A Novel System to Relieve Global Severe Water Shortage with Massive Mobile IoT, Machine Learning and Wireless (MMW) Solution

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Abstract

Drought has been crippling many regions of the world. As a novel method to relieve this issue, this solution implements a low-power MMW (Massive Mobile IoT, Machine Learning, and Wireless). Massive Mobile IoT sensors provide real time data on weather, soil, and temperature conditions. Machine Learning is used to detect different growth stages of crops, with the ESP32 low-power microcontroller, therefore able to accurately control water usage through plant identification. LoRa Wireless is chosen as a low-power wireless transmission method for long-range and large-area applications. Simulation and field-testing are processed to compare the MMW method with a traditional method, the control group. The results demonstrate a 40%-53% reduction in water use. Therefore, this solution has the potential to be used as a water-saving irrigation system for agriculture crops, municipal landscaping, and other heavy water usage scenarios.

Keywords: **Garlic, Honey, Microbiology, Drug Resistance, Antibiotic**

Introduction

Drought has been a global problem, pushing many rivers and lakes worldwide to the lowest levels ever seen. Some hotly discussed methods, such as atmospheric water collection, will take many years to fully support current infrastructure. Monitoring the hydrological level, while providing valuable data, does not contribute to resolving the shortage. Water cuts have been implemented in many regions and adversely affected agriculture, which accounts for ~70% of all water usage. Therefore it is urgent to call for innovative ideas in water technologies and partnerships. Most current irrigation systems are based on farmers' prior experience, not real-time data from the field. In addition, different plants/crops have different water needs at various stages of growth. Overwatering and underwatering are both detrimental to plant yield. A novel solution is introduced to use accessible technologies including massive Mobile IoT and Machine Learning to overcome existing hurdles, saving water significantly within agricultural and municipal contexts, and maximizing water efficiency based on various growth stages of plants.

Methods

This solution is a water control system (Figure 1) to optimize water use in a heavy water usage scenario in agriculture and municipal, combining low power Mobile IoT sensors that collect and process data, machine learning that provides reliable identification of growth events of a plant/crop, wireless technologies, and a processing algorithm. The low-power microcontroller ESP32 and various Mobile IoT sensors (rain sensor, soil moisture sensor, soil temperature sensor, and ultrasonic sensor) collect real-time weather and soil conditions. TinyML Machine Learning algorithm and ESP32-CAM to detect and classify plant objects for different plant growth stages. LoRa Wireless transmission systems provide long-range communication capabilities, up to 5 kilometers in urban areas and up to 40 kilometers or more in rural areas, to transmit real-time data from the field to the control center (Kamal et al.). A data computing algorithm processes and returns data for use. Web server and data access provide remote monitoring and control.

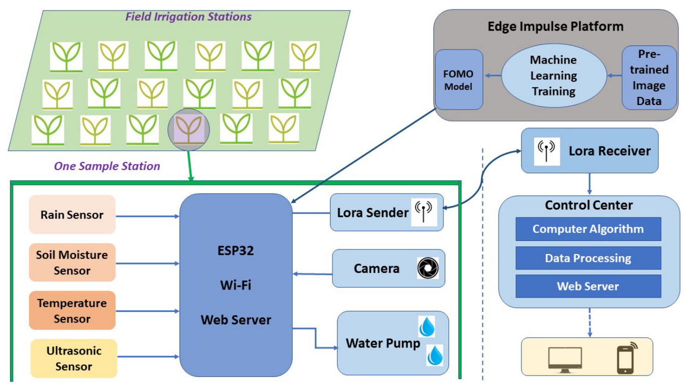

Fig. 1. Overall System Diagram

Procedure 1 is to build and test Mobile IoT with ESP32/Wi-Fi/LoRa (Figure 2), including building ESP32 with Wi-Fi and sensors, writing Arduino and algorithm, software code, running pumps and relays to verify system integrity, and building another hardware system and software utilizing ESP32 with LoRa Sender and Receiver.

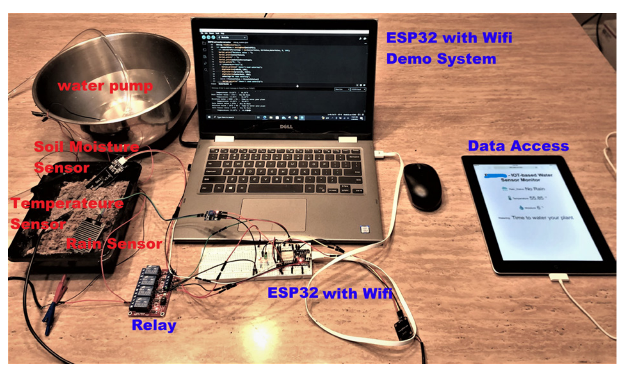

Fig. 2. The System and Monitor

Procedure 2 is a field test to evaluate how much water can be saved with the IoT System. Three soil areas are set up for comparison with Area 1 for targeted moisture 20~40%, Area 2 for 40~60%, and Area 3 for 60~80% (Figure 3). The system built in Procedure 1 is used to collect data for 5 days. Day 1 data is also used as the "Base amount" of water for the traditional method. The data collected in 5 days is compared with the Traditional Method.

Fig. 3. The Field Test and Monitor

Procedure 3 uses Machine Learning to train cotton images, build models, and test. It is acknowledged that different plants have different levels of water needs and different growth stages of the same plant entail different water amounts for growth productivity. To maximize irrigation efficiency, it is necessary to enable the system to recognize various crucial events of plant growth and adjust watering in real-time. Cotton plant, one of the most common and water-intensive crops, was adopted to test the system.

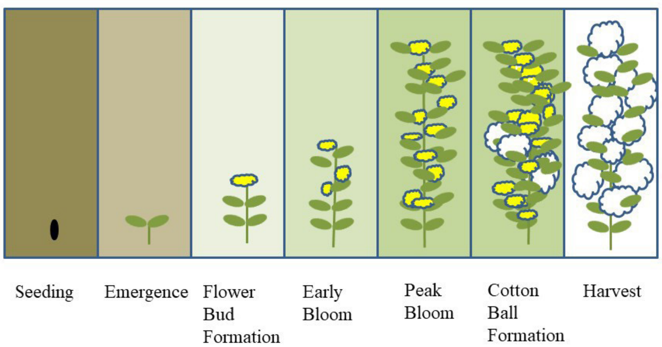

Fig. 4. Cotton Growth Events Timeline

Based on the cotton plant growth events (Gaber) (Figure 4), a Machine Learning mechanism based on Convolutional Neural Network Architecture to Detect Cotton Growth Stages was introduced to the system to train cotton image recognition.

IoT-based microcontrollers utilize TinyML to compile the Neural Network model data into a memory-efficient inference library (less than 256kB), which is written into the microcontroller for runtime object detection (Dickson). Figure 5 is the flow chart showing how the cotton pre-existing training data is collected by ESP32-CAM and entered into TinyML for training and compiled into TinyML MobileNetV2 model (Sandler and Howard). After the model is built into ESP32-CAM, the camera can capture real cotton objects in a particular growth stage. Figure 6 shows the computer algorithm utilizing Machine Learning.

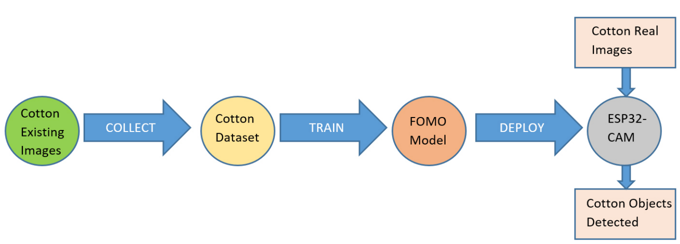

Fig. 5. The Neural Network to train the dataset into the TinyML MobileNetV2 model.

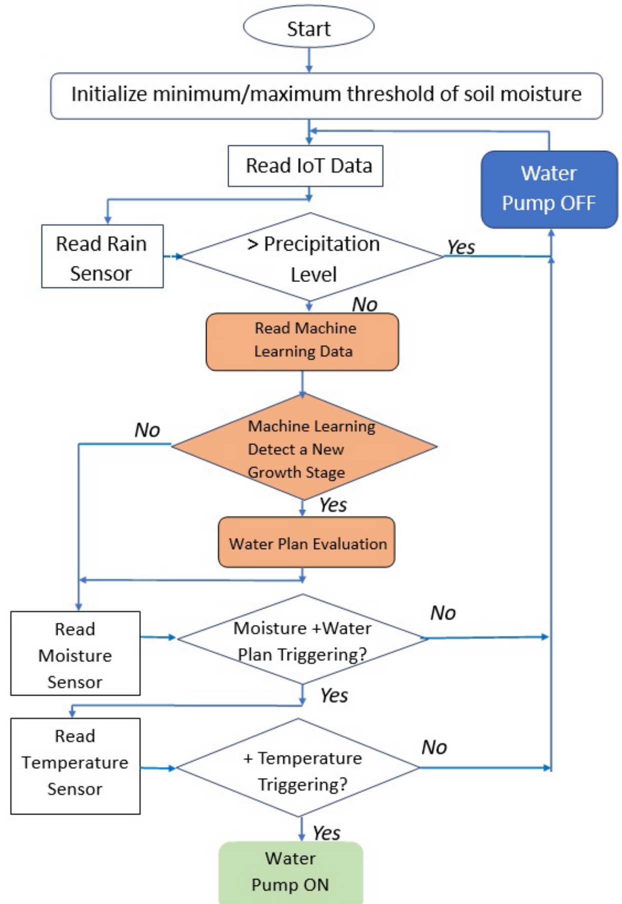

Fig. 6. Computer Algorithm

Procedure 4 performs a simulation to calculate the water saving on cotton with the Machine Learning method that detects each cotton growth stage even when emerging on different days, compared to the traditional method with a fixed water plan. A Monte Carlo simulation was deployed over 125 days, 100 times (Table 1).

Traditional Method

Stages	Duraion (Days)	Water (Inch per day)
Seedling to Emergence	9	0.05
Emergence to First Square	23	0.1
Flower Buds Formation	23	0.2
Early Bloom	35	0.28
Peak Bloom	20	0.2
Cotton Boll Formation	14	water stressed mode
After Harvest		0

Machine Learning Method

Events	Range (Day from Seeding)	Smart Water (Inch per day) from this event
Seeding	0	0.05
Emergence	4~14	0.1
First Square	27~38	0.1~0.2
First Flower	50~60	0.2~0.28
Peak bloom	85~95	0.28~0
Open boll	105~115	water stressed mode
Harvest Done		0

Table 1. Compare the total 125-day water plan via Traditional Method vs. Machine Learning Detection Method.

Results

In Procedure 1, ESP32 with Wi-Fi, LoRa, and Mobile IoT sensors were built successfully. In Procedure 2, data comparison between the traditional method and the Mobile IoT method showed 26%, 31%, and 42% water reduction respectively for three different desired soil moisture areas (Figure 7).

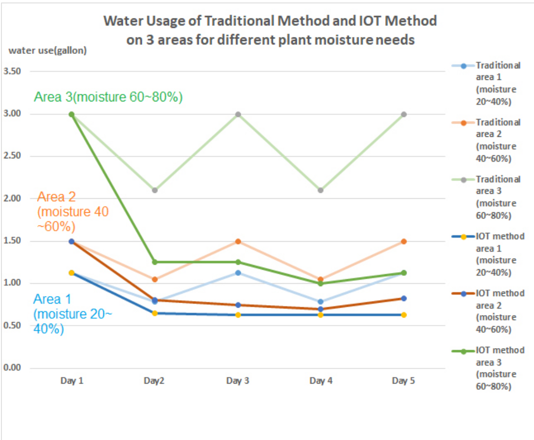

Fig. 7. Comparison of Water Consumption between Traditional Method and Mobile IoT System

In Procedure 3, images of pre-existing cotton objects are collected by ESP32-CAM, trained and compiled in the TinyML MobileNetV2 model, and deployed into ESP32-CAM. The real cotton object was detected successfully (Figure 8).

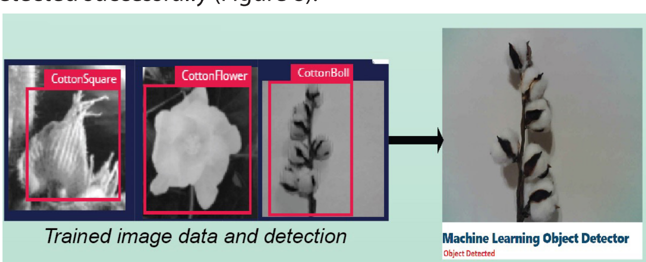

Fig. 8. Object detected by ESP32-CAM and displayed on the web server.

In Procedure 4, the Monte Carlo simulation result showed that the Machine Learning Detection Method used a total of water levels between 15.64 inches and 18.86 inches with an average of 17.24 inches, an 18.5% saving of water use, compared to the Traditional Method which used a total of 21.15 inches of water (Figure 9).

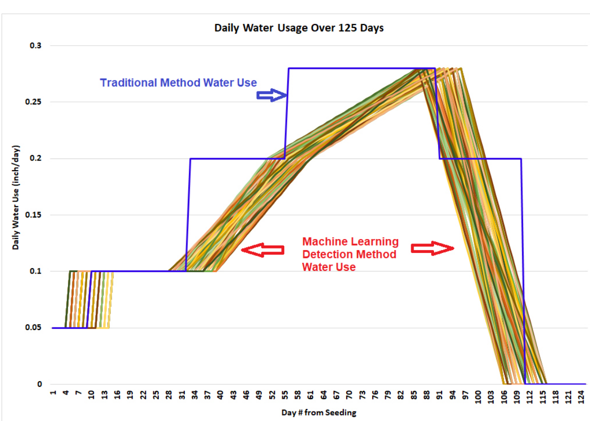

Fig. 9. Comparison of Water Consumption between Traditional Method and Machine Learning Method

The field-testing data showed a roughly 26~42% reduction in water use with the Mobile IoT method compared to traditional methods. Furthermore, after the Machine Learning Detection was integrated into the prototype based on cotton plant growth stages, there was an 18.5% additional reduction in water use using the Machine Learning Detection method compared to traditional methods. Overall there was a 40%~53% water saving when the Mobile IoT method and Machine Learning Detection method were combined.

Discussion

The key innovation of the system (Figure 10) is that it has established a complete low-power solution that can be applied on a large scale, with Mobile IoT and Machine Learning mechanisms based on crop growth stages and specific soil moisture requirements. It therefore has achieved precision irrigation capabilities which improve not only water efficiencies but also crop yields.

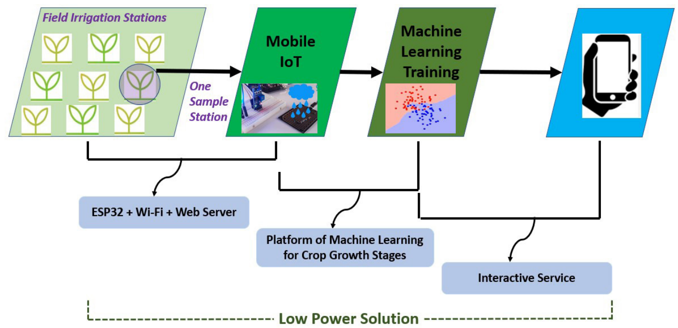

Fig. 10. The low power solution system flow

Energy sustainability must be considered in large-scale agriculture fields, necessitating low-power Mobile IoT sensors, low-power ESP32 microcontrollers and systems, and LoRa for Low Power Long Range Radio technology transmission.

A precise irrigation system not only saves water but also improves yield; Machine Learning is an ideal method to detect a plant's growth stage and provide data for water control. A new TinyML algorithm trains and compiles pre-existing images offline and writes a small-sized library into the microcontroller for runtime plant detection, resulting in a combined 40%~53% water saving.

One major challenge in the system is multi-function IoT sensors with higher accuracy and stability are needed. Another challenge calls for an extensive database with growth stage information of various crop types as input to the machine learning algorithm.

Conclusion

In conclusion, this MMW solution has the potential to be used as a water-saving system for agriculture crop growth, municipal landscaping, and other heavy water usage scenarios.

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