Spatio-temporal characterization of crop growth with multi-category data based on deep learning

A. Fuentes[1,2], S. Yoon[3], J. Park[1], J. Lee[4], M.H. Lee[5] and D.S. Park[1,2,a]

[1]Department of Electronics Engineering, Jeonbuk National University, Jeonju, South Korea; [2]Core Institute of Intelligent Robots, Jeonbuk National University, Jeonju, South Korea; [3]Department of Computer Engineering, Mokpo National University, Muan, South Korea; [4]National Institute of Agricultural Sciences, Wanju, South Korea; [5]Fruit Vegetable Research Institute, Chungnam A.R.E.S, Buyeo, South Korea.

Abstract

Monitoring plant growth is critical for sustainable agriculture. Traditionally, this complex analysis has been done manually as a trial and error or by growers' perception. Encouraged by the recent advances in precision agriculture and deep learning, we sought further improvements to facilitate the efficient use of resources and avoid losses caused by internal or external conditions that affect the growth process. In this work, we proposed a learnable approach based on deep learning techniques to understand the influence of these factors and automatically determine the appropriate conditions of crop growth in the spatio-temporal domain using multi-category data. To demonstrate the performance of our research, we collected data from various sensors installed in controlled tomato greenhouse environments in South Korea. Our model enables plant growth prediction based on the measured variables and formalizes a systematic and learnable way to analyze the growing conditions of crops by combining spatio-temporal characterization of multi-category data with existing deep learning-based research. The result of this research could potentially help farmers and researchers to understand the changes in the behavior of plants and thus achieve maximum productivity and avoid losses caused during the growth process.

Keywords: deep learning, plant growth modeling, tomato plant, smart agriculture

INTRODUCTION

Monitoring the growing conditions of crops is essential for sustainable agriculture. The interpretation of crop responses to environmental and nutritional factors is facilitated by distinguishing between growth and development. Growth is defined as the increase of biomass and dimensions of a plant or organs in quantitative aspects. Development can be defined as an ordered change or progress toward higher, more ordered, or more complex states (Heuvelink, 2005). During development, a plant is subject to irreversible changes over time (Galieni et al., 2021). It is often possible to visually identify events related to these changes; however, understanding these processes is complex and demands a higher level of expertise, traditionally performed by common intuition or knowledge of the growers or domain experts.

Developmental processes such as stem, leaves, flower development, and fruit ripening strongly impact the plant yield, determined by the quality and quantity of final products (Geelen et al., 2018). To identify such changes, phenotyping is a significant process. For instance, in tomato plants, the color, shape, size of the leaves, stem diameter, and number of flowers are essential information for phenotyping. These changes are immensely variable and influenced by the conditions of the environment. Plants have various ways to respond to changes, which are a complete manifestation of the environment (Yao et al., 2021). To deepen the relationship between phenotyping and the environment and make it more targeted, it is necessary to find a stronger correlation that can help estimate and predict the ideal conditions for plant growth.

Over the last few years, with the emergence of deep learning and computer vision

[a]E-mail: dspark@jbnu.ac.kr

techniques, the study of plants has become a key target for researchers. From these studies, valuable information has been obtained from the plants, such as detecting plant diseases and pests (Fuentes et al., 2017, 2021), counting the number of leaves (Farjon et al., 2021) or detecting fruits (Afonso et al., 2020). With the continuous development of this research area, new challenges and opportunities have further arisen toward understanding plants from different perspectives to enable appropriate crop development throughout their cultivation period (Hemming et al., 2019, 2020). A particular interest has been directed to studying the relationship between phenotyping information and environmental factors. Recent studies have been focused on quantifying these variables to improve cultivation methods, such as crop monitoring (Halstead et al., 2021), water stress study (Kamarudin et al., 2021), optimal control and monitoring of sugar content (Durán-Soria et al., 2020), and assessment of plant growth status (Nagano et al., 2019; Samiei et al., 2020). However, an aspect that has not yet been considered is the potential for establishing a learnable way that can help determine these correlations in data by performing spatio-temporal modeling and, at the same time predicting changes that can occur in response to the present situation. Also, another point to consider is that this research area lacks a complete data set of growth data that associates environment and image data captured through the crop life cycle. Therefore, combinatorial use of multiple sensors to acquire data could enable researchers to non-invasively obtain a series of data sets, including variables related to crop development and physiological responses.

This study investigates the spatio-temporal dynamics of crops using data acquired from multi-category sensors such as environmental, root zone, and images, in a controlled greenhouse environment. Our proposed work enables prediction based on the measured variables and formalizes a systematic and learnable way to understand the growing conditions of crops by combining spatio-temporal characterization of multi-category data with deep learning-based research. We propose an architecture and perform the required experiments on our data set of tomato plant growth. Finally, our study is expected to play an essential role in predicting crop present and future characteristics by mapping the variables and growth principles involved in the cultivation process and facilitating the efficient use of resources while avoiding losses caused by internal or external conditions.

MATERIALS AND METHODS

Multi-category data collection

Our proposed research investigates plant growth using multicategory data collected from our experimental site, a controlled greenhouse environment for tomato production. Multi-category data corresponds to the data obtained from various sources, including 1) environmental data: temperature, humidity, CO_2, and light; 2) root zone data: temperature, moisture, EC; 3) image data: plant state from RGB images (left, right, and top views). Figure 1 illustrates the variables utilized in our study.

To build our data set, this research work was carried out in close collaboration with domain experts in horticulture, who supervised the crop cultivation and control the required parameters involved during the process. The data set was collected during the first cultivation batch of the year, which lasted from January to June, based on the following strategy:

1. Environmental and root zone data acquisition.

The greenhouse site had an automatic control system for nutrition and water supply and sensors such as temperature, humidity, light, and CO_2 to monitor the environmental factors. It also had sensors in the slabs to monitor the root zone, such as EC, temperature, and moisture. Environmental and root zone data were directly obtained from the sensors and the associated control platform during the entire cultivation period. Each variable was measured on a minute basis. Figure 1 shows the variables and their corresponding location in the experimental site.

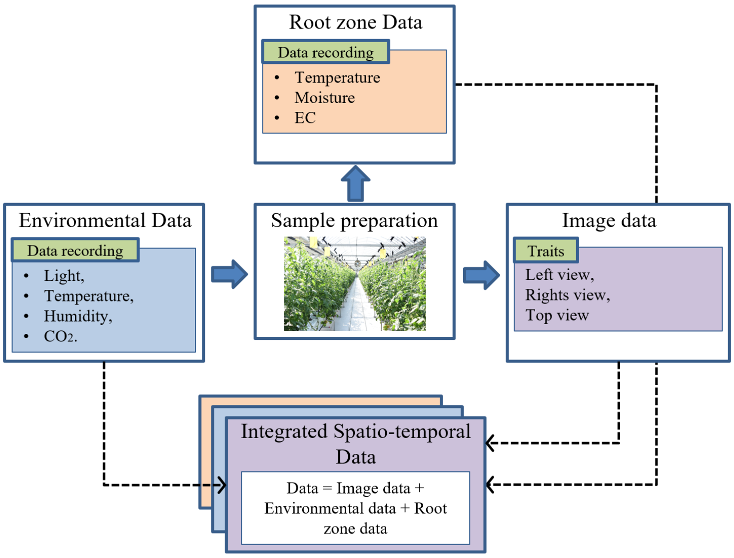
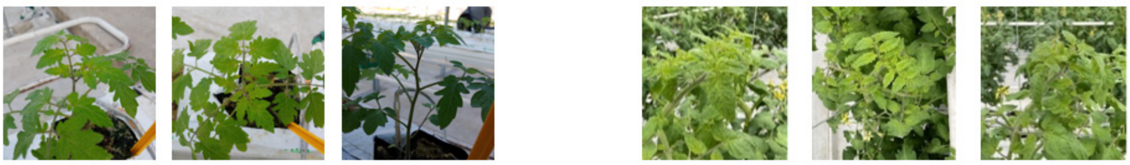


Figure 1. Multi-category data: environmental, image data, and root zone data.

2. Image data.

A number of 100 plants were studied in this research, where half correspond to cherry tomatoes and the other half to 'Amos coli' tomatoes. We captured image data once a week during the entire cultivation period, which lasted for 21 weeks. These images potentially helped evaluate the changes in the plants' visual characteristics and determine possible causes that originate such symptoms. We focused on the stem development at the top of the plant, as this is a particular indicator to evaluate the state of development in tomato plants. We took three pictures of each plant using various RGB camera devices, including left, right, and top views. Figure 2 shows two cases of collected samples at different growth stages.



(a) Cherry tomatoes 1st week (b) 'Amos coli' tomatoes 11th week

Figure 2. Example of the captured images at different growth stages from the left, top, and right views for cherry and 'Amos coli' tomatoes, respectively.

Spatio-temporal model

This part introduces our deep learning-based model that uses multi-category data to work in the spatio-temporal domain. Specifically, we explored the potential of long-short-term memories (LSTM) (Hochreiter and Schmidhuber, 1997) for sequence learning tasks. LSTMs are a special kind of recurrent neural network that incorporates a built-in memory call to store information and exploit long-range contexts. They can learn long dependencies, and when integrated into sequential tasks, LSTMs are not limited to fixed-length inputs or outputs, allowing simple modeling for sequential data of various lengths. Therefore, based on these fundamentals, we identified the following main targets of our model:

1) Given a portion of available time-series data corresponding to a defined period, the spatio-temporal characterization should be able to estimate future situations for any chosen variable;
2) Each estimated variable can be further associated with the conditions of the crop. In other words, this strategy is based on looking back at what happened in the past

growth stages and how this has influenced the current and future plant state.

Figure 3 shows an overview of the growth model for spatio-temporal characterization of environmental and controlled variables. We used environmental and root zone time-series data to model this relationship as input to the system. These data were pre-processed to obtain the desired variables and time-steps posteriorly used by an LSTM network working as a sequential learning task to characterize the relationship in the spatio-temporal domain. Finally, the output results were expressed in the actual and predicted data representing the evaluated variable's expected conditions for a defined period.

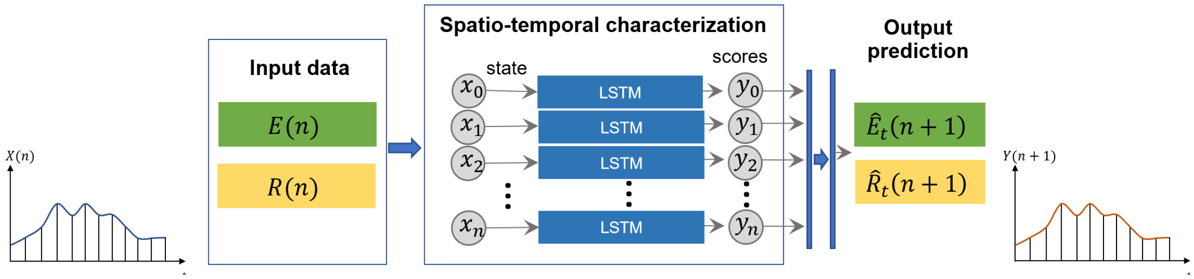


Figure 3. LSTM model for spatio-temporal characterization.

Our spatio-temporal model used time-series data of length t as input. Let$I$ $\{i_1, i_2, \ldots, i_t\}$ be the set of input features, LSTM computes a sequence of hidden states $\{h_1, h_2, \ldots, h_n\}$, and a sequence of outputs $\{y_1, y_2, \ldots, y_n\}$, by the following equations:

$$f_t = \sigma\left(W_f \cdot [C_{t-1}, h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i \cdot [C_{t-1}, h_{t-1}, x_t] + b_i) \tag{2}$$

$$c_t = f_t c_{t-1} + i_t \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{3}$$

$$o_t = \sigma(W_o \cdot [C_t, h_{t-1}, x_t] + b_o) \tag{4}$$

$$h_t = o_t \tanh(c_t) \tag{5}$$

where σ is a sigmoid function, and i, f, o, and c are the input gate, forget gate, cell activation vectors, and output gate, respectively. W_i, W_f, W_c, and W_o are the learnable parameters, and all b are biased. The output vector y_c generates the sequence of output predictions.

Implementation details

Our spatio-temporal model used the environmental data such as temperature, humidity, light, and CO_2, and root zone data obtained directly from the slab such as temperature, EC, and moisture. To conduct experiments, we trained the model using 65% of the cumulative data obtained from 2022.01.01-2022.03.01 and used the rest 35% for testing. Sampling data were recorded every minute.

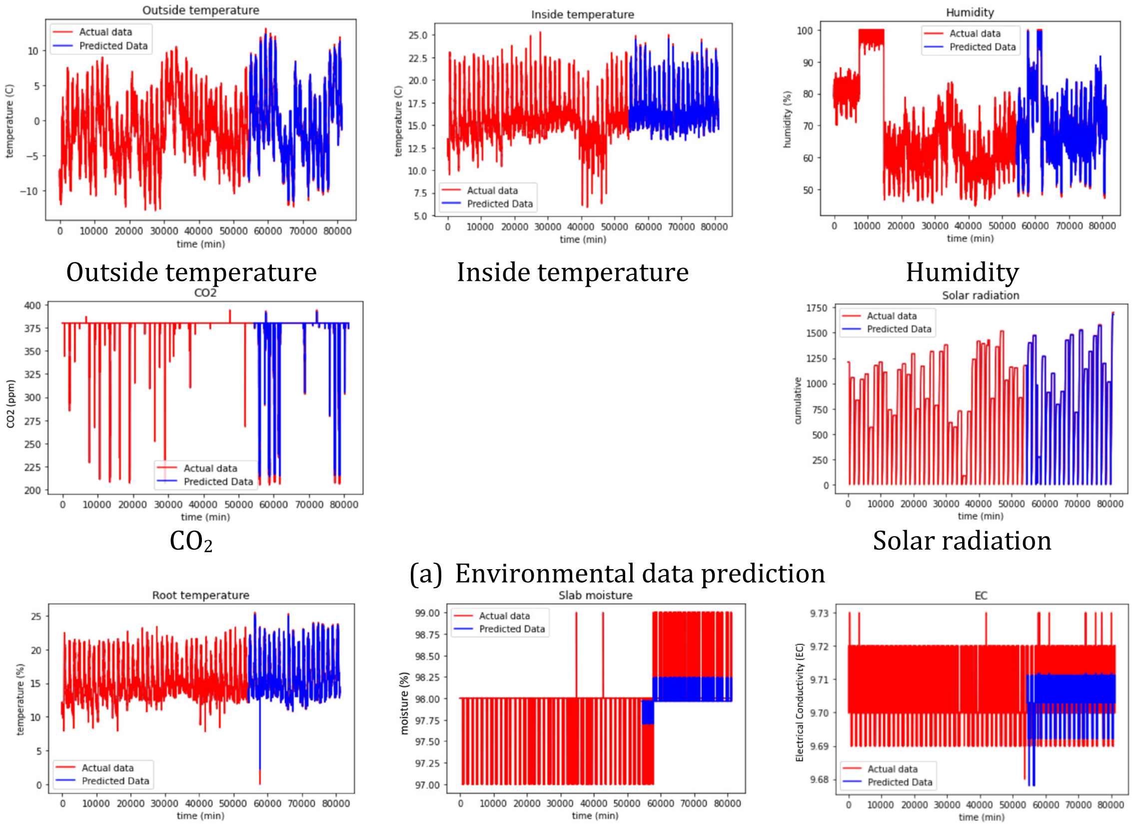
The LSTM model consisted of four layers, each with 512 nodes and an output layer with a sigmoid function. The model was trained using a batch size of 512 and a learning rate of 0.001 during 1,000 epochs. The performance of the proposed model was evaluated in terms of precision. We used mean square error as the loss function and Adam optimizer. To improve the performance of this architecture, optimization techniques were added to the main framework based on the required conditions during training and testing.

RESULTS AND DISCUSSION

In this section, we present the results and evaluate the performance of our framework for spatio-temporal characterization of the environmental and root zone data are presented.

Starting from the initial stage, then continuing with the development of the plant until its subsequence decline, each variable was precisely monitored throughout the crop life cycle. We trained the model using the above data and obtained a satisfactory performance by comparing the actual and predicted data on the testing data set. Of the total data available for training, 50% corresponds to data recorded in January and 15% in February. Then the remaining 35% used for testing exclusively corresponds to the remaining time in February. Consequently, the model enables the prediction of unseen data based on the historical data provided for training.

Figure 4 demonstrates the obtained results. From the figure, we can evidence that prediction and the actual values somewhat overlap. However, in the cases of slab moisture and EC, the model shows a decreased performance. This should be expected because we performed prediction. In other words, when predicting the future state, there is a high possibility that the model output is uncertain for a more significant period. The model's output depends on the data quality used as input during training.



Outside temperature | Inside temperature | Humidity

CO_2 | Solar radiation

(a) Environmental data prediction

Root temperature | Slab moisture | EC

(b) Root zone data prediction

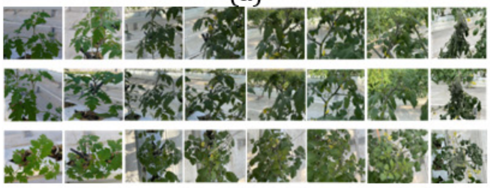
Figure 4. Spatio-temporal characterization and prediction of time-series data. (a) Environmental data; (b) Root zone data.

The model achieved an acceptable performance in the evaluated cases. Although the implemented model was simplified to focus on analyzing each variable independently, it can predict future trends accurately. Under those circumstances, we believe that understanding the environmental and root zone variables in the spatial-temporal domain is essential to estimating the conditions for plant development in the upcoming stages.

Related to the collected image data, these allowed us to obtain a general balance of the management period of the plants lasting for a total of 25 weeks. In some cases, as shown in Figure 5, certain plants showed stress symptoms at different growth stages. For example, an

‘Amos colie’ tomato plant lasted 18 weeks (Figure 5a), and a cherry tomato plant lasted even 8 weeks (Figure 5b). The appearance of these symptoms was closely related to environmental conditions, the amount of light, and the nutrients received by certain plants. Of the total number of plants monitored, 16% of the ‘Amos colie’ plants showed symptoms that forced their removal during weeks 19 and 24. Contrarily, cherry tomatoes showed a better reaction with only 6% of plants removed due to failure conditions in the nutrition system, during weeks 9 and 13.

(a)



(b)

Figure 5. Examples of plants during the cultivation process before stress symptoms appeared. (a) ‘Amos colie’ tomato lasted 18 weeks; (b) Cherry tomato lasted 8 weeks.

Overall, our proposed research shows a learnable way to estimate plant growth conditions utilizing data obtained directly from the sensors, providing hard facts required to control and improve the cultivation process through a proper understanding of the variables to find the optimal conditions. Also, it could help to identify growth phases and stress influences on yield development. To complement this estimation, the collected images could further provide a visual representation of the effects caused by the impact of the evaluated variables. Future work will focus on data fusion and join estimation of causes and symptoms of plant stress.

CONCLUSIONS

This paper presented a framework to estimate the spatio-temporal characterization of crop growth based on deep learning. Our proposed research showed a learnable way to estimate growth conditions utilizing time-series data obtained directly from sensors, providing hard facts required to control and improve the cultivation process through a proper understanding of the variables. We used environmental and root zone data to predict their state in future time steps. Finally, we believe that our research work can deliver significant advantages regarding production and quality, plant health, and resource savings. Additionally, our model provides the guidelines for further innovations based on knowledge and experience obtained from data rather than perception. The impact of our research is expected to make substantial changes, as it constitutes a pioneer work in the field based on deep learning technology and multi-category data. Our research project uses tomatoes as our target crop; however, it could also be expanded to other types of crops.

ACKNOWLEDGEMENTS

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No. 2019R1A6A1A09031717), by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT). (NRF-2021R1A2C1012174), and by the Korea Institute of Planning and Evaluation for Technology in Food, Agriculture and Forestry (IPET) and Korea

Smart Farm R&D Foundation (KosFarm) through Smart Farm Innovation Technology Development Program, funded by Ministry of Agriculture, Food and Rural Affairs (MAFRA) and Ministry of Science and ICT(MSIT), Rural Development Administration (RDA) (421027-04).

Literature cited

Afonso, M., Fonteijn, H., Fiorentin, F.S., Lensink, D., Mooij, M., Faber, N., Polder, G., and Wehrens, R. (2020). Tomato fruit detection and counting in greenhouses using deep learning. Front Plant Sci *11*, 571299 https://doi.org/10.3389/fpls.2020.571299. PubMed

Durán-Soria, S., Pott, D.M., Osorio, S., and Vallarino, J.G. (2020). Sugar signaling during fruit ripening. Front Plant Sci *11*, 564917 https://doi.org/10.3389/fpls.2020.564917. PubMed

Farjon, G., Itzhaky, Y., Khoroshevsky, F., and Bar-Hillel, A. (2021). Leaf counting: fusing network components for improved accuracy. Front Plant Sci *12*, 575751 https://doi.org/10.3389/fpls.2021.575751. PubMed

Fuentes, A., Yoon, S., Kim, S.C., and Park, D.S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors (Basel) *17* (*9*), 2022 https://doi.org/10.3390/s17092022. PubMed

Fuentes, A., Yoon, S., Lee, M.H., and Park, D.S. (2021). Improving accuracy of tomato plant disease diagnosis based on deep learning with explicit control of hidden classes. Front Plant Sci *12*, 682230 https://doi.org/10.3389/fpls.2021.682230. PubMed

Galieni, A., D'Ascenzo, N., Stagnari, F., Pagnani, G., Xie, Q., and Pisante, M. (2021). Past and future of plant stress detection: an overview from remote sensing to positron emission tomography. Front Plant Sci *11*, 609155 https://doi.org/10.3389/fpls.2020.609155. PubMed

Geelen, P.A.M., Voogt, J.O. and van Weel, P.A. (2018). Plant Empowerment: The Basic Principles (The Netherlands: plantempowerment.academy).

Halstead, M., Ahmadi, A., Smitt, C., Schmittmann, O., and McCool, C. (2021). Crop agnostic monitoring driven by deep learning. Front Plant Sci *12*, 786702 https://doi.org/10.3389/fpls.2021.786702. PubMed

Hemming, S., de Zwart, F., Elings, A., Righini, I., and Petropoulou, A. (2019). Remote control of greenhouse vegetable production with artificial intelligence: greenhouse climate, irrigation, and crop production. Sensors (Basel) *19* (*8*), 1807 https://doi.org/10.3390/s19081807. PubMed

Hemming, S., de Zwart, F., Elings, A., Petropoulou, A., and Righini, I. (2020). Cherry tomato production in intelligent greenhouses: sensors and AI for control of climate, irrigation, crop yield, and quality. Sensors (Basel) *20* (*22*), 6430 https://doi.org/10.3390/s20226430. PubMed

Heuvelink, E. (2005). Tomatoes, 13th edn (CAB International).

Hochreiter, S., and Schmidhuber, J. (1997). Long short-term memory. Neural Comput *9* (*8*), 1735–1780 https://doi.org/10.1162/neco.1997.9.8.1735. PubMed

Kamarudin, M.H., Ismail, Z.H., and Saidi, N.B. (2021). Deep learning sensor fusion in plant water stress assessment: a comprehensive review. Appl. Sci. (Basel) *11* (*4*), 1403 https://doi.org/10.3390/app11041403.

Nagano, S., Moriyuki, S., Wakamori, K., Mineno, H., and Fukuda, H. (2019). Leaf-movement-based growth prediction model using optical flow analysis and machine learning in plant factory. Front Plant Sci *10*, 227 https://doi.org/10.3389/fpls.2019.00227. PubMed

Samiei, S., Rasti, P., Ly Vu, J., Buitink, J., and Rousseau, D. (2020). Deep learning-based detection of seedling development. Plant Methods *16* (*1*), 103 https://doi.org/10.1186/s13007-020-00647-9. PubMed

Yao, L., van de Zedde, R., and Kowalchuk, G. (2021). Recent developments and potential of robotics in plant eco-phenotyping. Emerg Top Life Sci *5* (*2*), 289–300 https://doi.org/10.1042/ETLS20200275. PubMed