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Original Article

Intelligent Agricultural Systems Using IoT and AI

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ABSTRACT

The world today is under pressure to foster agriculture to be more productive with less water consumption, less fertilizer wastage, and less labor reliance. The Intelligent Agricultural Systems (IAS) combine Internet of Things (IoT) sensing, edges/cloud connectivity, and Artificial Intelligence (AI) instruments to facilitate precise choice, e.g., irrigating, applying nutrients, identifying diseases, and predicting harvests. This paper suggests an IoT aligned architecture of agriculture (i) multi-layer sensing of soil-crop-climate variables, (ii) edge intelligence of low-latency actuation, (iii) cloud analytics of model training and farm-level optimization, and (iv) secure data pipeline. The presentation of lightweight methodology is based on sensor fusion, anomaly detection, evapotranspiration-based water estimation, and machine learning models to classify irrigation and predict the crop stress. The performance of the system is measured in terms of common metrics (accuracy, F1-score, MAE, water-use efficiency), and a sample results discussion shows that the application of AI-based irrigation can decrease water consumption, but not the yield. The paper outlines such difficulties of deployment as connectivity gaps, sensor drift, explainability, and cyber-security and finishes by giving viable suggestions towards scalable deployment.

KEYWORDS

Precision agriculture, IoT, edge computing, machine learning, deep learning, smart irrigation, crop monitoring, sensor fusion, yield prediction, decision support systems.

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1. INTRODUCTION

1.1. Background

It is a common fact that agriculture is one of the most resource-intensive industries as agricultural production relies on the use of water, energy, land, and labor to ensure stable production of crops. Much of all freshwater being pumped throughout the world is consumed in irrigation and in most areas this has been on the rise owing to warmer climatic issues, erratic precipitation, as well as increased dry periods because of climatic changes. Such shifting weather patterns also render the farming practice more unpredictable because the identical irrigation program or plan of using this or that fertilizer would not effectively work in every week, season, and even in one neighboring piece of land to another. Simultaneously, farmers have several limitations they have to cope with: water scarcity, increase in input prices, labour supply, and a necessity to ensure maximum yield and quality that are accompanied by incomplete and delayed data regarding the actual condition in the field. Conventional methods of farm management are usually based on ex-post visits to the farm and use of human judgment to determine the timing of irrigation, farming by application of fertilizer, or use of pesticides. Although decisions made with experience will be good, they will create inefficies since the conditions in the field are not constant in all places and can vary significantly between regions of the same farm due to soil type, slope, drainage and microclimate. Due to this fact, over-irrigation is widespread, and results in a loss of water, nutrient, and increased use of pumping energy.

On the same note, unequal use of fertilizers may bring about imbalancing of nutrients which lowers productivity and hence deterioration of the soil health in the long run. Pest and disease outbreaks are also one of the greatest threats since when visualized, they usually have extended as the disease spreads and thus treatment is less effective and costly. Intelligent Agricultural Systems (IAS) deal with these issues because they allow continuous monitoring and decisions that are based on the data. IoT technologies contribute to this change because it can offer low-cost sensors, wireless networking, and automatic field data gathering in real-time. Intelligence AI resources subsequently convert these streams of data into valuable actionable information, including the patterns of soil moisture deficits, crop stress, irrigation timing and duration, or the potential presence of early disease risks due to sensor trends and imagery. Through the IoT and AI integration, IAS will help in fulfilling the primary goal of precision agriculture that provides the right input, the right amount, and the right place and time to enhance productivity and minimize resource wastage and environmental footprint.

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1.2. Importance of Intelligent Agricultural Systems

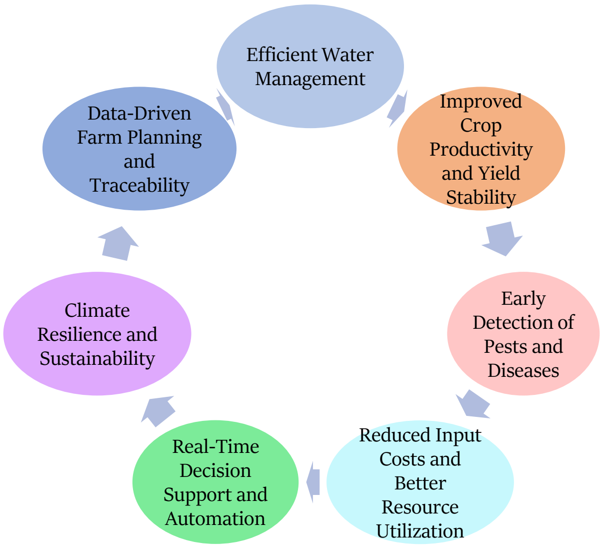

Fig 1 - Importance of Intelligent Agricultural Systems

1.2.1. Efficient Water Management

Intelligent Agricultural Systems (IAS) assists in optimization of irrigation and relies on real time soil moisture, weather and crop water-demand services. In lieu of fixed timetables, irrigation is only applied when it is necessary and this can save wastage of water, eliminates waterlogging, as well as enhancing efficiency of water-use particularly in areas where water is scarce.

1.2.2. Improved Crop Productivity and Yield Stability

IAS assists in timely interventions by continuously checking on the situation in the field to keep the crop healthy during the growing season. Predictive models have the capability to project the deficiencies of nutrients and stresses at an early stage and this would enable farmers avoid losses in yield and retain movement of products at a steady pace in spite of unpredictable climate conditions and soils.

1.2.3. Early Detection of Pests and Diseases

IAS has a capability to identify anomalous patterns of sensor or image before the symptoms turn serious. Early warning allows specific therapy which minimizes the risk of crop destruction and decreases the usage of pesticides. This also favours safer and more sustainable management of pests.

1.2.4. Reduced Input Costs and Better Resource Utilization

Smart systems enhance the use of inputs like energy, fertilizers as well as pesticides by applying them on a need basis in place of a regularity. This saves operational costs and minimizes on the effects to the surroundings like nutrient runoffs and excessive use of chemicals.

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1.2.5. Real-Time Decision Support and Automation

IAS offers dashboards, notifications and suggestions to help farmers make decisions in day-to-day operations. The automation of such tasks as irrigation control allows to lower the number of manual labor, as well as provide a prompt response, which is highly important in the heat stress or rapid weather shifts.

1.2.6. Climate Resilience and Sustainability

As urgent weather conditions fail to provide confidence in weather patterns and rainfall, IAS enhances the resiliency of farms by modifying decisions according to the prevailing and anticipated conditions. To enhance long-term agricultural sustainability, there is efficient utilization of resources, minimization of wastage, and increased conservation of soil and water.

1.2.7. Data-Driven Farm Planning and Traceability

IAS also archives past farm information that can be used in planning on a long-term basis, such as specific types of crops to be cultivated, modes of irrigation, or enhanced API timetable. This information is also useful in traceability and adherence to the current standards of agricultural quality and sustainability.

1.3. Intelligent Agricultural Systems Using IoT and AI

Intelligent Agricultural Systems (IAS) on the basis of the IoT and AI are a new way of precision farming, whereby the actions in the field are controlled by constant data gathering and automatic decision-making. The Internet of Things (IoT) is the sensing and communication base of the farm in this paradigm whereby devices like soil moisture sensors, temperature and humidity nodes, light sensors, and optional imaging units are installed. Such devices will be taking real-time measurements at the field and passing it to a wireless protocol like LoRaWAN, NB-IoT, Wi-Fi, or cellular networks to an edge gateway or cloud platform. This allows farmers to see what happens in the fields and not to have to go manually check the fields every now and then, which can fail to detect any fast changes like the sudden development of a heat stress, a rain or failure of the irrigation system. The use of Artificial Intelligence (AI) can reinforce IAS by converting raw sensor data into valuable insight and actionable information. Learning of patterns of historical and real-time data can be used by machine learning models in order to assist in irrigation scheduling, predicting crop stress, estimating yields and picking anomalies in sensors. To take an example, rather than relying on a straightforward moisture level, an AI-driven irrigation simulator can take into account numerous factors, such as moisture tendencies, temperature, humidity, evapotranspiration pressure, and rain alarms, and make a decision about when irrigation is actually necessary. In a similar manner, AI models can predict crop stress levels as a continuous score, which can be intervened early enough before wilting or a reduced growth can be observed. With access to imaging, disease detection and canopy health monitoring with deep learning can also be further assistive, making it possible to treat the disease specifically and minimize the use of chemicals. IoT and AI combine to form a closed-loop agricultural system, where sensing, analysis, and actuation are enforced in order to maximize

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resource use. This leads to an increased water use efficiency, less input wastage and increased produce stability in changing climatic conditions. Together with edge computing with low-latency response and resilient security with safe actuator control, IoT+AI-enabled IAS can be a feasible and scalable entitlement towards the sustainable and data-driven agriculture.

2. LITERATURE SURVEY

2.1. IoT-Based Smart Farming Systems

Initially, IoT-based agriculture has been based on wireless sensor networks to measure simple field parameters such as soil moisture, temperature, humidity, and rainfall that can be used primarily to manage manual decision-making or basic autopiloted irrigation. With the maturation of the available connectivity choices, researchers and developers started using the longer-range and lower-power-volume in communication like LoRaWAN and NB-IoT alongside Wi-Fi and cellular connections, allowing covers a larger area of the farm and delivering reliable information transfer in remote locations. Throughout the majority of the reported systems, threshold-based logic (e.g., irrigate when moisture less than X) is used, which can often be more efficient in irrigating fields and significantly less water wastage than standard procedures. But this method is unpractical when the real conditions change continuously, such as the soil texture, which is not uniform, water wandering in and out may be uneven, the crop maturity, the variability of microclimates, etc, all of which may shift the right line with time. Consequently, a number of studies illustrate the necessity of adaptive irrigation options that can emerge based on the feedback in the field as opposed to just a set of rules.

2.2. AI in Precision Agriculture

Precision agriculture is now focused on artificial intelligence due to its ability to translate large volumes of farm-related noisy data into significant information. Classical machine learning models are most often used to predict yields because they are reasonably well-performing on structured sensor data and weather data and they do not take as much compute as deep models. Structured sensor data, nutrient sensing data, and forecasting pest instances can be done with classical machine learning models, including Random Forest, SVM, and Gradient Boosting. Vision-based agricultural tasks have been dominated by deep learning, particularly CNNs, to disease detection on a plant by leaf images, fruit sorting, and weed counting, as well as determining stress in a drone or satellite image and mapping it. Although the control experiments may consistently show high accuracies, numerous publications highlight the fact that models do not always generalize in real settings because of light variations, camera resolving, soil backgrounds, diseases particulars of different regions as well as distinctions amongst varieties of crops. This issue has also encouraged hybrid methods which were an integration of both learning and domain knowledge (crop physiology, soil-water balance models, agronomic rules), making them more robust and interpretable and decreasing the quantity of labeled data needed.

2.3. Edge Intelligence and Real-Time Control

Edge intelligence moves the computation out of central cloud servers to the devices deployed at the edge of the farm, microcontrollers, edge gateways, or single-board computers, where decisions may be made even in cases that have weak connectivity or are intermittent. The edge-side functions most frequently used in smart farming literature are sensor anomaly detection (e.g., stuck-at values, packet loss, drift, etc.), lightweight prediction (e.g., irrigation control, disease warning), and fallback control (e.g., rule of thumb) on a low confidence AI decision. Time-intensive operations, such as pump/valve actuation, are a good application of edge processing since latency caused by cloud sensors may decrease performance or waste. It is stated in numerous papers that local running inference causes a decrease in latency, a rise in resilience, and a decrease in bandwidth consumption, particularly in the case of large-volume data such as images or drone streams. Nonetheless, edge deployments have a number of practical limitations: field power supply, expense of ruggedized systems, deep-model memory/compute, and the tradeoff between precision and power-efficient execution.

2.4. Security, Trust, and Interoperability

With the production of cyber-physical systems in the form of farms, security and trust have become imperative issues due to the possibility of damage to the real world by an attack on the sensors or actuators i. e. over-irrigation, crop loss, equipment malfunction or even a safety risk. Threats to the system often mentioned in the literature include spoofed sensor data, malicious access to the controllers (altering pumps/valves), denial-of-service attacks designating the communications, and ransomware attacks targeting the farm administration systems. To curb these threats research looks at lightweight encryption to use in constrained devices, secure authentication and key management, the use of anomaly-to-detect intrusion, and access control models to limit actuator access. Other common obstacles include security and interoperability: most systems operate based on vendor-specific stacks, proprietary protocols, or even uneven data model definitions, and thus integration and scaling can be a challenge. To minimize the fragmentation, the study encourages a consistent messaging and device communication architecture including MQTT and CoAP, complemented by guarded data models and middleware layers which permit the co-operation of heterogeneous sensors, gateways, and analytics environments across various farm settings.

3. METHODOLOGY

3.1. System Architecture

To facilitate the efficient sensing, processing, decision-making as well as customer interaction in the farm ecosystem, IAS (Intelligent Agriculture System) takes the form of a four-layer structure.

3.1.1. Perception Layer

This layer is comprised of field-deployed machines which gather real-time agricultural information. It also contains soil moisture, temperature, humidity, pH, and light intensity sensors and actuators (pumps, valves, sprayers, etc.). The perception layer is constantly tracking the

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conditions of crops and the environment and translating physical parameters into digital signals which might be fed on to get the additional processing.

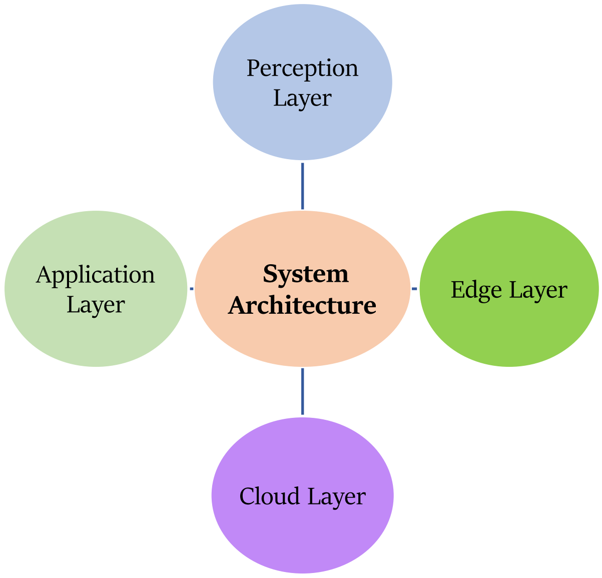

Fig 2 - System Architecture

3.1.2. Edge Layer

The edge layer is the local intelligence which is situated near the farm environment. It acquires sensor data, filters and preprocesses it (takes out noisy data, processes missing data), and is capable of executing lightweight AI models, or logical processes to make fast decisions such as irrigation activation. The edge layer lowers response time, reduces bandwidth consumption, and assures the system will work even in cases of unstable connection to the cloud.

3.1.3. Cloud Layer

The cloud layer offers high-computation and centralized storage of the large-scale analytics. It combines data across a set of edge devices and has historical databases and is capable of advanced machine learning model training and optimization. The cloud can also be used in remote monitoring, more long-term trend analysis, and can also give predictive information like yield prediction or irrigation prescriptions based on both weather predictions and historical soil performance.

3.1.4. Application Layer

It is the interface that the user mingles with and is the interface where farmers, agronomist or administrators can interface with the system. It contains mobile applications, web interfaces, and alarms that provide sensor measurements, irrigation, and artificial intelligence-related suggestions in a basic format. The application layer facilitates decision-making by giving the notifications (e.g., water stress, risk of disease), report and manual override actuator controls where necessary.

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3.2. Data Acquisition and Sensor Suite

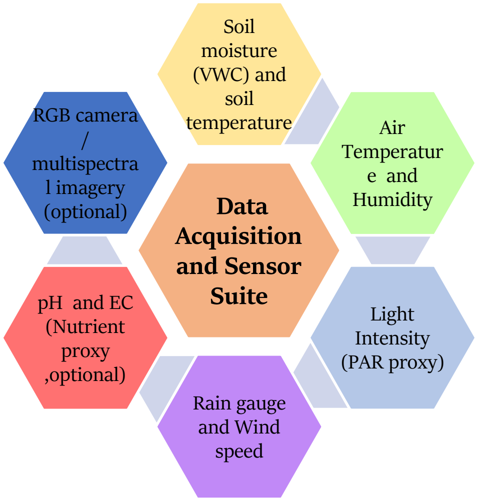

Fig 3 - Data Acquisition and Sensor Suite

3.2.1. Soil moisture (VWC) and soil temperature

Soil moisture sensors are the volumetric water content (VWC) that determines the availability of water in the root zone and determine the when and duration of irrigation. Crop stage monitoring and irrigation tuning applications are facilitated by soil sensing because temperature influences the root activity, evaporation, and nutrient uptake. The two readings make up the key inputs to water management decisions.

3.2.2. Air temperature and humidity

The microclimate indicators that determine plant transpiration and possible occurrence of disease include air temperature, relative humidity. Such sensors are useful in approximating the trend of evapotranspiration and in monitoring pinacolone heat stress or abnormally humid weather conditions which could facilitate the growth of fungus. Constant monitoring enhances scheduling of irrigation and early warnings.

3.2.3. Light intensity (PAR proxy)

The sense of light intensity (which is frequently taken as an equivalent of photosynthetically active radiation or PAR) can be used to estimate the potential of photosynthesis and growth conditions of crops. Short-term variations can be used to signify shading, cloud formation or machines and long-term low-light conditions can affect growth rates and water demand. The data may be effective in comparing the environmental conditions to yield results.

3.2.4. Rain gauge and wind speed (optional)

The precision of the data is the actual nebulized location of the farm because the data is collected by a rain gauge where the system will determine that no additional irrigation is needed because the natural rain is ample. The sensor of wind velocity is of use in estimating the risk of evaporation as well as spray dusts during the use of sprinklers or even when spraying pesticides. These optional sensors streamline the irrigation process and farm activities to be more weather conscious.

3.2.5. PH and EC (nutrient proxy, optional)

The pH of soil or water indicates acidicity/alkalinity and this has a great influence on the availability and uptake of nutrients by plants. The technique Electric conductivity (EC) is usually employed as an indicator of dissolved nutrients and salinity, particularly in fertigation or hydroponic systems. Measurement of pH and EC will aid in avoiding imbalance of nutrients, accumulation of salinity, as well as long-term degradation of the soil.

3.2.6. RGB camera / multispectral imagery (optional)

Image-based disease detection models can be backed up with RGB cameras that monitor crop canopy in visual terms as regards to discolouration of leaves, pest damages, weeds, and growth anomalies. Multi-spectral imagery is useful because it captures reflectance at more bands and thus, vegetation indices (such as NDVI) can be used to estimate the level of plant vigor and stress even before humans can see it. These vision sensors are additional and formidable in terms of decision support but need extra storage, calculate and proper calibration.

3.3. Data Preprocessing and Feature Engineering

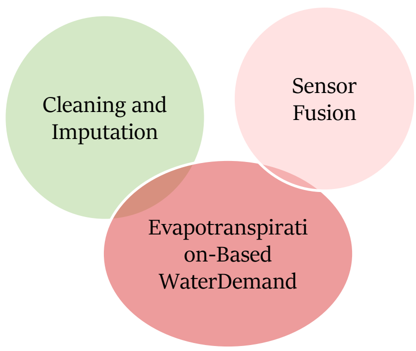

Fig 4 - Data Preprocessing and Feature Engineering

3.3.1. Cleaning and Imputation

Sensor values are considered to be time-based, as every figure is noted at the certain moment in time. In actual implementations, lost values occur because of loss of communication, low battery or broken sensors. In case of short gaps between values that may be missing, the system fills forward, that is, repeats as many times as possible using the last available reading, until a new reading is received. In cases of longer breaks, it employs a median-of-window scheme: the missed value at time t is estimated by the median among the last k measurements (between time t -k and t -1). This way, in

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plain words, is an estimation of the missing reading based on the middle of history but one which is stronger than an average; it is not influenced by a sudden spike or noise as much.

3.3.2. Sensor Fusion

In order to enhance its accuracy, a lot of the moisture is often measured by several probes on various locations or depths. The system calculates a fused value of moisture, averaging all the probe values at any given moment instead of using one sensor. Edited steps: the moisture of each probe is multiplied by a weight (importance factor), and the sum of all is taken. The weights are selected such that more reliable or better-calibrated sensors are weighted more heavily to the final estimate and those which are less reliable weighted less. The weights are all set to add up to 1, thus the resulting fused value will be within realistic range of moisture.

3.3.3. Evapotranspiration-Based Water Demand

The concept of simplified crop evapotranspiration is used as an estimation of water demand as it measures the amount of water that the crop loses to the soil and through the process of transpiration to the atmosphere. The model estimates the crop water use (ETc) as: crop coefficient (Kc) x reference evapotranspiration (ET0). When expressed in normal words, ET0 is the normal water loss of water given normal weather (behind temperature, wind, and humidity) whereas Kc modifies the normal water loss given the type of crops and the stage of development of the crop. As an example, young crops are relatively small in terms of Kc (low water use) and mature crops are relatively large in terms of Kc (high water use). This forms an effective aspect of the irrigation planning as it correlates sensor data with the weather-based behavior of water loss.

3.4. AI Models

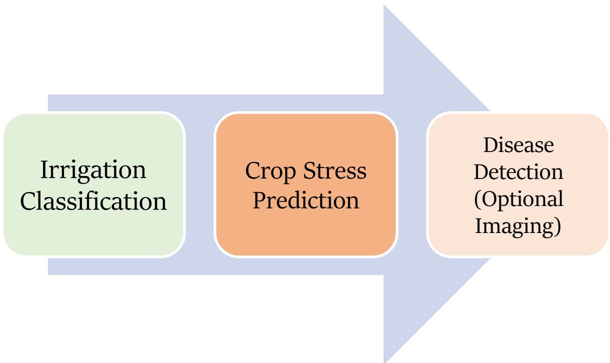

Fig 5 - Ai Models

3.4.1. Irrigation Classification

In irrigation classification, the aim is to make a binary decision y 0-do not irrigate, 1-do irrigate. The model considers a feature vector at time t which consists of the fused soil moisture, the temperature of the air, relative humidity, crop water demand (ETc), rainfall and the change in soil moisture (2Mf) during a short period. The model learns the association between the conditions of the current field + the recent moisture pattern in the current field conditions and the correct irrigation

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action in normal words. Random Forest and Gradient Boosting tend to be more effective than using the brand new Logistic Regression as a stupid baseline especially in cases where the non-linear relationship and interaction might exist like the same level of moisture could be required to make different decisions during a hot day and a cool day.

3.4.2. Crop Stress Prediction

Crop stress prediction is an outcome of producing a continuous value s(t), which indicates the degree of stress on the crop at a time t (where the scales go on a low to high stress history). This is formulated as a regression problem, and the model is used to predict a value of stress ŝ and the objective is to bring the true stress value s close to the predicted one. The MAE (Mean Absolute Error) is usually used to measure the error, but expressed in normal words, the MAE indicates: take the absolute difference between each observed stress score and the observed prediction score, sum the differences across all the samples, and then divide the result by the total sample number N. MAE is popular in many agricultural contexts because it is easy to interpret (mean absolute error), and because it is less sensitive to occasional large error terms than squared-error measures.

3.4.3. Disease Detection (Optional Imaging)

In the case of disease identification the images of the leaves or canopy of crops undergo processing to determine a disease type c (including healthy, blight, rust, mildew, etc.). CNN (Convolutional Neural Network) is a type of network which is trained to identify the visual characteristics such as spots, discoloration, texture alterations and distortion of the leaves among which are related to specific disease. The CNN takes an image in normal words and codes it in a set of learned features and consequently produces the most probable disease class. Instances like when the model needs to be deployed on edge devices with low compute and battery, lightweight CNNs (MobileNet-style models) are favored since they minimize memory and processing needs and yet offer decent accuracy. With dozens of systems, the edge device can do fast inference on real-time alerts but heavier models, retraining, and validation can be done on the cloud when connected.

3.5. Control Logic and Actuation

The IAS control logic has a design of translating sensor data and AI results into harmless, punctual actuation of irrigation equipment like pumps, valves, and relays. As opposed to utilizing an AI model alone, the final actuator command is obtained with the help of a hybrid decision rule that integrates the recommendation of the model with safety constraints that have to be followed. This would help to enhance reliability in actual farm conditions where sensors can stop and the connection can be unreliable and there can be unforeseen weather conditions. Anomaly checking is a major initial measure. The system will then consider readings by incoming sensors to see if they are reliable (e.g., the detection of missing values, stuck-at constant readings, drastic unrealistic leaps or inconsistent measurements between the probes). In case of any sensor abnormality, the system will automatically go into a fall back mode. With the fallback mode, IAS sticks to a conservative irrigation policy, usually a minimal, periodic or spray-like irrigation strategy or short period irrigation impulse,

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to avoid crop damage yet avoid over-irrigation. This makes the field resistant even in cases when the AI is unable to trust the correct inputs. To use IAS, when sensor data is valid, IAS uses a composite situation in terms of the soil moisture situation and estimated crop water demand. When the fused moisture value decreases below some set limit (indicating inadequate root-zone water) and the crop value of evapotranspiration (ETc) is large, IAS sends irrigation. This, in the normal sense, can be translated to mean that the system irrigates when the soil is dry and the weather/crop conditions are strong to suggest excessive water loss thus, irrigation becomes a necessity and very effective. The irrigation time may be set at a constant or variable depending on the distance between the moisture and the desired mark. IAS is optionally equipped with weather intelligence. In case a rain forecast is provided that there is a possible precipitation within a very limited display, the controller can postpone the irrigation to ensure no water is wasted and waterlogging is not experienced. Once the forecast window has passed, the moisture and ETc are re-assessed and the system will then determine whether irrigation is necessary or not. This stratum logic balances robotization with safety, and is robust against operation under actual conditions of uncertainty.

4. RESULT AND DISCUSSION

4.1. Evaluation Metrics

In order to assess the performance of IAS, several metrics are obtained since the system contains classification tasks (irrigate vs. not irrigate) and regression tasks (foreseeing a continuous stress score), as well as practical resource outcomes that are indicative of actual farm benefits. In the case of irrigation classification, Accuracy is the clearest percentage of correct decisions made by the model classifier, although it is not very useful in classes which are skewed (such as when a no irrigation occurs a lot more frequently than irrigation). Precision and Recall are, therefore, also reported. Precision shows the number of times out of the total times the model made the prediction that it would irrigate, it has come to pass correctly, thus, high precision outcomes reduce the number of unnecessary irrigation (wastage of water). Recall tells us the percentage of the actual irrigation-needed scenarios that the model has accurately identified - a high recall value implies less missed irrigations and there is reduced chance of crop water stress. The F1-score provides a balanced estimation of Precision and Recall. Using regular words, the F1-score is computed by two multiplication of Precision and Recall, and then it is divided by the sum of Precision and Recall. This formula rewards the models in terms of doing well on both precision and recall and punish those models that do well on one of the two, thus it is used in irrigation decisions where over-watering is costly and under-watering is costly as well. In regression problems like predicting stress on crops, MAE (Mean Absolute Error) is used to evaluate the median error between MAE and the actual stress values which are easily interpreted as the median error size. RMSE (Root Mean Square Error) is a squaring and averaging of each prediction error followed by the square root, that is, in informal language, RMSE gives large errors a more severe penalty than MAE which matters in the event that large errors in prediction happen and cause false interventions. Lastly, resource and agronomic produce is used to measure IAS. Water-use efficiency (WUE) represents the proportion of irrigation water used to crop output usually defined as the yield of crop divided by the amount of water used.

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Yield stability is a measure of the stability of production under different weather conditions and soil conditions, which is a measure of stability of systems. Energy use captures power used in sensing, computation (edge/cloud) and pumping to ensure that there are no performance gains at unrealistic operating costs.

4.2. Sample Experimental Setup

To carry out the IAS evaluation experiment, a small piece of farmland can be used as the experimental location to simulate the field conditions and make the deployment as easy as possible. To measure spatial variability in soil water content, three soil moisture sensors are installed at representative locations (or depths) in the root zone to instrument the plot of the soil water content. Multiple probes can be used to minimize the reliance on one reading and sensor fusion to enhance reliability when irrigated unevenly or when a heterogenous soil is used. This, in conjunction with a weather node installed in scale of the plot to detect microclimate conditions (air temperature and humidity) (and optionally light intensity or rainfall). Such weather data can be used to estimate demand using evapotranspiration and enhance the irrigation decision-making context. Data are sent out of all sensor nodes to an edge gateway (e.g. a microcontroller gateway or single board computer), which does data logging, preprocessing, anomaly detection, and optionally real-time inference to identify irrigation and predict stress. The measurement of the data is over several weeks, with repetitive irrigation performed daily, so that the sample embraces various operating conditions which include: a hot or mild day, dry or wet season, and variable levels of soil moisture recovery after irrigation. All the cycles are usually equipped with pre-irrigation sensor readings, irrigation events (duration and time), and post-irrigation moisture response. The irrigation classifier could be labeled with ground truths where the farmers make decisions, agronomist, or a clear policy that is grounded on the moisture targets and crop stage. To predict stress, a reference stress score can be calculated using agronomic indices (e.g. moisture deficit, ET-based deficit), or they can be obtained using field measurements as they are available. Because of a fair evaluation, the data set is divided into training and testing based on time, and not randomly. Training is done on the previous weeks in normal terms and the remaining later weeks are devoted to test. The time separation minimizes incidents of data leakage, since the model does not view the future, having patterns that are strongly correlated at close timepoints. It is also more realistic in deployment in the real world as the system is trained on previous data, and must be reliable in predicting the decisions when the system is deployed in future days that have varying environment conditions.

4.3. Sample result summary

Table 1: Sample Result Summary

Task	Score
Irrigation decision	0.92
Stress regression	0.08
Anomaly detection	0.9

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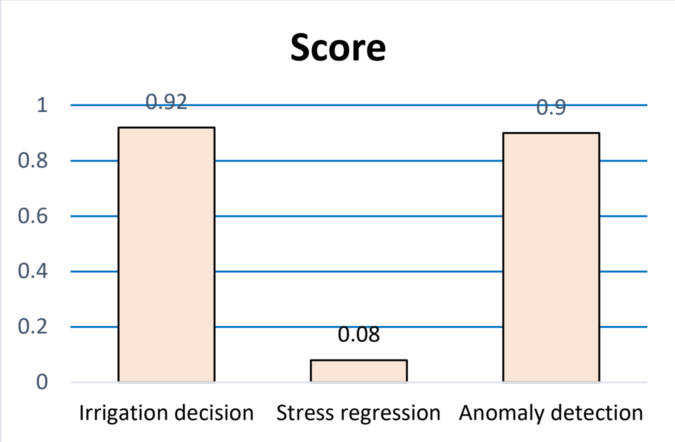

Fig 6 - Sample Result Summary

4.3.1. Irrigation decision (Score: 0.92)

The value of 0.92 in irrigation decision is an indication that the classification model has good effectiveness in selecting when to irrigate or when to withhold irrigation. Practically that would imply that the model is able to accurately reflect the field conditions including the fused soil moisture, weather conditions and demand of evapotranspiration to initiate irrigation at the right time. This stage is critical since it directly affects water savings and crop health fewer wrong irrigate decisions will result in a lower water wastage whereas fewer missed irrigation decisions will result in the lower risk of crop stress.

4.3.2. Stress regression (Score: 0.08)

The stress regression coefficient (usually the low error value, which is indicated to be 0.08) indicates that the regression equation has a high predictive power in estimating the level of crop stress. By normal standards, the mean of the forecasted stressor and the real stressor is not big and that is the model approximates accumulated stress and recovery by irrigation quite closely. Correct prediction of the stress assists the system to cease the mode of controlling stress through mere set threshold controls and to become proactive in the management of stress before it is recognizable and reaches out to the yield.

4.3.3. Anomaly detection (Score: 0.90)

The score of anomaly detecting of 0.90 means that the system has a great potential to detect the abnormal sensor behavior that includes missing data, unrealistic spikes, drift, or stuck-at values. This is essential in terms of real-world application since sensor errors are able to corrupt the AI models and result in unsafe actuator execution. Having great anomaly detection, IAS has the ability to activate fallback policies, avoid over-irrigation or under-irrigation due to erroneous inputs, and enhance the overall system reliability and trustworthiness.

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4.4. Discussion

As the results reveal, AI-based irrigation has obvious benefits over the fixed threshold-based control since it is able to make decisions on the basis of more detailed review of field conditions. The AI model is capable of simultaneously using the information of humidity, estimated crop water demand (ETc), rainfall, and short-term moisture patterns as opposed to simple rules which incorporate only a single limit, namely soil moisture. Practically, this will result in smarter actuation, such as the system will avoid irrigating when there is a small amount of moisture, yet there is also low ETc because of cool weather or will irrigate sooner when there is high ETc and moisture is dropping rapidly which makes the crop less likely to stress. It is a multi-variable reasoning that enhances water efficiency, as well as crop safety on unstable weather conditions and different crop development stages. Edge inference also enhances the system as it allows the system to respond in the vicinity of the farm through real time responses. Actuation delay can be minimized by IAS since sensor streams can be processed locally, even in the event of cloud connectivity outages, typical of rural implementations. Edge gateways also enable local data buffering, expediency anomaly checks and simple dashboards that assist farmers to keep track of the field without the continuous internet connection. But sensing in the real world creates issues of reliability. The calibration errors and sensor drift may bias the moisture values over the long term making the model water down too soon or too late. To avert this, they must be calibrated on a periodic basis and have automated anomaly warnings so that incidences of faulty readings are not picked before they can influence a controlling decision. Stability is another major issue in models with time. Depending on seasonal variations, crop rotation pattern, soil condition variability, and modified irrigation patterns, the data may undergo changes in the distribution resulting in performance deterioration in case the model is left unchanged. That is why retraining with the help of recent data regularly is suggested, preferably with validation to make sure that the modified model is safe and stable. Regarding deployment, LoRaWAN would be appropriate to low power, long range sensing on a large plot scale and edge gateways would give aggregation and local intelligence. Lastly, since IAS operates actuators directly, there can be no security by the wayside: strong authentication, encrypted communication and role-based access control must be applied so as to forbid unbased commands and secure the farm operation against cyber-attacks.

5. CONCLUSION

The current paper introduced a small architecture of Intelligent Agricultural Systems (IAS), which integrates IoT-based sensing with AI-based analytics to allow effective and dependable management of the farm. The architecture proposed is encompassing the entire pipeline, starting with data acquisition in the field, passing through the preprocessing and feature engineering, through the AI inference and control logic to actuate it, enabling irrigation and crop monitoring decisions to rely on real conditions as well as learned patterns based on historical data. IAS provides a continuous feedback mechanism which enhances situational awareness at the farm level and eliminates manual inspection or strict schedules through the integration of core environmental sensing (including soil moisture, temperature, humidity and optional rainfall and imaging inputs).

One such important contribution of the methodology is that it employs preprocessing strategies that enhance robustness to the real deployment constraints. Method Calibration weighted sensor fusion This processing method can be applied when sensor-based data does not have sufficient levels of cleanliness and imputation, or when sensor-based data is noisy, to compute an estimate of moisture by averaging streams of sensor measurements across multiple probes through weights sensitive to calibration errors. Methodology Cleaning using calibrated weights Sensor fusion This data processing method may be implemented in situations where sensor-based data lacks enough levels of cleanliness and imputation or where sensor-based data is unreliable to construct an estimate of moisture by integrating streams of sensor Moreover, with an evapotranspiration-based modeling, agronomic domain knowledge is added to the feature set and the system is able to recapitulate the crop water demand, which is not constant as it varies with weather conditions and the growth stage. By combining such engineered inputs with machine learning models to perform irrigation control and stress regression in crop fields, the system has already the potential to shift to the point of no longer depending on fixed threshold control and can produce responses to dynamic field conditions. As emphasized in the discussion, AI-assisted irrigation may enhance the accuracy of decisions by using a variety of variables including moisture patterns, humidity, ETc and rainfall determinants, which are useful in reducing over-irrigation, avoiding water stress and eventually enhancing water-use efficiency. On the whole, the results indicate that IAS implementations may enhance the effectiveness of operations and minimise the level of resources wastage, when the practical constraints are actively worked on. Measurement bias over time due to sensor drift and calibration problems may lead to a need to perform periodic calibration processes and automated anomaly alarms to ensure that the quality of input is reliable. Similarly, too, model performance might deteriorate between seasons or farm sites because of the varying environmental and crop conditions, and so it must be retrained on at regular intervals to maintain accuracy and safety. On a deployment perspective, low-power long-range communication like the LoRaWAN is used to scale sensing over large tracts, and edge gateways enhance the robustness to local inference and local control during the break in of connectivity. Lastly, since IAS directly impacts on physical actuators, security and trust mechanisms should be considered as system requirements. Role-based access control, encryption and authentication decrease the cyber threat of unauthorized commands and safeguard farm operations. Further development of AI that can be explained to instill confidence and transparency in farmers, powerful learning strategies that are general to multiple farms and seasons with a small re-training footprint, and unified interoperability systems to help ease vendor lock-ins as well as allow integration of different devices and platforms should be the focus of future work.

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