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Fusion of Physical and Human Sensors for Condition Prediction: Preliminary Experiments in Smart Agriculture

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Abstract

In recent years, the internet of things (IoT) has been used effectively in smart agriculture, where farmers can make decisions and transfer knowledge based on sensor data. However, the physical sensors (temperature, humidity, and illuminance sensors) of IoT systems have limitations in capturing various changes in crops and environment in the actual fields. Combining physical sensors with the human five senses (human sensors) can flexibly record changes that cannot be captured by physical sensors alone. In this study, a smart voice messaging system is used for recording the five human senses via voice messages. Assisted by machine learning, preliminary experiments are conducted using planter boxes for predicting soil condition in the watering process. Our results confirm the effectiveness and validation of fusing physical and human sensors.

Keywords: Internet of Things, Human Sensor, Machine Learning, Condition Prediction, Smart Voice Messaging System

1 Introduction

In recent years, digital technology including the internet of things (IoT), artificial intelligence (AI), and cloud computing, has produced various innovations and applications [1][2]. Smart agriculture supported by digital technology is one of the most promising approaches for increasing agricultural efficiency and productivity. In particular, the rapid aging of farmers presents a serious social problem, especially in Japan. Older farmers have abundant tacit knowledge based on their experiences. However, there are insufficient means and efforts for them to externalize and transfer their knowledge to younger generations. Thus, digital technology becomes very important in recording and analyzing agricultural data and supporting farming activities. Recently, there have been numerous studies and practical applications of IoT in agriculture. Many researchers focus on physical sensors and networks to visualize agricultural processes [3], and some have proposed the application of machine learning techniques to agriculture [4].

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Physical sensors used in agriculture, such as temperature, humidity, and illuminance, are insufficient for understanding the detailed conditions of crops and cultivated land, and human confirmation is essential. In addition, the high cost and rather complicated operation of physical sensors makes their use impractical for actual farmers and occasionally for research purposes. In reality, farmers use their five senses (sight, hearing, touch, smell, and taste) and a wealth of experience (often tacit knowledge) to detect pests and environmental changes in crops, make decisions, and perform their work. In this study, these are called "human sensors." As a mechanism for collecting data from human sensors, we developed a smart voice messaging system (SVMS) [5] that can verbalize farmers' awareness (observations, operations, and judgments) of crops and field environments, which can be recorded directory in the field as voice messages and photographs. The objective of this study is to use this system to record detailed field conditions by combining physical sensor data and human sensor data and analyze the data using machine learning to extract patterns for knowledge sharing and transfer in agriculture.

Combining the data from physical sensor and human sensor collected by SVMS, we describe a preliminary experiment for predicting soil conditions in planter cultivation

2 Literature Review

Numerous studies have investigated the application of digital technology to agricultural support [3][6]. Applied agricaltural research that uses data collected by physical sensors includes a warning system that monitors the water level in agricultural water tanks [7], crop health diagnosis using image analysis, and control of environmental parameters through IoT [8]. Although these past studies have shown that methods using physical sensors effectively improve work efficiency, in many cases, all of these efforts have focused on one specific task and have been unable to adequately capture the more subjective changing agricaltural crop and environmental conditions.

Dey[9] proposed context-aware computing as a method for computers to sense their surroundings and situations, and defined "context" as follows: "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves." Context-aware methods that uses IoT have been proposed, such as CA4IoT (context awareness for internet of things) [10], which is a broad classification system that combines information from multiple sensors and describes it in an ontology-based approach; nonetheless, incorporating the environmental changes and experiences perceived by experienced field workers remains a challenge.

Uchihira et al. [11] have shown the importance of "Gen-Ba knowledge," which can be defined as knowledge possessed by humans that cannot be captured by IoT sensors. It is latent knowledge that can be expressed in the field, which blends tacit knowledge and explicit knowledge, suggesting the concept of a human-centric digital twin that utilizes Gen-Ba knowledge in cyberspace. Uchihira et al. state that SVMS is an effective tool to gather this knowledge. In agriculture, it is also effective to collect and apply this on-site Gen-Ba knowledge. However, analyzing Gen-Ba knowledge using AI remains a future challenge.

In addition, recent years have seen revolutionary advances in natural language processing with the advent of Transformer[12], BERT[13], GPT[14], among others. The performance of highly accurate tasks with minimal information could be an effective method for integrating human sensor data and physical sensor data for improving knowledge about the fields.

3 Fusion of Physical and Human Sensors

In corp fields, the type of information that can be collected by physical sensors is limited, and in reality, humans (farmers) make decisions and take actions based on their empirical knowledge. We have been developing a SVMS[5] to record human awareness based on their experiential knowledge on the field. We call this the "human sensor." The fusion of physical sensors and a human sensor, described as sensor fusion, makes it possible to accumulate data for an on-site situation that cannot be acquired by physical sensors alone. Data gathered is usually simply fusion among physical sensors, but human-sensor-physical-sensor fusion is an unusual and unique approach. This concept is shown in Figure 1, which was originally proposed by the authors [15]. Up to this point, however, pattern extraction by applying machine learning remained a future issue.

Through a simple experimental environment, we show in this report that an effective prediction model can be created by using physical and human sensor data in a complementary manner. Machine learning models for predicting soil and other conditions are used to extract patterns in actual field and cultivation knowledge.

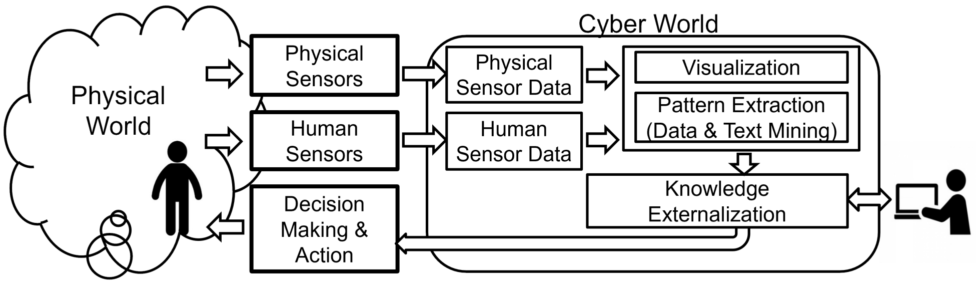

Figure 1: Fusion of Physical and Human Sensors (Conceptual Model) [15]

4 Preliminary Experiments

4.1 Experiment Overview

In this experiment, we integrate and analyze physical sensor data (air temperature, humidity, illuminance, soil temperature, and soil moisture content) and human sensor data (sunlight intensity, soil surface wetness, soil texture, and weather conditions) collected from planter cultivation to predict future soil conditions. The collected data is important to cultivate Japanese white radish. In particular, handling soil water conditions affects corps quality. Specifically, we cultivated radishes in three planters of the same size (90L) and made of plastic, collected physical sensor data (two circuits were installed in each planter), and recorded soil observations for the planters daily for two months (late October to late December 2022) using SVMS. Table 1 shows the experiment conditions.

Table 1: Experiment Conditions

Experimental Period	20 October, 2022 to 19 December, 2022
Participant / Hunam Sensor	1 person (one of authors)
Location	Veranda in student dormitory
Captured Physics Sensor Data	Temperature, humidity, illuminance, soil temperature, soil moisture
Captured Human Sensor Data	Intensity of sunlight, apparent soil surface wetness, feel of soil
Amount of Water Per Day	Planter1: 1 liter per day, Planter2: 2 liter per day, Planter3: 3 liter per day

4.2 Experimental System Configuration

The experimental system configuration for planter cultivation is shown in Figure 2. For physical sensors, we developed a prototype system to measure air temperature, humidity, illuminance, soil temperature, and soil moisture content (Figure 3). The data obtained from the physical sensors were collected and stored in a time-series database (InfluxDB) using message queuing telemetry transport, including the environmental information around the planter. For the collection of human sensor data, we used a commercial version (RECAIUS, Toshiba Digital Solutions Corporation) of the SVMS [5] noted in the previous sections (Figure 4). Figure 5 shows an image of the three planters and the instrumentation.

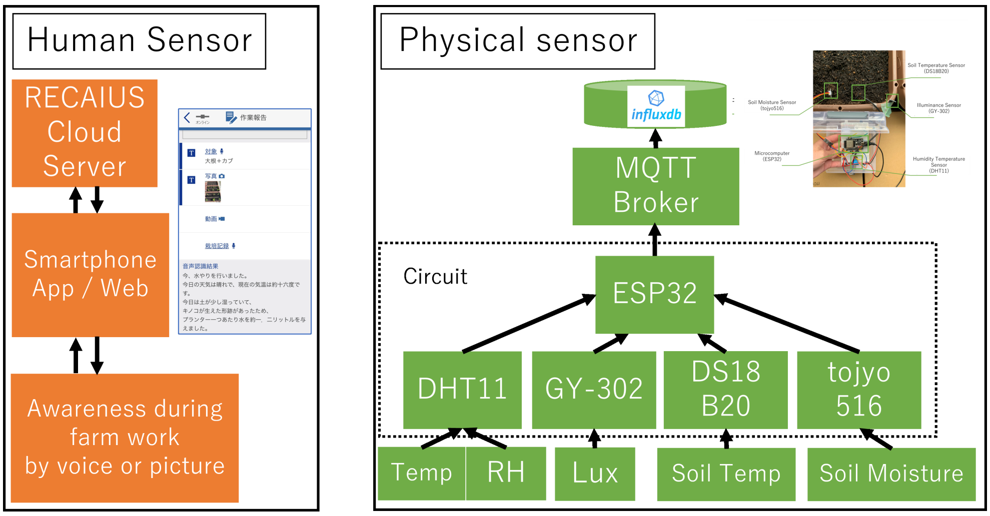

Figure 2: Configuration of the Experimental System

4.3 Data Collection and Method

Using a decision tree based machine learning model, lightGBM [16], the acquired physical and human sensor data were used to build models to predict the soil moisture content that would be present 3 hours later. An overview of the experimental method is shown in Figure 6.

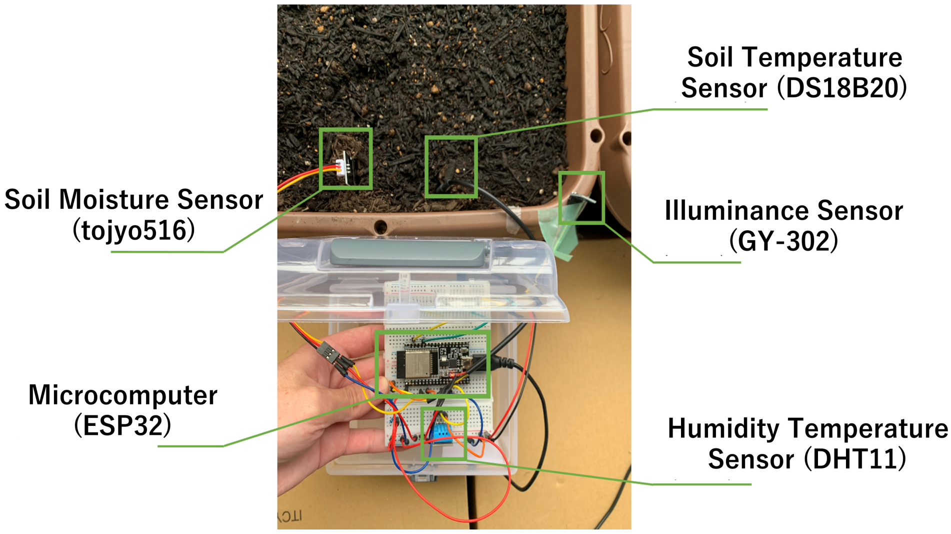

Figure 3: Physical Sensors in Experimental System

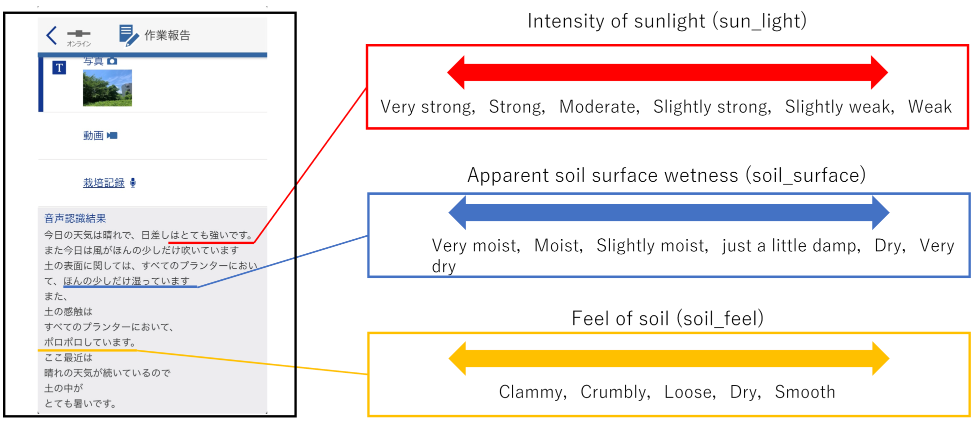

Figure 4: Human Sensor (SVMS Smart Phone Interface)

Figure 5: Conducting the Preliminary Experiment and Data Collection

Table 2 shows the features used in training. For the variables based on human sensor data, we applied an ordinal scale (Table 3) for sunlight, soil surface wetness, feel of soil, while for the variables related to weather, sun_dummy, rain_dummy, and clouds_dummy were transformed into dummies (Table 4) and used in the analysis. After adding the data for spoiled_water and the amount of water added to the planter, the data from planter1-3 were combined vertically to create machine learning models.

4.4 Results

To confirm the effectiveness of physical and human sensor fusion, we compare the accuracy of predictive models generated from the physical sensor data alone with models generated from physical and human sensor data. Here, root mean squared error (RMSE) was used to evaluate the models. The results of the built prediction models and hyperparameters are shown in Tables 5 and 6, respectively; a lower value of the RMSE score, the better the accuracy. The lower RMSE score (7.07413) or physical and human sensor fusion, which includes the human sensor data model, relative to physical sensors (7.32872) confirms that adding the human sensor data model provides an accurate prediction by adding soil conditions that are not captured by the physical sensors.

RMSE is known to provide a correspondingly larger penalty for large errors. The models predict the soil moisture content after 3 hours, but the planter environment is changing continuously during the time up to 3 hours. Accordingly, it is difficult to predict with high accuracy. Therefore, RMSE was utilized in this forecasting because some small errors can be tolerated. The value of the RMSE rating can be directly converted to units, and the forecasting model including the human sensor data can have errors in the forecast value that approximately the average RMSE score.

5 Discussion

To evaluate the effect of each of the model values on the predicted values, the Shapley additive explanation (SHAP)[17][18] is used to show the contribution to the 3-hour soil

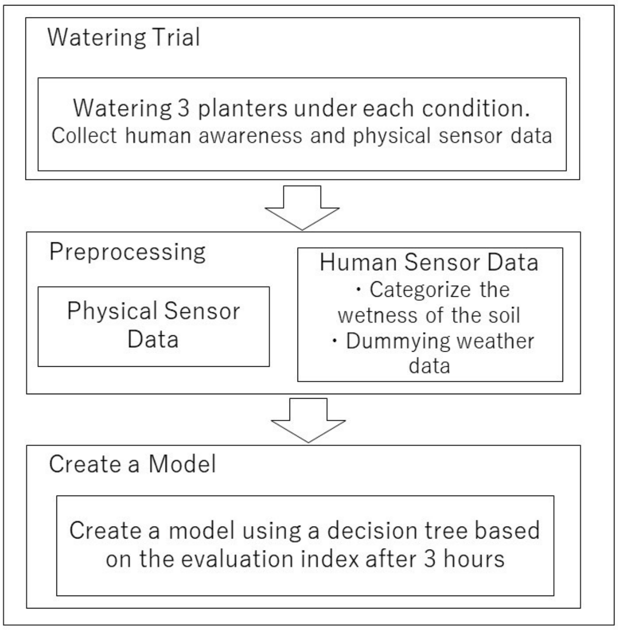

Figure 6: Process of Preliminary Experiments

Table 2: Features Used for the Prediction Model

Explanatory Variable	Variables of physical sensor	Temperature humidity illuminance ground_temperature(soil temperature) soil_moisture (soil moisture rate)
	Variables of human sensor	sun_light (intensity of sunlight) soil_surface (apparent soil surface wetness) soil_feel (feel of the soil) sunny_dummy (dummy data for sunny condition) rainy_dummy (dummy data of rainy condition)
	Variables that do not belong to either physical or human sensors	Spoiled_water (amount of spoiled water)
Target Variable	Variables of Physics sensor	Soil moisture after 3_hours (3_hours later soil moisture rate)

Table 3: Ordinal Scale of Sunlight, Soil_Surface Wetness, Soil_Feel

Intensity of sunlight (sunlight)		Apparent soil surface wetness (soil_surface)		Feel of soil condition (soil_feel)	
Very strong	5	Very moist	6	Clammy	4
Strong	4	Moist	5	Crumbly	3
Moderate	3	Slightly moist	4	Loose	2
Slightly strong	2	Just a little damp	3	Dry	1
Slightly weak	1	Slightly dry	2	Smooth	0
Weak	0	dry	1		
		very dry	0		

Table 4: Dummy Conversion of Sun, Rain, and Clouds Dummy

Weather	Sun_dummy	Rain_dummy
Sun	1	0
Rain	0	1
Clouds	0	0

Table 5: Predicted Model Scores

Model type	Train RMSE score	Test RMSE score
With human sensor model	1.43178	7.07417
Without human sensor model	3.26528	7.32872

Table 6: Hyperparameters

Parameters	Value
Max epoch	100
Tree max depth	4
Min data in leaf	3
Early stopping	50
Number of leaves	30
Learning rate	0.1

moisture content prediction using the model includes the human sensor (Figure 7). In addition to physical sensor values such as soil moisture content and temperature, human sensor values such as soil surface and condition also contributed to the prediction. However, the effect of the amount of water applied was less than expected. In the experiments, the soil condition was considerably affected by environmental factors. Hence, the evaluation of soil condition using the human sensor is effective in terms of appropriately capturing the plant environment.

Figure 7: With Human Sensor Model Visualized by SHAP

6 Conclusion

In this study, we showed that in a simple experimental environment of planter cultivation, the data obtained using physical and human sensors can be integrated within a model, and that machine learning can be used to provide more accurate estimation than physical sensor data alone. Although the combination of physical and human sensors had been shown at the conceptual level [15], this study demonstrates its effectiveness using actual experimental data.

In our preliminary experiment, a predictive model was constructed using the messages (e.g., feel of soil condition: clammy (4), crumbly (3), loose (2), dry (1), smooth (0)) that could be quantified from the planter cultivation conditions as perceived by the human sensor. Nonetheless, there remain many messages in the SVMS regarding human awareness and senses that were not quantified (e.g., “weather is sunny, and the wind is blowing strong today!”). Using natural language processing technology, which has become increasingly innovative in recent years, we plan to construct more accurate prediction models that reflect farmers' experiential knowledge and extract cultivation knowledge (know-how) by directly using all messages input by SVMS.

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