Microcilmate-Based Predictive Weather Station Platform: A Case Study for Frost Forecast

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***Abstract*—Severe weather conditions decrease agricultural productivity. Recent years have witnessed a plethora of IoT solutions beneficial to various application domains. This paper presents a predictive IoT weather station platform for smart farming. Specifically, we built an online frost forecasting service that collects microclimate data from weather stations in real-time and provides frost forecasts for the next day using several machine learning algorithms. The proposed system can effectively help boost agricultural productivity by providing farmers with more accurate frost forecast, thereby reducing the risk of frost damage.**

***Index Terms*—IoT, machine learning, microclimate, frost prediction**

I. Introduction

Severe weather conditions decrease agricultural productivity in many countries around the world. In the agriculture industry, advanced decision support through IoT (Internet of Things) technologies is gaining attention as it enables precision farming. Smart agriculture based on microclimate data analysis helps improve productivity, avoid unnecessary costs related to harvesting, and use proper pesticide and fertilizers [1], [2].

A microclimate is a distinctive climate of a small area where the atmospheric conditions such as temperature and humidity are different from those in the surrounding area due to geographical characteristics. Table I shows a comparison of the global climate collected at the meteorological station and the microclimate collected at four weather stations. There is a noticeable difference between the global and the microclimate data in terms of RMSE (Root Mean Square Error). The RMSEs of temperature are between 3.47 and 3.84. The RMSE of the humidity ranges from 16.28 to 24.75. This is because meteorological stations are located farther from the crops whereas the microclimate is measured near the crops, hence there is a difference in altitude, humidity, and other conditions between the global and microclimate measures.

Among several climate effects impacting agricultural yields, frost, especially during the flowering period, can harm the blossoms, resulting in significant crop failures [3], [4]. To avoid this problem, Matzneller et al. [4] developed four empirical functions which indicate possible frost damages on sweet cherry buds. If there were an accurate frost forecast, it would be possible to prevent damages from frost proactively, e.g., by driving a fan around the crop. Chung et al. [5] forecasted frost using global climate, where the accuracy could have been improved if the temperature close to the crop (microclimate) was used. Crop yields are also sensitive to humidity.

TABLE I
Comparison of microclimate at the reference stations and global climate at the closest meteorological station.

Station	Latitude	Longitude	RMSE Temp	MAX Temp	RMSE Humidity	MAX Humidity
S1	35.98	129.05	3.84	11.18	16.28	49.97
S2	36.03	128.98	3.58	10.76	24.75	49.3
S3	36.13	128.94	3.47	10.17	23.1	51.6
S4	36.11	128.88	3.5	11.14	23.96	52

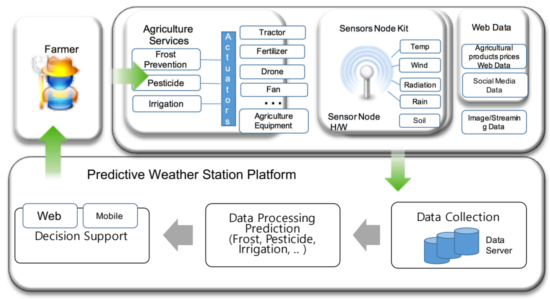

Fig. 1. The architecture of predictive weather station platform.

To forecast frost more accurately, several prior studies used microclimate data such as temperatures measured at lower altitude, grass minimum temperature, diurnal, average relative humidity, minimum relative humidity, mean wind speed, etc [5], [6]. The grass temperature is measured using thermometers just above the grass, about 10cm above ground. In [7], the authors used the cloud cover, the atmospheric temperature measured at midnight, and 5-day precipitation and predicted the possibility of frost with 87% of accuracy. It is, however, difficult to automatically gather the total amount of cloud.

II. Proposed predictive weather station platform

Our predictive weather station platform, depicted in Fig. 1, collects microclimate information around crops as well as crop images and global weather information from the web. Currently, all sensor data are collected every minute and summarized as hourly averaged formats in a remote database. Solar radiation is calculated as cumulative light intensity per day. As shown in several recent studies, temperature inversion plays an important role in determining the formation of precipitation. As a result, convection produced by the heating of air from below is limited to levels below the inversion, and then frost is highly likely to occur.

We use two measures of thermometer sensor data: one collected from 10cm above the ground (T_g) and the other from 1.5m above the ground (T_a). We then calculate a temperature inversion layer using those two temperatures. The temperature inversion, denoted as *I*, is calculated as follows:

$$\Delta T_t = T_g(t) - T_a(t),\ T_s \leq t \leq T_e. \tag{1}$$

$$I = \sum \Delta T_t, \quad \text{if } \Delta T_t < 0. \tag{2}$$

At a specific time t, ΔT_t is the difference between the grass temperature and the air temperature. We start measuring these temperature changes from 5 PM and continue until 11 PM (our forecast time).

After collecting all these information and calculating ΔT, we performed data analysis on data patterns on days when frost occurred by using five machine learning (ML) algorithms: decision tree, boosted tree, random forest, support vector machine (SVM), and regression. Details about how we applied individual ML are as follows. Given a set of features x_i and a label $y_i \in \{0, 1\}$, logistic regression interprets the probability that the label is in one class as a logistic function of a linear combination of the features, which is represented as:

$$f_i(\theta) = p(y_i = 1|x) = \frac{1}{1 + \exp(-\theta^\gamma x)}. \tag{3}$$

Given the same set of features x_i, and the label $y_i \in \{0, 1\}$, SVM minimizes the loss function:

$$f_i(\theta) = \max(1 - \theta^\gamma x, 0). \tag{4}$$

The decision tree and boosted tree can also be used as a classifier for our purposes. In contrast to linear models like logistic regression or SVM, these algorithms can model nonlinear interactions between the features and the target values. Boosted tree is based on a collection of base learners, i.e., decision tree classifiers, and combines them using a technique called gradient boosting. It should be noted that, in this paper, we do not propose a new ML algorithm but evaluate five widely used ML algorithms on their performance of classifying the presence/absence of frost.

a) Evaluation: For evaluation, we collected frost data in four regions of Yeongcheon, South Korea, from October 1 to November 23 in 2015. The number of actual frost occurrence is 19 out of entire 216 observed data points (54 days per each station). We predict the possibility of frost in the next morning using microclimate data. We use machine learning toolkits available in GraphLab [8] to train and evaluate five machine learning algorithms. We use 80% data for training and the remaining 20% for testing.

Fig. 2 shows the classification results from our dataset. As shown in the figure, the random forest and SVM show the highest F1 scores among all five algorithms we evaluated. The reason algorithms like decision tree and boosted tree did not perform well is that they are less suitable for classifying continuous variables. Based on our analysis, the proposed system can inform the possibilities of frost to farmers in advance such that they can proactively take preventive actions to protect the crops from frost damage.

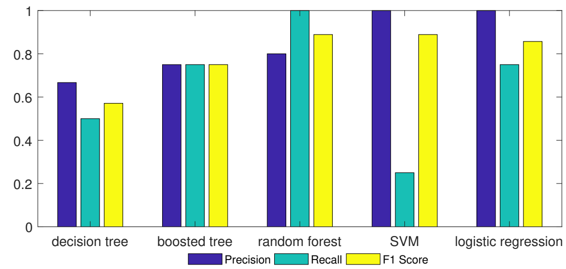

Fig. 2. Performance of proposed frost classification models.

b) User Interface: The proposed platform provides both the web and a mobile services for farmers who can subscribe agricultural services for their farming decisions. We forecast at 11 PM through the web and mobile services so that farmers can proactively implement preventive actions. For farmers who receive forecast services automatically, they are notified with updated, more accurate information at 1 AM. Moreover, it provides an interface for farmers to easily provide the system feedback for more accurate data collection. The location of observation stations are displayed on the map, and frost prediction/occurrence information, micro-weather information, etc., are displayed in real time on our project website[1].

III. Conclusion and Future Work

The proposed platform is successfully deployed in 12 locations and is continuously collecting microclimate data. Subscribed users are notified about accurate frost prediction from the system. In the future, we plan to deploy other forecast services like the spread of crop disease and consider configuring a weather station as a sensor node for scalability [9]. Stations are expanding and data is increasing dramatically, so we will carry out research to improve issues such as data compression in big data.

References

[1] M. Bendre, R. Thool, and V. Thool, "Big Data in Precision Agriculture Through ICT: Rainfall Prediction Using Neural Network Approach," in *Proceedings of the International Congress on Information and Communication Technology*, 2016, pp. 165–175.

[2] R. D. A. Ludena and A. Ahrary, "A Big Data Approach for a New ICT Agriculture Application Development," in *Proceedings of the International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery*, Oct 2013, pp. 140–143.

[3] M. A. K. Jaradat, M. A. Al-Nimr, and M. N. Alhamad, "Smoke Modified Environment for Crop Frost Protection: A Fuzzy Logic Approach," *Comput. Electron. Agric.*, vol. 64, no. 2, pp. 104–110, Dec. 2008.

[4] P. Matzneller, K.-P. Götz, and F.-M. Chmielewski, "Spring frost vulnerability of sweet cherries under controlled conditions," *International Journal of Biometeorology*, vol. 60, no. 1, pp. 123–130, 2016.

[5] U. Chung, H. C. Seo, and J. I. Yun, "Site-Specific Frost Warning Based on Topoclimatic Estimation of Daily Minimum Temperature," *Korean Journal of Agricultural and Forest Meteorology*, vol. 6, no. 3, pp. 164–169, 2004.

[6] Y. Kwon, H. Lee, W. Kwon, and K. Boo, "The Weather Characteristics of Frost Occurrence Days for Protecting Crops against Frost Damage," *The Korean Geographic Society*, pp. 824–842, 2008.

[7] J. H. et al., "Frostfall Forecasting in the Naju Pear Production Area Based on Discriminant Analysis of Climatic," *Korean Journal of Agricultural and Forest Meteorology*, vol. 11, no. 4, pp. 135–142, 2009.

[8] https://turi.com/products/create/docs/graphlab.toolkits.classifier.html.

[9] http://www.mcs.anl.gov/project/waggle-open-platform-intelligent-attentive-sensors.

[1] http://183.106.117.219/. (Korean website)