirements on the soil. This method will result in maximum hydration of and the least amount of water wastage and manual oversight.

3. Predictive Market Analysis Predictive future market trends using support vector machine (SVM) and Long Short- Term Memory (LSTM) network applications by training using the past prices of commodities and using better predictive accuracy.

4. Data Visualization and Decision Support To develop an interactive graphical interface to display environmental readings and price predictions in easy to understand format to allow farmers to be able to make informed decisions regarding irrigation and crop sale decisions on time.

II. Suggested System Architecture.

The offered system architecture is created as a single technology environment that combines real- time monitoring of the agricultural field and predictive economic analytics The architecture is implemented in such a way that there is an interaction between the virtual farm conditions and the digital intelligence systems without interruption allowing agronomic automation as well as financial decision support. In the field setting, the environmental sensing devices are installed to monitor the most relevant cultivation parameters in the form of soil moisture levels, atmospheric temperature, and relative humidity constantly. The sensors can work in real-time and detect even minor changes in the soil and weather conditions, which have a direct impact on the necessity of irrigation. The data obtained is sent to an embedded system comprising of a microcontroller which is the working unit of the irrigation module. Irrigation pumps automatically turn on by the relay switching circuits whenever the soil moisture level becomes lower than the stated range. When the appropriate moisture level is maintained, the system will shut down the water supply hence guaranteeing accuracy in irrigation and eliminating unnecessary waste of water resources. In order to go beyond the local control system, environmental data is transmitted to centralized cloud or server platforms via wireless communication modules. This connectivity will enable the system to keep real time data logging, remote monitoring and long term storage of cultivation data. Due to the presence of properly arranged historical data, it is now possible to conduct large-scale analytics and model training.

The system architecture also consists of an automated irrigation as well as a Machine Learning-based analytics engine, which is expected to forecast the prices of agricultural commodities based on historical market data. Random Forest, Support Vector Machines, and Long Short-Term Memory (LSTM) networks are some of the algorithms used to compare the price trends and time variances. These models produce forecasted price signals that can be used to guide the farmer to know the most opportune harvesting time and also to decide on the optimal way of storing the product in order to optimize the economic benefits. The analyses of the environmental conditions and market predictions are displayed to the users in the form of an interactive display.

II. METHODOLOGY

The suggested system combines the environmental sensing, automated control of irrigation, cloud-based processing of data, and market prediction analytics into one system. The system has a systematic pipeline where physical field data and economic data are handled by synchronized hardware and software layers to come up with useful agricultural insights.

A. Embedded Processing and Irrigation automation

The sensor values are sent to a microcontroller powered embedded platform which acts as the irrigation control unit. In this module, the raw sensor signals are calibrated, transformed to digital values and contrasted with set levels of soil moisture thresholds which are based on crop needs.

When the moisture content of the soil becomes so low that it lacks the necessary amount, the controller will automatically turn on irrigation pumps by relays switching circuits. When the soil moisture comes to the required level, the system halts the irrigation process. This automation in a loop is what allows to have a good control of the process of irrigation, minimize the use of water, limit the human factor and ensure that the soil has the right soil conditions to grow crops.

B. Commodity Price Data processing.

The system also gathers historical price information on agricultural commodities in the market repositories along with environmental monitoring. The datasets collected are subjected to a number of preprocessing activities such as noise elimination, normalization, missing value processing, and time sequence.

These processing tasks improve the quality of the dataset and process the information so that it is appropriate to machine learning methods applied in predictive forecasting.

C. Machine Learning Model Development.

The predictive analytics is done through supervised machine learning and deep learning. Here, nonlinear relationships between market variables are determined using algorithms like the Random Forest Regression and the Support Vector Machines, whereas time-series forecasting is done with Long Short-Memory (LSTM) neural networks.

The LSTM models are especially useful at predicting patterns of the season and the long-term temporal variations of prices of the commodity. Segmented training and validation datasets are used to train the models and each measure of forecasting performance and error is used to select the most reliable prediction model.

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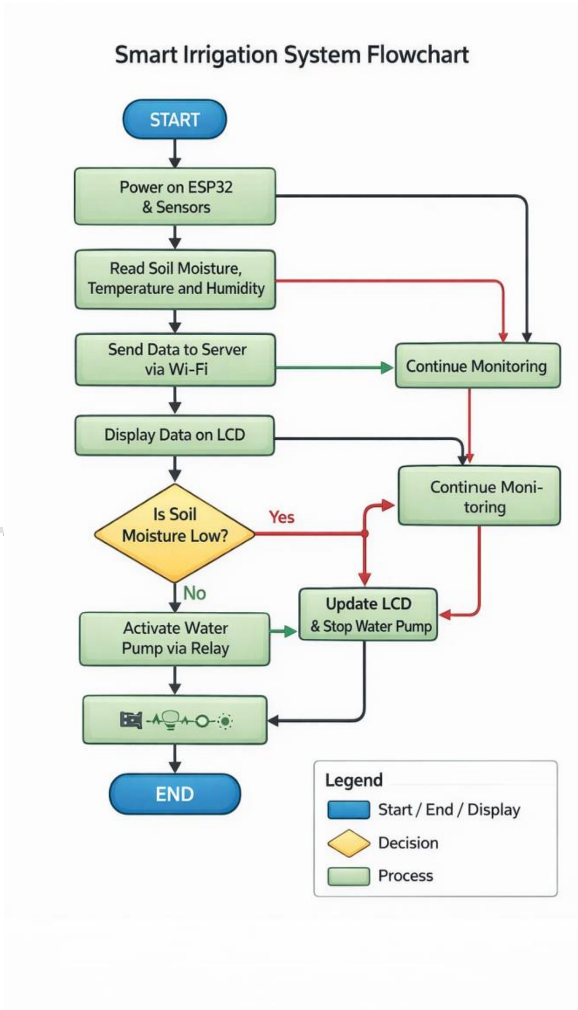
II. ALGORITHMS AND WORKFLOW

Data Acquisition and Sensor Calibration The first step in the workflow is the continuous measurement of environmental parameters based on the distributed sensors of the IoT that are located throughout the agricultural field. The soil moisture sensors are used to measure the volumetric water content at root depth and the temperature and humidity sensors measure the atmospheric conditions that affect evapotranspiration. Each sensor is first of all calibrated to standard measuring because this helps reduce drift and reliability of the data before it can be deployed live. The calibrated sensors send out the readings at a specified time and frequency to the central processing unit via a wireless communication protocolTo overcome this, the system uses preprocessing algorithms which entail missing values imputations, moving-average smoothing and outliers. Time- synchronization is also carried out in such a manner



synchronization is also carried out in such a manner that the environment readings are matched on historical market dataSoil Moisture Threshold Algorithm A threshold algorithm that is adaptive controls irrigation. The system does not have set watering schedules but dynamically calculates the moisture cut-off levels according to the type of crop, the soil texture and the stage of crop growth. The controller triggers irrigation pumps when the real-time value of moisture is lower than the calculated threshold. The closed-loop control helps avoid unnecessary irrigation and use of water resources, and the hydration of the root-zone remains ideal.

Climate Impact Adjustment Logic Temperature and humidity are environmental factors that have a direct impact on the rates of soil moisture evaporation. A rule based adjustment model alters the irrigation time by including these parameters. An example is that when the temperature is high and there is low humidity, the intensity of evapotranspiration is high, and there is the need to have slightly longer irrigation periods compared to humid or cold weather, which has less intensity of watering. This context-dependent logic makes sure that the decisions regarding the irrigation are not made in the vacuum and consider the actual cultivation conditions.

Price history of commodities is handled Long Short-Term Memory (LSTM) and other sequential models can be used to analyze the temporal price patterns, seasonal demand patterns and volatility patterns. The regression Support Vector Machine (SVM) is also used to compare stability in forecasting. These models are trained by the system on the records of the multi-year prices, cross-validated by the system using the cross-validation methods, and produce both short-term and seasonal price projections. Such forecasts assist the farmers in making decisions on the best time to sell their harvests.

V. IMPLEMENTATION DETAILS

1.Hardware Deployment

System implementation would involve on-field installation of IoT sensing units that have the ability to work under different conditions of agricultural conditions. They are soil moisture probes that are installed at the root-zone depth to measure soil availability of effective plant water instead of surface moisture. The temperature and humidity sensors are set at a level of canopy above ventilated enclosures to avoid distortion of direct solar radiations. Individual sensing nodes are connected to a microcontroller which carries out some preliminary signal conditioning, analog to digital conversion and packet construction. The hardware level is designed with low-power consumption through sleep-wake scheduling in order to allow field deployment over a long period even in power-constrained rural areas.

2.Communication and Data Transmission an arrangement.

The sensor nodes use range and energy efficient wireless transmission protocols with the gateway module. The gateway will combine multi-node information and send it to the cloud server via the internet connection. To ensure stability in low-network areas, there is a buffering system which temporarily stores the readings in the area during the outage and syncs them once the connection is restored again. Times logged will ensure the lost of no environmental events when transmission gaps occur.

3.Cloud Infrastructure and Database Design.

A centralized cloud service is established to deal with real-time data ingestion, storage and processing. Environmental data of reading types are stored in structured time-series databases, whereas the data on commodity prices are tabulated in relational databases where they can be analytically queried. Continuous sensor inflow is managed with no latency through the use of data indexing and compression methods. Machine learning models, irrigation control logic, and API services (by linking with user dashboards and field controllers) are also found in the cloudaloons.

4.Control implementation of Irrigation System.

The cloud decision engine sends control signals to the field controller when the moisture readings are lower than the calculated values. There is also a manual override feature which enables farmers to turn on or turn off irrigation regardless of automation choices. Safety interlocks avoid dry-running the motor and cycle pump operation to prolong the equipment life.

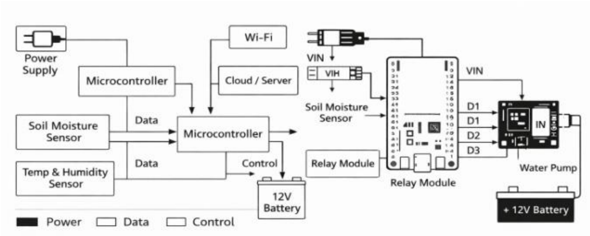
5.Deployment of machine learning model.

Forecasting models in the cloud analytics context utilize historical data on commodity prices as an input and train it to predict future commodity prices. The sequential deep learning structures capture the overall long-term seasonal price changes, whereas short-term changes are considered using regression models. The models are trained and made into prediction services after being containerized. These services produce periodic forecasts that are automatically updated with new market data that is added.

6. Integration of Decision Engine.

It is not limited to the parallel operation of irrigation and prediction modules. An intermediate analysis engine matches the indicators on environmental crop readiness with anticipated price windows. Such engine calculates advisory signals as optimal irrigation continuation, harvest delay recommendation or market-ready signal. The rules that govern logic are adjustable such that the system can follow various crop cycles and farming practices in the region.

VI. EXPERIMENTAL SETUP



The proposed AI-IoT agricultural system was estimated with the experimental setup to test the performance of the proposed agricultural automation system and the commodity price prediction system in controlled and real-field conditions. The experiment in the field was done in one observed plot of an agricultural land where several sensing units were strategically placed in order to measure spatial variations in soil and atmospheric conditions. The soil moisture sensors were placed at depths that were different in the crop root zone to make the water available realistic as opposed to estimating the water available at the surface. The temperature and humidity sensors were placed on high platforms to prevent being blocked by the crop foliage as well as to guarantee an accurate reading of the ambient temperature and humidity. The usefulness of all sensors was checked before deployment against conventional measurement references to reduce the instrumentation deviation.

Sensing hardware was connected to a microcontroller based processing unit that received, digitized and sent out environmental data at a specified time interval. The experimental power consumption and monitoring precision were balanced through data sampling frequency. The readings were collected using a wireless communication module and sent to a centralized gateway which sent the data to a cloud-hosted analytics server. Test of reliability was also conducted whereby the system was tested with intermittent network access where local buffering allowed no data to be lost during synchronisation delays. To do irrigation testing, the water delivery system was composed of electric pump linked to automated relay switch and controlled valve. The values of moisture threshold were not arbitrarily determined but were obtained based on agronomic recommendations with respect to the chosen type of crop. The automation engine activated when soil moisture fell below the specified limit, which caused irrigation. The amount of water flowing was recorded, the time it took the soil moisture to be replenished and the frequency of pump on were all recorded. A control plot was also monitored using the practice of manual irrigation to have a comparative baseline of water.

usage and crop response. Similar to the hardware experiment in the field, the economic prediction module was tested on historical data of agricultural commodity prices available at regulated market outlets. The data was also covering several years and comprised seasonal price changes, volumes of arrivals, and regional demand changes. Sequential deep learning network and regression-based predictor Machine Learners were then trained and tested on a train- test split methodology. Statistical measures that were used to forecast performance were: Mean Absolute Error (MAE) root mean square error (RMSE) and percent prediction accuracy.In order to measure the behavior of integrated systems, joint experiments were implemented in which the irrigation automation outputs and price forecasts were obtained and studied. This assisted in the assessment of the crop readiness status as compared to the potential advantageous market opportunities. The advisory engine of the system provided decision prompts, which were analyzed in terms of feasibility in practice by comparison with the old-fashioned farmer decision schedules. The set up also included energy consumption analysis to be used in determining operational sustainability. Current consumption during sensing, communication and actuation operations in the sensing node, communication and actuation devices was measured to determine battery life and feasibility in the long term. Hardware units were tested to environmental durability in different conditions of humidity, heat and dust to confirm ruggedness in the agricultural environment. The constructed experimental environment, therefore, established a two-assessment framework; one of agronomic efficiency in the automated irrigation precision, and the other of economic intelligence in the predictive analytics precision. The combination of controlled testing, the live field deployment, and the data-based validation allowed the setup to make sure that system performance could be measured in a holistic manner such as in terms of technologicreliability, resource optimization, and the effectiveness of the farmer-centric decisions.

VII. PERFORMANCE ANALYSIS and RESULTS.

The assessment of the offered AI-IoT farm solution generated quite systematic outcomes covering the efficiency of environmental automations, optimization of water sources, accuracy of predictive markets, and the performance of integrated decision support. The evaluation was conducted with the comparison of the performance of the automated systems with the usual farming processes and traditional forecasting techniques in order to define the quantifiable enhancements. The outcomes of field implementation proved that the use of real-time soil monitoring has a significant impact on the precision of irrigation. The control system was automated to switch on the water delivery once the moisture was below agronomically set levels. This removed unnecessary irrigation cycles as may be seen in timer based or manually timed watering. Throughout the experimental cultivation period, the system registered a significant decrease in total water usage and at the same time ensured maximum water hydration of the soil to support crop growth. The recovery curve of soil revealed that the irrigation period was adjusted dynamically according to the rate of absorption and not according to constant watering periods, which resulted in evenly distributed moisture in root zone. Irrigation decisions were also narrowed down on by temperature and humidity monitoring. The system would slightly lengthen the watering time during the high evaporation to counterbalance the loss of moisture to the atmosphere and it would shorten the watering cycle during wet weather. This adaptive mechanism inhibited damage of under-watering stress as well as waterlogging. Observations of crop health reported better turgidity of the leaves, less wilting events and better uniform growth of the vegetation than on the control plot. The time of communication delay between the field nodes and the cloud server was within acceptable operational ranges, and thus it was very responsive in real-time. Tests of buffer synchronization under network interruption conditions revealed that there was no loss of data, which confirmed the robustness of the system when it was subjected to the rural connection limitations.

The economic intelligence module had good predictive results. The models of Machine Learning that were trained using multi-year data of commodity prices were able to capture seasonal changes, cyclical demand changes as well as short term volatility changes. Validation of the forecasts to unknown test data showed a high degree of correlation between the predicted and actual prices of the market. The metrics of error like Mean Absolute Error and Root Mean Square Error were kept within low deviation parameters and this ensured that the model was stable.

Sequential deep learning models were also found to perform better at long-range predictions because of their temporal dependence retention capability whereas regression based models were found to be efficient when it comes to short term predicting of price. The results of ensemble evaluation indicated that hybrid forecasting (a combination of the forecasts produced by several algorithms) gave the most balanced performance in terms of accuracy under different forecasting horizons. The comparisons conducted on simulation revealed that, farmers who applied system advisories might have had a potential of gaining a high market rate compared to those who made decisions based on only the traditional knowledge. The visualization dashboards were proven to be a factor in the adoption of the decisions. The group of farmers who were involved in pilot testing stated that they found it easier to understand the information in the graphs of soil status, irrigation history, and price trends. The alert-based messages minimized the necessity to monitor manually on a regular basis, which indirectly decreased the amount of labor and time spent under supervision. The analysis of the energy performance revealed that the low power sensing cycles and scheduled data transmission increased the operation battery life of the system, rendering it useful in the long term. Durability of the hardware was proven to remain stable to varying environmental conditions such as heat and humidity stress.

In general benchmarking of the system indicated four key performance improvements, including significant water savings, more accurate and reliable irrigation timing, strong commodity price forecasting, and greater confidence in decision making by the farmers. The 2-module integration was found to be more advantageous than either single irrigation or prediction systems because it was a requirement that straddling the gap between the efficiency of crop cultivation and the profitability planning of the market. This combined performance framework does not only conserve natural resources but it also enhances financial resilience of farmers by having a data-based operational and market decision making.

VIII. CONCLUSION

The study introduced the design and deployment of a hybrid AI-IoT agricultural system designed to solve two most long-standing problems in the field of modern agriculture inefficient use of resources and financial instability. Integrating real-time environmental monitoring with predictive market intelligence, the system will not only be able to go beyond a single-purpose smart farming device but also create a comprehensive and decision-oriented precision agriculture framework. Agronomically, the automated irrigation module showed how agro-irrigation practices of continuous monitoring of soil moisture, temperature and humidity could evolve the traditional water management into responsive water management according to need. The system optioned dynamic regulation of the water delivery based on the real-time field conditions instead of being fixed in schedule or dependent on human judgment. This led to the optimization of the soil hydration, minimizing of water wastage, decreased energy use, and improved crop growth patterns. The adaptive irrigation rationale also turned out to be able to react to climatic changes so that the water use could remain sustainable without undermining productivity.

The Machine Learning prediction engine also achieved success on the economic front in terms of turning past data on price of commodities into future market intelligence. The forecasting models helped to produce accurate price trend projections by examining the seasonal behavior, demand cycles and fluctuations. These forecasts gave meaningful information to the farmers on what to do with their crops (when to sell and when to keep them), which minimised exposure to the risks inherent in fluctuating market prices. The validation of the experiment proved that data-driven forecasting is capable of bringing a lot of improvements to financial planning in agriculture. The union of these two areas of functioning is the most influential result of the research. Instead of running irrigation automation and price prediction as two separate facilities, the suggested system provided an analytical connection between readiness measures of crops and good market opportunity. This integration made it possible to make informed decisions throughout the whole agricultural lifecycle - including the time to cultivate or to irrigate crops, or when to harvest products or to sell them. This form of synchronization is a transition towards the predictive and strategy-based agriculture rather than reactive. Operational feasibility was also identified in the results of system implementation. The IoT hardware was shown to be robust in the field conditions, wireless communication proved to be reliable in data flow, and analytics processing can be scaled in the cloud infrastructure. System tests by the users showed that the system outputs could be understood by the farmers (even those with limited technical exposure) through visual dashboards and alert messages

The system does not only save on the natural resources, but enhances the profitability of the farmers and confidence in their farm planning. Improvements that can be done in the future are integration of satellite imagery, crop disease prediction, multilingual voice advisor system and linkage of supply chain using blockchain technology. In this case, the platform can grow to become a full-fledged digital farm assistant that can assist farmers in all aspects of production, protection, and profit.

IX .FUTURE WORK

Even though the proposed AI-IoT system of agricultural infrastructure is balanced, in terms of optimizing irrigation and predicting the prices of the goods, it also offers a spectrum of opportunities of the technological development and functional improvement. This would be developed further in the future where the current integrated model would be oriented into a more autonomous, scaled and intelligent farm ecosystem with the capability of offering the end-to-end management of farms. One of the primary directions is the application of the remote sensing technique based on the usage of satellites and drones. The information that the system presents can be utilized in maintaining the system at the highest level of ground sensors in addition to aerial imagery which will enable the system to shift to entire-field visualization. The vegetation indices used to map crop vigor, canopy density analysis and early stress mapping could be determined by multispectral imaging. This would also allow optimization of the irrigation and nutrient recommendations rather than global application. The other development is expansion of the environmental intelligence on the current sensing parameters. In the future, smart soil pH sensors, electrical conductivity, nutrient composition as well as rainfall detectors can be included. The complex of these variables and the current moisture and climatic measurements would give a full picture of soil health analytics and would possibly be used in automated fertigation planning and irrigation control. The future of predictive analytics may be both hybrid time series-based deep learning systems, in which time-series prediction is paired with external economic information, such as export demand, weather, transportation costs, and political changes. Further incorporation of reinforcement learning may also enable the system to continue evolving forecasting plans based on real-market performance rather than historical learning.

The localization and personalization also have massive growth opportunities. The models of growth of crops can be designed so as to dynamically vary with the type of plants, soils and the weather conditions in the region so that irrigation alert and the harvesting guidance is provided accordingly. Such customization would allow the platform to be implemented in other forms of agro-ecological areas without any redesigning structure. The user interaction mechanisms can be enhanced with multilingual voice assistant and talking advisory systems. Research on scalability will aim at changing solitary farm installations into collaborative agricultural systems. The optimization of the cloud infrastructure and the integration of edge computing will be examined in order to control the mass sensor deployment with the lowest amount of latency. Future development of the system will also be affected by security and data integrity. The transaction logging system using blockchain can be incorporated to form transparent results of commodity pricing, contract farming, and supply chain traceability. This would enhance the level of trust of farmers in the digital advisories besides decreasing the chances of market exploitation.Predictive maintenance algorithms are able to detect a degradation of the hardware and prevent a failure in its operations.

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