Prediction Method of Plant Irrigation Timing Considering Data Imbalance

Ryosuke Mizuno[1], Masaya Goto[1] and Hiroshi Mineno[1,2]
[1]Graduate School of Integrated Science and Technology, Shizuoka University, Japan
[2]Research Institute of Green Science and Technology, Shizuoka University, Japan

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Abstract: Predicting the plant irrigation timing is an essential task in the domain of agriculture. A model that can predict the irrigation timing in tomato cultivation can assist new farmers who do not have sufficient experience and intuition. In this study, we propose an irrigation timing prediction method based on past irrigation data, environmental data, and plant water stress using a Random Forest model, which is a general machine learning method. Our proposed model reproduces irrigation decision making by an expert farmer for new farmers. Furthermore, we propose a method for resolving imbalances, focusing on the change in the characteristics of the state of plants due to irrigation. This is because irrigation timing data has a large imbalance, which is known to be difficult to formulate. Our proposed model clarifies the characteristics of the irrigation class, and can suppress its misjudgment. We evaluated the proposed method using tomato cultivation greenhouse data in Shizuoka, Japan. The results show a recall of 92% and f-measure 69% and hence, the irrigation timing can be predicted with high accuracy. In addition, the results show that the model works effectively to automatically determine the irrigation timing in greenhouse tomato cultivation.

1 INTRODUCTION

The internet of things (IoT) and artificial intelligence technology have been advanced and spread, and computers now support human decision making. In the domain of agriculture, several studies have been conducted to address the problems arising from the aging of the farmer population and the lack of heirs. These studies can be categorized as: studies to support the work process of farmers using technology (Vasconez, Kantor, & Auat Cheein, 2019), and studies to formulate and mechanize the decision making of farmers (Yukimasa et al., 2017; Navarro-Hellín et al., 2016).

Studies to support and mechanize the work performed by farmers use sensors, robots, and IoT technology to make farming efficient. For example, a farmer can monitor and control a farm without even visiting it by checking and controlling the sensors installed on the farm through the web or a smartphone (Capraro, Tosetti, Rossomando, Mut, & Serman, 2018; Joaquín,Gutiérrez, Jua, Francisco, Aracely, & Miguel, Porta-Gándara, 2015). In addition, by using autonomously operated tractors and drones, crops can be harvested without the farmer's effort and agricultural chemicals can be efficiently sprayed with little effort (Vasconez et al., 2019).

Studies to formulate and mechanize decision making of farmers reproduce advanced cultivation techniques based on farmer's experience and intuition. For this, the plant status, which is complex, is analyzed and quantified using various sensing data, such as temperature, humidity, scattered light, plant image, evapotranspiration, and plant water stress. In particular, a few studies z (Yukimasa et al., 2017; Liu et al., 2017; Peng et al., 2019) have formulated the decision-making with small and frequent irrigation which is known as water stress cultivation. This is convenient to automatically cultivate high-quality fruits and crops. Peng et al. (2019) proposed a crop water demand prediction system by using the back propagation (BP) neural network. The BP neural network was trained using various environmental data such as the solar radiation, soil moisture, soil electrical conductivity, and temperature. The water demand was evapotranspiration calculated by the Penman-

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FAO formula (Liu et al., 2017). In order to realize automatic cultivation, it is necessary to determine the predicted water demand threshold based on appropriate irrigating timing. Determining the threshold value is difficult for new farmers because this requires experience and intuition cultivated over a long period of time. Yukimasa et al. (2017) proposed a model for predicting future plant water stress by using the Sliding Window-based Support Vector Regression (SW-SVR). The method was evaluated using environmental data inside the greenhouse and image data being generated from the movement of plant leaves. This study made it easy to understand future water stress using a simple and economical sensor. In addition, the model can understand the water stress from the data of the cultivation environment. Therefore, not only expert farmers, but also, new farmers who do not possess sufficient experience of cultivation can understand the water stress with the prediction of future water stress by this method. However, in order to realize automatic cultivation, it is necessary to determine the predicted water stress threshold based on appropriate irrigating timing likewise Peng et al. (2019).

We propose an irrigation timing prediction method based on past irrigation data, environmental data, and plant state data by using machine learning. Our proposed method reproduces irrigation decision making by experts and helps new farmers. Furthermore, we propose a method that resolves imbalances by focusing on the change characteristics of the state of plants from irrigation. This is because the small and frequent irrigation data such as that of the cultivation of tomato and strawberry has a large imbalance that is known to be difficult to formulate. The small and frequent irrigation is conducted approximately 50 times (total time is approximately 50 minutes) during the day, and non-irrigation accounts for the major part of the day.

This paper brings two key contributions to the field of agriculture research: (1) New farmers can achieve automatic cultivation of fruits of high quality. This is because the proposed model uses IoT devices in the greenhouse. (2) Our proposed model leads to the technology development of modeling of small and frequent irrigation with data imbalance in the domain of agriculture.

The rest of the paper is organized as follows: Section 2 presents a discussion of related techniques of resolving imbalanced data. Section 3 describes the proposed method. Section 4 presents the results from the evaluation of the proposed method using actual agricultural data. Finally, we present the conclusions and future work in Section 5.

2 TECHNIQUES TO RESOLVE IMBALANCED DATA

To solve the imbalance of datasets is an important task in predicting irrigation timing using machine learning. There are a few methods to solve data imbalance such as classifier level methods and data level methods.

Classifier level methods are cost-sensitive learning methods that vary the error transmitted to each class. Cost-sensitive learning methods assign weights to the samples to match a specific data distribution. Weighting by inverse class frequency (Chen, Change, & Xiaoou, 2016; Yu-Xiong et al., 2017) has often been adopted. To rephrase, the minority data which is difficult to classify, weights the penalty. In our evaluation, we adopt cost-sensitive learning, in which the reciprocal of the ratio of minority data to the number of data points is multiplied as a penalty for errors in the minority data.

Data level methods are data sampling techniques. Two types of sampling techniques are shown in Figure 1: oversampling methods that increase the number of minority data and undersampling methods that reduce the number of majority data. Oversampling methods add or reuse new data to increase the minority data. Random sampling repeatedly samples from the minority data. Synthetic Minority Over-sampling Technique (SMOTE) (Chawla et al., 2002) and Adaptive Synthetic Sampling (ADASYN) (Haibo et al., 2008) share the concept of generating new data on a line connecting minority data. SMOTE adds a random number multiplied with the sample on the line connecting the selected minority samples. In ADASYN, the value to be multiplied is determined according to the number of majority data contained in the K neighbors of the selected minority sample. Therefore, ADASYN reduces the frequency with which minority data is generated near the majority data. However in irrigation timing data, the minority data is similar to the majority data, and hence, we consider the data generated near the majority data.

Undersampling methods eliminate a few samples from the majority data. Random sampling randomly

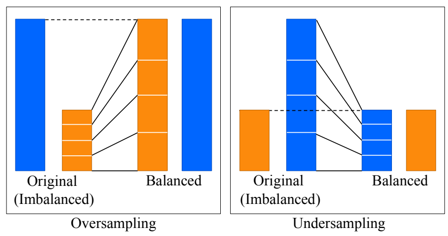


Figure 1: Addressing imbalanced data with resampling.

Algorithm 1: Undersampling for eliminating data based on near irrigation timing.

Input:

Imbalanced dataset： $D_{imbal} = \{(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_N, y_N)\}$ $where\ x_i \in X,\ y_i \in Y$

Distance parameter： *n, m*

Output:

Balanced dataset: $D_{bal} = \{(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_N, y_N)\}$ $where\ x_i \in X,\ y_i \in Y$

Definition of Undersampling for eliminating data based on near irrigation timing:

For *t=1* to *N*

    if y_t is irrigation

        Eliminate non-irrigation data for period $(t-n)$ to $(t-1)$

        Eliminate non-irrigation data for period $(t+1)$ to $(t+m)$

D_{bal} ← Remaining data not eliminated

determines the samples to be removed from the majority data. NearMiss algorithm (Jianping & Inderjeet, 2003; Yen & Lee, 2009) uses the K-nearest neighbor method to remove clearly identifiable majority data. This eliminates data that is difficult to distinguish from between the minority class and the majority class. Therefore, it is possible to separate the details of the decision boundary by using data after applying the NearMiss algorithm. However, it is difficult to determine the parameters of the K-neighbor method using NearMiss. This is because the irrigation timing data has a characteristic minority data and majority data that are similar. We consider that undersampling is suitable for resolving irrigation data imbalance. Therefore, we propose an undersampling method considering the characteristics of the irrigation data of plants. This is because the farmer does not irrigate depending on the moisture state of the plant even at the same temperature. Irrigation is performed depending on the amount of solar radiation and season even in different plant water states. Therefore, we consider it better to reduce the data so that the irrigation class and the non-irrigation class are clear rather than increasing the data using oversampling or by considering the cost.

3 MODEL DESCRIPTION

We propose a method for resolving imbalances suitable for irrigation timing to build the model. We aim to build the model to predict the irrigation timing by farmers using the environmental data of the greenhouse and hereby, reproduce the irrigation timing automatically. Furthermore, we aim to automatically cultivate by controlling IoT devices, which are able to control the irrigation timing in the greenhouse based on the proposed method. The process is composed of two main elements to build the irrigation timing model. First, we address the imbalance of irrigation timing data by using undersampling for eliminating data based on near irrigation timing (ENIT). Next, we build the model to predict the irrigation timing using the balanced data after solving imbalance. Section 3.1 presents the algorithm of ENIT and Section 3.2 presents the irrigation timing prediction method using machine learning.

3.1 Addressing Irrigation Data Imbalance

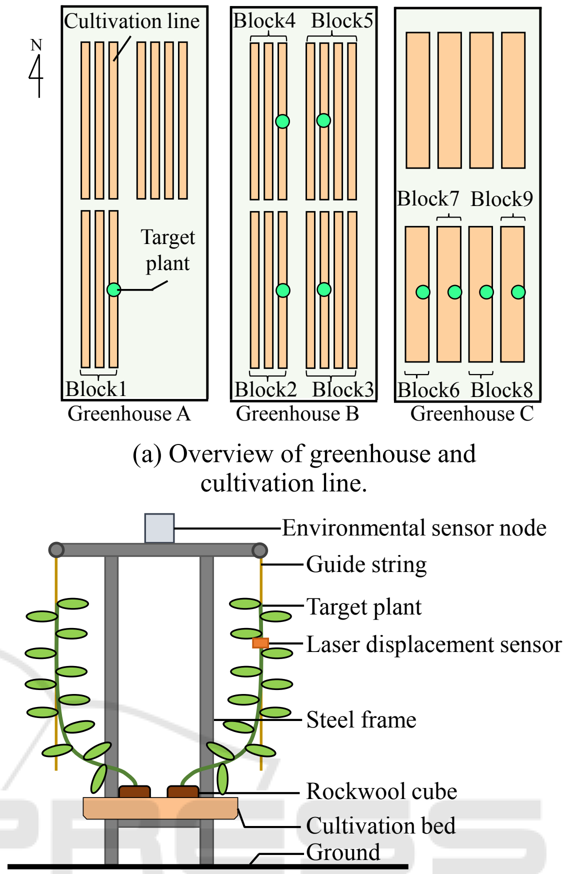
We address the imbalance in the irrigation timing data by using undersampling for eliminating data based on near irrigation timing (ENIT) to eliminate the data of majority class (non-irrigation data) near the time of the data of minority class (irrigation data) (Algorithm 1). It may be noted that the irrigation timing data is imbalanced because the frequency of irrigation time is approximately 50 (total time is approximately 50 minutes) during the day, and non-irrigation accounts for the major part of the day. One of the decisions on irrigation timing is to use the value of solar radiation accumulated from the previous irrigation (Takayoshi et al., 2018). Similarly, the value of evapotranspiration is used for the decision on irrigation timing (Pawlowski et al., 2017; Peng et al., 2019). Irrigation is performed when the accumulated value exceeds the threshold. Therefore, we have considered that the plant state at the time of irrigation and the plant state in the past direction for a certain period of time from the start of irrigation are similar. The accumulated environmental data, for example temperature and evapotranspiration from the last irrigation, are also assumed to be characteristically similar. In addition, we have considered that the state of the plants near irrigation are similar because irrigated plants need time to absorb moisture from the soil through the roots and through evapotranspiration from the leaves to allow water to enter the body. For this reason, we have eliminated the data of the majority class (non-irrigation class) which is near the data of minority class (irrigation timing class) by using ENIT. ENIT is an undersampling method that removes the non-irrigation data that is nearer in the time series based on irrigation timing, and the algorithm is shown in Algorithm 1. In the ENIT algorithm, when the duration of irrigation timing is t, the non-irrigation data represented by $(t\text{-}n), \cdots, (t\text{-}1)$ is eliminated for the parameter n in the past direction and the non-irrigation data represented by $(t+1), \cdots, (t+m)$ is eliminated for the parameter m in the future direction. As a result, the non-irrigation class data that has similar characteristics to the irrigation class is eliminated by selecting the data from the non-irrigation class of the majority based on the irrigation class of the minority. In addition, the characteristics of the irrigation class are clarified and misjudgment is suppressed.

3.2 Predicting the Irrigation Timing

We have used Random Forest (RF) to predict the irrigation timing when irrigation is necessary. The RF is one of the general machine learning methods and is an ensemble learning method combining multiple decision trees. An ensemble learning method is a modeling method that consists of a combination of prediction of multiple classifiers rather than the prediction of a single classifier. By applying ensemble learning, the predictive value is diverse and can be predicted robustly for unknown data. Therefore, we have adopted ensemble learning in order to make a robust prediction model.

4 EXPERIMENTAL PROCEDURE

In this section, we describe the dataset of the experiment for evaluation, the experimental parameters, and the results.



(a) Overview of greenhouse and cultivation line.

(b) Layout of measurement sensors.

Figure 2: Dataset collection environment.

4.1 Data Collection and Preprocessing

A system was developed to collect agricultural data in a greenhouse of tomato (*Solanum lycopersicum L.* cultivar Frutica) at Fukuroi, Japan. We installed environmental sensor nodes, laser displacement sensors (HL-T1010A Panasonic Corporation), and a datalogger (midi LOGGER GL840 Graphtech Corporation) on the greenhouse. An overview of the greenhouse and cultivation line and the layout of measurement sensors are shown in Figure 2 (a) and (b), respectively. Environment data such as temperature, relative humidity, solar radiation, and vapor pressure deficit (VPD) was collected along with the data of the plant stem-diameter and irrigation timing. Drip irrigation was used in which a certain amount of water was released in one irrigation. In addition, time series features related to water stress and tomato irrigation were calculated to create datasets. Stem-diameter represented the plant growth and water stress. However, Kazumasa et al. (2019) showed that the diameter could not be used as a water stress index directly because it changed with the growth of the plant and diurnal variation. Therefore, we have defined the difference in stem diameter calculated using the most recent irrigation (DSR) as a water stress index in accordance with the work of Kazumasa et al. (2019). The DSR is a value calculated by subtracting the current stem diameter from the maximum stem diameter. The recent irrigation in current time *t* is calculated as follows:

$$dsr_t = max(stem_{t-n}, stem_{t-n+1}, \ldots, stem_t) - stem_t. \quad (1)$$

Where *t* is the current time and *n* is the time elapsed since the most recent irrigation. Additionally, we have defined the time series features such as the elapsed time since sunrise, elapsed time since the previous irrigation, and accumulated environmental data from the previous irrigation. This is because Kazumasa et al. (Kazumasa et al., 2018) showed that the machine learning method without recursion can be improved by considering the time series features. Table 1 shows the features of the dataset that were finally calculated. All data were collected at a frequency of once every minute and during the periods A (from March 28 to October 22, 2018 in greenhouse A), B (from October 23, 2018 to January 16, 2019 in greenhouse B), and C (from April 25 to June 20, 2019 in greenhouse C). During periods A, B, and C, the irrigation data was collected for one, four and four blocks, respectively. Therefore, we have collected irrigation data for nine blocks, or to paraphrase, datasets were created for nine different scenarios.

4.2 Experimental Condition

We have evaluated the performance of the proposed method using actual agricultural data. In the evaluation, the prediction accuracy of the irrigation timing was compared by using environmental data related to the irrigation of tomato as shown in Table 1. The recall and f-measure were used as error indicators when the threshold for classification judgment is 0.5 (50%). Recall shows the rate at which the irrigation timing predicted by the model matches the irrigation timing by the farmer. F-measure shows the accuracy and completeness of the irrigation timing predicted by the model. The conditions are detailed in Table 2. There are seventeen different conditions: no addressing of imbalance, cost-sensitive learning, three oversampling methods, two undersampling methods, with and without ENIT before applying undersampling method, and changing the undersampling rate. The important parameters of the RF method were tuned by using grid search:

Table 1: Features of dataset.

Type	Feature
Environmental data	Temperature Relative humidity Solar radiation Vapor pressure deficit
Plant water stress	Stem-diameter DSR
Time-series feature	Elapsed time since sunrise Elapsed time since last irrigation Accumulated Environmental data

Table 2: Evaluation condition.

Name	Address imbalanced
Base	No
Cost	Inverse Class Frequency
OverRandom	RandomSampling
SMOTE	SMOTE
ADASYN	ADASYN
UnderRandom02* UnderRandom04* UnderRandom06* UnderRandom08* UnderRandom10*	RandomSampling
ENIT_UnderRandom10*	ENIT & RandomSampling
NearMiss02* NearMiss04* NearMiss06* NearMiss08* NearMiss10*	NearMiss-1
ENIT_NearMiss10*	ENIT & NearMiss-1

*: "02" means that the number of minority data is 2 when the number of majority data 10 and "10" means balanced between majority data and minority data.

Table 3: The number of training and validation data points.

Name	The number of data points (Non-irrigation/irrigation)
Base, Cost	231,250 / 11,047
OverRandom,SMOTE,ADASYN	231,250 / 231,250
UnderRandom02, NearMiss02	55,235 / 11,047
UnderRandom04, NearMiss04	27,617 / 11,047
UnderRandom06, NearMiss06	18,411 / 11,047
UnderRandom08, NearMiss08	13,808 / 11,047
UnderRandom10, NearMiss10, ENIT_UnderRandom10, ENIT_UnderRandom10	11,047 / 11,047

n_estimators (10, 20, 30) and max_depth (15, 20, 40). In addition, we set the ENIT hyperparameter *n* and *m* to 2.

Evaluation data such as training, validation, and test data were divided as per the following procedure. First, the data set was divided into periods A to C. Next, a day was calculated that included 80% of the total number of irrigations in each period. The data of the period after that date was set as the test data. For training and validation data, the data excluding the test data was divided into 5 parts, and 5-fold cross validation was applied. In addition, from the test and validation data, the majority data was deleted to random to create equilibrium data to obtain the correct accuracy. The number of test data points were 4,896 (of which 2,448 were irrigation data). The number of training and validation data points before 5-fold cross validation were shown in Table 3.

4.3 Results and Discussion

Figure 3 shows the errors of each comparison for the testing data. The combination of the proposed method and NearMiss has the highest score for both recall and f-measure: 0.92 recall and 0.69 f-measure. Only NearMiss has a score of 0.91 recall and 0.69 f-measure. In addition, the combination of the proposed method and random undersampling scores better than only random undersampling. This is because, the combination of the proposed method and random sampling and only random sampling have a score of 0.78 recall and 0.69 f-measure and 0.71 recall and 0.66 f-measure, respectively. These

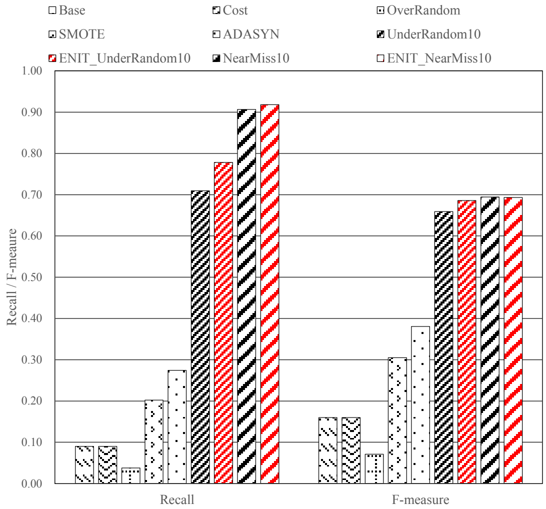


Figure 3: The results of each approach for imbalanced data.

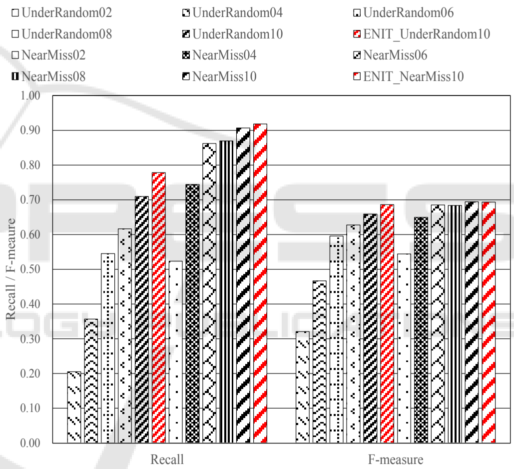


Figure 4: The results of undersampling with changing rate.

results show that the proposed method works effectively. In addition, the results show that undersampling is superior to cost-sensitive learning and oversampling. Random oversampling is considered to be inaccurate because irrigation data that provide useful features are not selected. In SMOTE and ADASYN, the data is generated on a line connecting minority data. Therefore, minority data may be generated in the majority area. However, undersampling by NearMiss, which has the highest accuracy, does not generate data near the majority data. NearMiss has the characteristic that the majority data near the decision boundary is unchanged when ideal processing is performed. Therefore, the model using NearMiss learns detailed decision boundaries and the accuracy is improved.

Figure 4 shows the result of changing the sampling rate of undersampling. Both random sampling and NearMiss increase in accuracy as the sampling rate increases. To paraphrase, the accuracy is higher for the cases having data closer to the balanced data. In particular, ENIT_UnderNearMiss10 has a recall of 0.92 and can predict irrigation timing with high accuracy.

5 CONCLUSIONS

We proposed a novel method for resolving imbalances suitable for irrigation timing and its prediction. We addressed the imbalance of irrigation timing data by using undersampling for eliminating data based on near irrigation timing (ENIT), to eliminate the non-irrigation data near the time of irrigation. The performance of the proposed method was evaluated using actual agricultural data. In the evaluation, the prediction accuracy of irrigation timing was compared by using environmental data related to the irrigation of tomato. In the results, The accuracy was improved by the two methods that applied the proposed method. We showed that the prediction accuracy of small frequent irrigation can be improved by applying the method for eliminating imbalances that takes into account the characteristics of irrigation timing data. This result shows that it is necessary to eliminate the imbalance in the prediction of irrigation timing. Furthermore, the result shows that it is effective to consider irrigation characteristics to eliminate imbalance. The aim in future is to automatically cultivate various crops by controlling through IoT devices, which are able to control the irrigation timing in greenhouses based on the proposed method. IoT technology has already been introduced in the agricultural domain.

In future, we will evaluate the general purpose of the proposed method under various conditions with different greenhouses, cultivation methods, and water supply. In addition, the prediction model will be examined. Specifically, the application of Long-Short Term Memory (LSTM) (Sepp & Jurgen, 1997), which is one of the most powerful deep learning methods, will be considered. LSTM can be considered for irrigation timing because it can consider long-term time series. In addition, we will consider Dynamic Time Warping (DTW) (Bemdt & Clifford, 1994) to error indicator. Recall and F-measure are evaluated for one point in time without considering time series. Thus, a model that is off by only one point in time and a model that cannot be predicted at all are both incorrect. Therefore, we evaluate the similarity between two time-series sequences using DTW.

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