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IoT-Based Irrigation System Using Machine Learning for Precision Shallot Farming

Mardhiyyah Rafrin[1], Muh. Agus[2], Putri Ayu Maharani[3]
[1,2,3]Computer Science, Teknologi Produksi and Industri, Institut Teknologi Bacharuddin Jusuf Habibie, Parepare, Indonesia
[1]rafrinmardhiyyah@ith.ac.id, [2]muhagus@ith.ac.id, [3]maharani_putriayu@ith.ac.id

Abstract

Despite the massive production of shallots in Enrekang Regency, South Sulawesi Province, Indonesia, the cultivation method is still very conventional. Shallot cultivation is very challenging because it requires precision irrigation and pest prevention. In this research, we proposed a smart irrigation system to help farmers manage irrigation with more efficient water usage without hampering their pest prevention. The system outcomes were three options: 1) no water needed, 2) water is required and is efficient for watering and 3) water is required but it is not efficient for watering. We used Wireless Sensor Networks and IoT to collect yield parameters, designed a firebase database, and developed a mobile application and a web service embedded with a machine learning application. All applications interacted by using the Representational State Transfer Application Programming Interface. The proposed system architecture successfully gathered cropland data and distributed them to all applications within the system. Furthermore, we analyzed four supervised learning algorithms (decision trees, random forest, gradient boosting, and K-Nearest neighbor), and the random forest was deployed in the web service because it outperformed other algorithms with an accuracy of 94% and AUC Score of 0.90.

Keywords: *smart farming; WSN sensors; IoT; shallot farming; enrekang*

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1. Introduction

Shallots are the biggest vegetable commodity in South Sulawesi Province in 2022, accounting for 26% of total vegetable production. The highest cultivation of shallots in this province is in Enrekang Regency, with 146.690 tons [1]. Despite this massive production, shallot cultivation in Enrekang is still very conventional. It requires the very intensive care of the farmers particularly for its watering system. Shallots grow slowly on land that is too dry, and the harvest may be much lower. However, shallot bulbs will get rotten if over-watering [2]. Because of that, many farmers fail to grow shallots until the harvest season.

Another difficulty of shallot cultivation is pests such as wombs, butterflies, and leaf miners. These pests may cause a total failure of the cultivation. Farmers frequently spray pesticides either in the morning or afternoon to prevent these pests. As they use sprinkles for watering the cultivation, the water will wash pesticide on the leaves of the shallots. Therefore, every time they spray pesticide, they must postpone irrigation even though the soil is too dry.

Most of the time, the shallot irrigation happened in the midday. This practice is not suggested because when the temperature is higher and the humidity is low in midday, soil moisture dries faster due to evapotranspiration. As a result, farmers might provide more water to meet the shallot needs. Therefore, it is important to implement a smart irrigation system with emerging technology to help farmers maintain their irrigation schedule with more efficient water usage.

A combination of IoT and machine learning applies in many agriculture study areas. In [3], authors used decision trees to predict irrigation using three parameters: humidity, soil moisture and temperature from sensors. The prediction result would be sent to the farmers via email. This system reduced water usage for agriculture. In other work done by [4], they developed an irrigation system that used cropland parameters to predict upcoming days' moisture levels by using the KNN algorithm. In addition, the water

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level was measured before turning the water pump on or off. The system's architecture was designed for low memory, so the application would fit all kinds of devices.

In [5], researchers developed a smart irrigation system called SMCSIS for multi-crop to deal with the excessive irrigation problem due to precipitation. The system used sensed data from cropland and climate data prediction-based estimated evaporation to make real-time watering decisions based on predicted soil moisture at the time of precipitation. Evaporation was estimated from an online weather forecast that provided air temperature, wind speed and direction, UV and humidity using the Artificial Neural Network algorithm. The system also applied access control and blockchain technologies to maintain privacy and data integrity.

While the previous research and development of irrigation systems sent binary output (on or off) through applications to the farmers, in this work, we expanded the output to be three options: 1) no water needed, 2) water is required and is efficient to watering, 3) water is required but it is not efficient to water. The first option is when the soil moisture is > 70% according to farmers' experiences in successfully cultivating shallot. The second and the last options are for the scenario when the yield needs irrigation or soil moisture <50%. The difference is that the second option is when the temperature is low and humidity is high while the last option is otherwise. Giving information to farmers about when it is efficient or not to start irrigation will allow them to consider when the irrigation should start for efficient water utility, particularly after spraying pesticides.

This project aims to develop a smart irrigation system that informs farmers when the yield needs irrigation and when the irrigation is efficient in water usage using IoT and machine learning with high accuracy. We used WSN sensors to measure humidity, soil moisture and humidity from shallot yield. We experimented with and analyzed four machine-learning algorithms for predicting precision irrigation from the sensed data. The algorithms were decision tree, random forest, gradient boosting and k-nearest neighbors. A web service with embedded machine learning and a mobile application also has been developed for farmers to read the sensed data from time to time and the prediction result.

2. Research Methods

There are three components built in this research. The first component was WSN sensors and IoT to measure temperature, soil, and moisture from a shallot yield and then send the sensed data to a cloud-based database. WSN and IoT for smart irrigation systems are common technologies used for crop-yield monitoring [6], [7], [8]. The second component is a mobile application that monitors sensed data from the database in real-time. The third application is a web service application with an embedded machine learning system which would predict the irrigation decision from the sensed data stored in the database. The database used for this system was the Firebase real-time database, a real-time NoSQL database that supports various clients. As soon as data is stored in the Firebase database in a JSON format, all connected clients automatically receive the latest data. The architecture is illustrated in Figure 1.

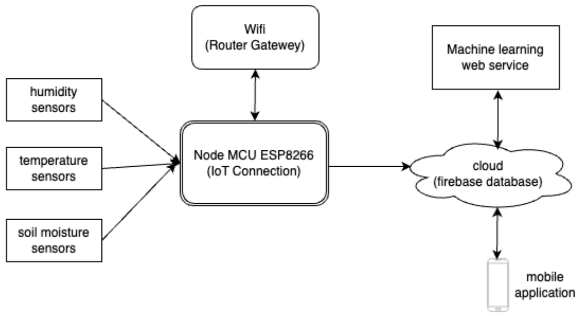

Figure 1. The architecture of the Smart Irrigation System is IoT-based using machine learning

2.1 Dataset

The dataset used to train and test the classification models was collected from sensed data in shallot yield in Malua District, Enrekang, within 16 days of monitoring in August 2023 which was a dry season. During this monitoring, all irrigation decisions were made by the shallot farmer.

The total number of records used was 1.387, splitting into 70% for data training and 30% for data testing. The dataset has been labelled into three classes. They are class 0 for "no water needed", class 1 for "water is required and is efficient for watering" and class 2 for "for water is required but it is not efficient for watering".

The classification method used for this system is one vs the rest. Thus, before the training process, the output class is binarized.

2.2 Hardware Components

Hardware components in this system consist of a soil moisture sensor, humidity and temperature sensor, and a microcontroller NodeMCU ESP8266. The soil moisture sensor is an underground sensor which is resistant to water, while the humidity and temperature sensors are placed above the ground to sense the environment. As this sensor and NodeMCU are not water resistant, these components are stored in a cover box attached to a pole placed in the yield. All sensors would send the captured parameters to the NodeMCU ESP8266. By Installing a wi-fi/router gateway in the yield and connecting the NodeMCU to the Internet, the system would send the data to the Firebase database. The microcontroller has been developed with C++ using Arduino. The sensory system had been developed with C++ using Arduino and tested by [9]. The system successfully worked in such settings. IoT associated with sensory systems for agriculture and farming helps farmers to understand corps' status [10].

2.3. Mobile Application and Web Service Embedded Machine Learning System

Mobile application is the platform developed to inform farmers of the sensed data from time to time as well as the prediction result. This application is connected to the Firebase database and immediately receives the newest data every time the microcontroller sends the sensed data to the database. Every parameter of yield was displayed in a line chart so the farmers could easily read the changes in the yield. This application was developed by using HTML5 and Javascript. With the help of Progressive Web Apps (PWA), this application can be an installed app and can reach any mobile OS such as Android and iPhone with a single codebase.

Web service embedded with a machine learning system was developed by using Flask, a web application framework written in Python. This framework uses the REST API (Representational State Transfer Application Programming Interface) to support interaction between the machine learning system and the Firebase database.

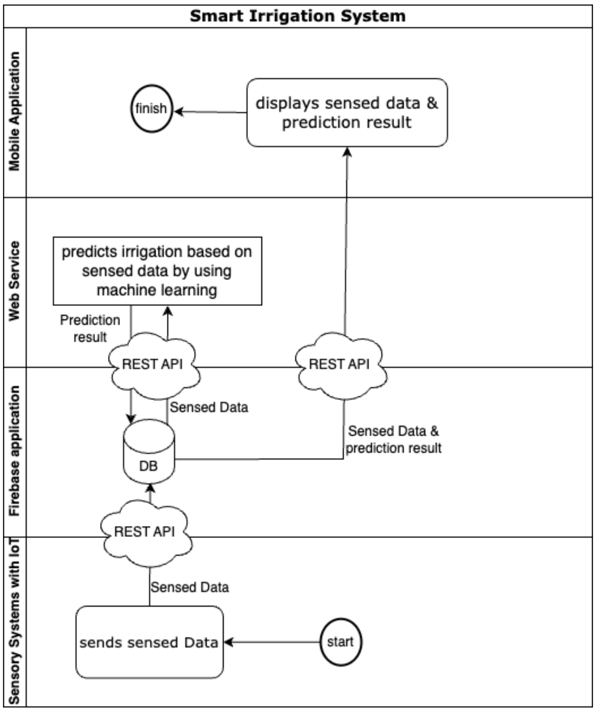

Figure 2. Flow map diagram of smart irrigation systems

Interaction between all applications in this system can be seen in the flaw map in Figure 2. The flow starts from IoT-based-sensory systems collecting the data from cropland and sending the data to the Firebase database. As soon as the data is updated in the database, the Firebase application sends the data to the web service and the mobile application. The Web service embedded with a machine learning system predicts the irrigation based on the sensed data and sends the prediction result to the Firebase. Finally, the Firebase application passes through that result to the mobile application.

2.5 Machine Learning Algorithms

So many machine learning algorithms can be used for classification tasks like this irrigation decision. Therefore, we have to conduct experiments by using several supervised learning algorithms and analyze the performances to consider the preferred model. We used Python and Scikit-Learn library [11] to train and test those algorithms. This research compared and analyzed 4 algorithms namely decision trees, random forest, gradient boosting, and K-nearest neighbors. The algorithms are explained below.

Decision Trees are a supervised machine learning algorithm popular for classification and regression. This algorithm aims to predict an output target by learning decision rules inferred from the data features. It is a tree-structured classifier whose internal nodes represent the features of the dataset, branches represent decision rules and each leaf node represents the target output. Decision Trees tend to overfit data, particularly with a large number of features in the dataset. Since this irrigation system only uses three features namely temperature, humidity, and soil moisture, there is no need to reduce the dataset dimensionality. This classifier succeeded in calculating the water needed for efficient irrigation with the help of sensors gathering data [12].

We used *Gini impurity* to measure the quality of the split. If p_1 and p_2 2 probabilities of the two classes, the gini impurity can be calculated with Formula 1. $Gini\ Impurity = 1 - (p_1)^2 - (p_2)^2$ (1)

Based on the formula, 0 impurity means that all instances belong to the same class and 0,5 impurity indicates that it is completely impure.

Random forest classification is one of the effective prediction algorithms proposed by Breiman in 2001. The random forest classification uses the Law of Large Numbers to control overfit prediction. The classifier's accuracy is gained by applying the right kind of randomness. Estimated by the Out-of-bag technique, this algorithm provides theoretical values of strength and correlation [13]. In the agriculture ecosystem, the random forest was used for crop recommender systems [14], [15], and for PH level detection in water used for irrigation [16].

In this work, we used 100 trees in the forest and Gini impurity to optimize the split of the node. The maximum depth of the tree is not set. Instead, the nodes of the trees are expanded until all leaves contain less than two-sample splits or are pure.

The gradient Boosting algorithm is an ensemble decision tree that can be used for classification and regression. The algorithm aims to subsequently reduce errors from the previous model and this method stands out for its prediction and accuracy, particularly with large datasets and complex features. For classification tasks, the model minimizes loss function by adding weak learners using gradient descent.

In this research, we used log loss as the loss function, which refers to binomial and multinomial deviance. The number of boosting stages is 100 and the criterion (function to measure the quality of a split) is the Mean Squared Error (MSE) with improvement by Friedman [17].

The k-nearest-neighbors classifier is a supervised learning algorithm which is non-parametric and applies proximity to make predictions based on the grouping of individual data points. In other words, this algorithm works by assuming that similar points can be located near one another. KNN algorithm has been utilized for variety classification including for smart irrigation systems [18], [19].

In this research, we use KNN with 5 numbers queries and all points are equally weighted in each neighborhood. The metric to use for distance computation is Minkowski distance which is a generalized form of Euclidean and Manhattan distance.

2.6 Evaluation Metrics

It is very important to measure a model of classification performance to consider the best classifier for this task. The model performance is measured by using a percentage of accuracy, AUC-ROC score, and average accuracy of k-fold cross-validation. The performance of the accuracy is measured by using Formula 2.

$$accuracy = \frac{true\ prediction}{total\ prediction} \quad (2)$$

A ROC curve (receiver operating characteristics curve) is a graph illustrating a classifier's performance at all classification thresholds. This curve displays two parameters namely True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds. TPR and FPR can be gained from the Formulas 3 and 4.

$$TPR = \frac{TP}{TP+FN} \quad (3)$$

$$FPR = \frac{FP}{FP+TN} \quad (4)$$

An AUC curve (Area Under the ROC Curve) provides a measure of the entire two-dimensional area underneath the ROC curve. AUC score ranges from 0 to 1. When a classification model predicts 100% incorrect, the AUC Score is equal to 0 and a score of 1 shows that the predictions are 100% correct.

K-Fold Cross Validation is an evaluation metric to assess the performance of predictive models. There are k folds or subsets of the dataset and the dataset is divided into several folds. The predictive models are trained and evaluated for k times using a different fold as the validation set. After that, the average of performances is calculated to estimate the model's generalization performance.

In this study, we divided the dataset into 10 folds and used an evaluation metric of accuracy to score the model performance.

3. Results and Discussions

The following section presents and discusses the result of the study including the sensed data in 16 days to monitor the irrigation solely by the farmer's decision, the evaluation of four selected machine learning performances and the front-end design of the client application.

3.1 Results

After the WSN sensors and IoT were installed in the shallot field, the sensed data was successfully sent to the Firebase database [9]. Table 1 shows some of the sensed data recorded in one full day (August 18, 2023).

Table 1. Sample of sensed data from cropland using WSN Sensors and IoT

Time	Temperature ($°C$)	Humidity (%)	Soil Moisture (%)
01:41:19	21,9	82,7	56,1
02:41:55	20,7	85	56,0
03:47:47	19,8	88	56,5
04:43:10	19,7	87,7	56,4
05:43:42	19,5	88	56,7
06:44:15	19,9	87,6	57,0
07:44:48	24,7	74	56,6
08:45:22	34,2	46	55,5
09:05:41	35,4	46,5	55,2
09:20:52	33,9	47,1	55,0
10:46:30	35,4	44,3	54,6
11:47:04	35,3	46,5	55,0
12:47:46	30,2	58,7	56,2
13:48:12	32,8	55,4	56,8
14:48:42	33	52,6	55,6
15:24:03	31	56,2	56,0
16:49:40	27,9	58,4	58,1
17:40:21	26,6	57,6	57,8
18:40:53	26,1	58,9	58,4
19:41:28	25,3	62,7	58,5
20:42:45	24	70,1	58,3
21:43:29	23,6	73,5	58,2
22:59:09	22,1	77,5	58,5
23:14:16	21,5	80,2	98,4

From Table 1, it can be interpreted that the increased percentage of soil moisture significantly from 58,5% to 98,4% within 15 minutes (from 22:59:09 to 23:14:16) was caused by the irrigation as there was no rain.

The sensed data from shallot yield was downloaded from the Firebase database and then processed and analyzed. The line charts of the average soil moisture, humidity, and temperature every hour are depicted in Figures 3, 4 and 5 respectively. Based on the line chart of soil moisture in Figure 3, it can be seen that the highest average soil moisture was 74% at night around 08:00 p.m., and the lowest point was 58% at midday around 10.00 a.m. From the line chart, it can be inferred that the average irrigation schedule done by shallot farmers happened from 10.00 a.m. when the temperature hit the highest level and the humidity fell to the lowest percentage. Also, the soil moisture needed for growing shallots in this village is between 50% and 70%.

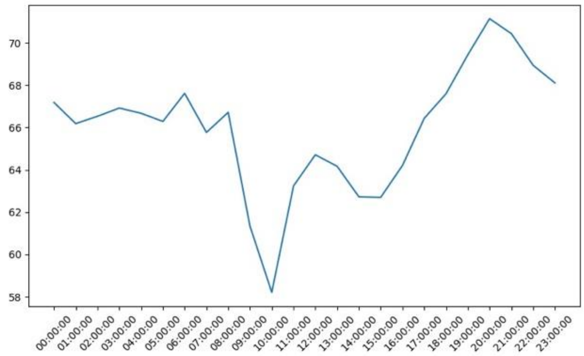

Figure 3. The average soil moisture in percentage per hour

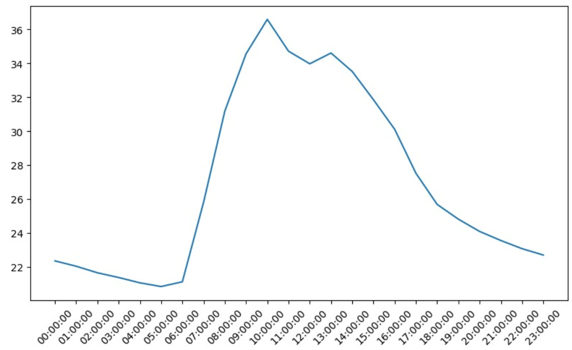

Figure 4. The average temperature in degrees Celsius per hour

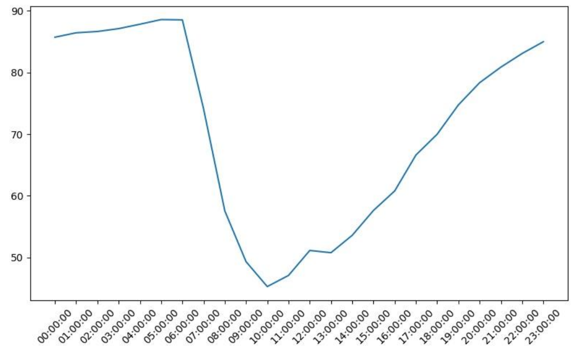

Figure 5. The average humidity in percentage

In terms of temperature in Figure 4, the lowest average temperature is 20 degrees Celsius, happening at dawn time, around 05.00 a.m. and the highest average temperature is at midday around 10.00 a.m. of 37 degrees Celsius. Temperature affects humidity significantly. The hottest the temperature, the lower the humidity and vice versa as can be seen in Figures 4 and Figure 5. After analyzing the sensed data, we evaluated four supervised learning algorithms trained using the dataset above. The performance of these algorithms can be compared in Table 2.

Based on the experiments, show that the performances of four different machine learning algorithms on this dataset are almost equally good. The percentages of accuracy for all algorithms were higher than 0.9 and the AUC scores were between 0.88 and 0.90. The highest accuracy is gained by using the random forest classifier with 0.94 and the lowest accuracy was the gradient boosting, with 0.90. We also compared this accuracy with k-fold cross-validation and found that the average accuracy of the decision tree, gradient boosting and KNN is less than 0.9. Only the random forest could gain an average accuracy of 0.9.

Table 2. Model Testing results of different machine learning algorithms

Classifier	Accuracy	AUC Score	K-Fold Cross Validation (mean of accuracy score)
Decision Tree	0.93	0.90	0.87
Random Forest	0.94	0.90	0.90
Gradient Boosting	0.90	0.87	0.81
K-Nearest Neighbors	0.92	0.88	0.86

Finally, the mobile application has been designed and built to help farmers monitor their shallot yield as well as to read the prediction result. The application used a single codebase with HTML5 and Javascript. Figure 6-8 displays the proposed front-end application.

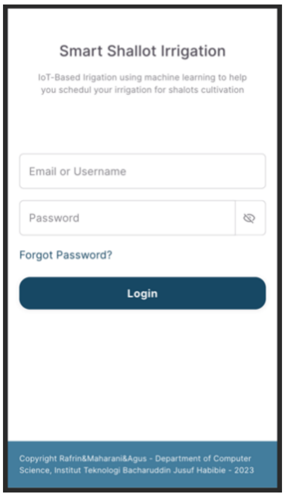

Figure 6. The login page.

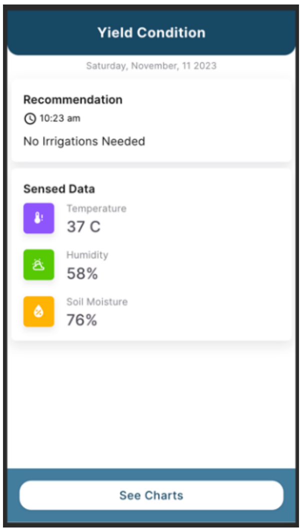

Figure 7. The Dashboard page provides information on sensed data and irrigation recommendations by the smart system

The mobile application consists of four pages. The first one is the login page (Figure 6). This page is to secure access so only the owner of the cropland can read their data.

The second page is the dashboard page where all sensed data from yield such as temperature, soil moisture and humidity as well as the recommendation of irrigation are displayed. Users also can see the data history by clicking the *See-Charts* button. The screenshot of this page can be seen in Figure 7.

The last page is the line charts of the changes of sensed parameters in real-time in Figure 8. This chart will help farmers understand the changes in their yield.

Figure 8. A page displaying line charts of sensed data informing the condition changes of the yield

3.2 Discussions

Like all smart systems, the result of models depends on the dataset. In irrigation systems, a smart system built for some areas may not be applicable in other areas due to the differences in atmosphere, soil texture and minerals, climate etc. Therefore, the success of sensory systems in the yield will lead to the system's ability to make predictions.

The designed sensory system assisting with IoT has been installed in a shallot yield in Malua District, Enrekang. It has gathered real-time parameters such as temperature, humidity and soil moisture and stored them in the database. The sensed data collected from the yield proved that the proposed architecture has connected and has succeeded in collecting and sending data from time to time. After receiving the sensed data, the firebase immediately sent them to both client applications: web service embedded with machine learning and mobile application. Such a system allowed users to read the latest data much faster without the user controlling the apps or sending a request.

We have trained and tested four different supervised learning algorithms using the dataset collected from the yield. The random forest and decision tree algorithms stand as the two highest performances for this task. (AUC score for both: 0.9, random forest accuracy: 0.94 while decision tree accuracy 0.93). We also compared this accuracy with k-fold cross-validation, and found that the performance of random forest is quite stable at an average of 0.90 of accuracy. Meanwhile, the decision tree only achieved an average accuracy of 0.87, KNN was 0.86, and gradient boosting was 0.81. Therefore, it is visible that the performance of the random forest outweighed the decision tree, KNN and gradient boosting algorithm.

The outcome suggested that the random forest classifier was more accurate in this task with an accuracy 0.94, average accuracy of k-fold cross validation 0.90 and AUC score 0.90. All these scores indicate that the prediction is almost all correct. The results make the system more potentially applicable for precision irrigation systems.

This system was not designed to be able to control water pumps on or off automatically like some smart irrigation systems in [20], [21], [22]. These systems only evaluated atmospheric parameters and yield conditions to decide irrigation yet avoided pest prevention. However, in actual farming practice, pest prevention by spraying pesticides cannot be done simultaneously with irrigating using sprinkles. Designing an automatic irrigation system without synchronizing pesticide utility may not be a best practice for shallot cultivation.

The system developed here also cannot predict the irrigation and pest prevention schedule because it is not integrated with a pest detection system. This system only gives recommendations of whether it is efficient or not to start irrigation even though it is needed because in shallot cultivation in Enrekang, farmers tend to postpone their irrigation until midday to allow pesticides to dry. Therefore, farmers' decision is still needed according to their practice, and the recommendation of efficient irrigation will provide consideration to them.

4. Conclusions

The research has been conducted in Enrekang Regency, South Sulawesi Province, Indonesia. The proposed architecture has successfully gathered cropland conditions through IoT-based sensors, sending the sensed data to the Firebase database, which forwarded the data to the web service and the mobile application. The best algorithm for the recommender system on this dataset was the random forest compared to other algorithms (the decision tree, gradient boosting, KNN). The random forest showed high performance with an AUC score of 0.94 and the average accuracy of k-fold cross-validation was 0.9. The mobile application informed the farmers whether the cropland was too dry or not and whether it was efficient to start irrigation. The information given will help the farmers consider when the best time to schedule irrigation is to use more efficient water usage. This system is applicable in real shallot farming.

From this research, we suggest that future work is to develop a smart irrigation system integrated with smart pest detection to help farmers manage irrigation alongside pest prevention.

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