An Intelligent VegeCare Tool for Corn Disease Classification

Natwadee Ruedeeniraman¹, Makoto Ikeda²(B), and Leonard Barolli²

¹ Graduate School of Engineering, Fukuoka Institute of Technology, 3-30-1 Wajiro-higashi, Higashi-ku, Fukuoka 811-0295, Japan
mgm19108@bene.fit.ac.jp

² Department of Information and Communication Engineering, Fukuoka Institute of Technology, 3-30-1 Wajiro-higashi, Higashi-ku, Fukuoka 811-0295, Japan
makoto.ikd@acm.org, barolli@fit.ac.jp

Abstract. Due to the decrease of the agricultural population, agriculture has widely applied to machine learning and deep learning. In this paper, we present the classification performance of the proposed VegeCare tool for corn disease classification. We classify the major leaf diseases of the corn crop. The dataset includes four classes: gray leaf spot, common rust, health and northern leaf blight. From this evaluation, we found that our proposed VegeCare tool has a good performance.

Keywords: Deep learning · VegeCare · Corn · Disease classification · Agriculture

1 Introduction

In recent years, Artificial Intelligence (AI) based advanced agriculture system has attracted attention due to the increase in the average age of farmers and decrease the cultivated area. Also, people are more interested in safer food due to the impact of the COVID-19 epidemic. AI-based agriculture systems are expected to deliver safe and high-quality food [15, 19]. AI systems focus on edge-AI, where daily learning is done in the cloud-AI and real-time prediction is done at the edge.

The application of Deep Neural Networks (DNNs) is expected to solve complicated problems for humans in various fields [16, 20, 21]. There is also a competition community [1], which provides many datasets on the Internet. To improve the accuracy of DNNs, both layered models and algorithms are essential.

For the next generation of farmers, the intelligent growth management system is important for increasing crops’ productivity [2, 6]. In [17, 18], we proposed a classification system considering potato and tomato diseases. We analyzed the classification performance in two of four major crop types as tubers, fruits, cereals and pulses. Potatoes are categorized as a tuber crop that grows in the ground. Tomatoes are categorized as a fruit crop.
In this paper, we present the performance evaluation of VegeCare tool for corn disease classification. We used four kinds of corn diseases. The VegeCare tool helps the growth management for farmers. Corns are categorized as a cereal crop, which are grasses cultivated for their edible seeds. From this work, we provide insight into the classification performance of three major crop types: tuber, fruit and cereal crops.

The structure of the paper is as follows. In Sect. 2, we describe the related work. In Sect. 3, we describe the proposed system. In Sect. 4, we described the evaluation results. Finally, conclusions and future work are given in Sect. 5.

2 Related Work

In recent years, new systems are used for rice cultivation, which automatically can measure the water level and water temperature of the paddy field. Also, a cultivation management system was proposed to collect the knowledge and skill of farmers. However, there are many problems, such as the growing conditions and physiological conditions in the field of biological information sensing.

The autonomous agricultural machines (e.g., rice planter and tractor) have been developed for remote monitoring by farmers [10]. For rice harvesting, the system applies object detection and straight-line assistance to autonomously move the target area by coordinating GPS and GIS modules.

Most of the areas of crop cultivation are near mountains and suburbs. Therefore, animals often come down from the mountains and bite the cultivated crops in the fields. So, bird and animal removal systems are developed. Wireless communication using Unmanned Aerial Vehicle (UAV) and LoRa have attracted attention for transmitting the sensed agricultural data [3–5].

In [7], the authors presented a framework for classifier fusion, which can support the automatic recognition of fruits and vegetables in a supermarket environment. The authors show that the proposed framework yields better results than several related works found in the literature.

In [8], the authors proposed nine layers of Convolutional Neural Network (CNN) for leaf disease classification. They reported that the accuracy of their model is better than traditional approaches.

DNN has a deep hierarchy that connects multiple internal layers for feature detection and representation learning. Representation learning is used to express the extracting essential information from observation data in the real world. Feature extraction uses trial and error by artificial operations. However, DNN uses the pixel level of the image as an input value and acquires the most suitable characteristic to identify it [9,13]. The CNN uses the backpropagation model like a conventional multi-layer perceptron. To update the weighting filter and coupling coefficient, CNN uses stochastic gradient descent. In this way, CNN recognizes the optimized feature using convolutional and pooling operations [12,14].
3 Proposed System

3.1 Overview of the Proposed System

The structure of our proposed system is shown in Fig. 1. The proposed system consists of the VegeCare tool used at the edge and the VegeCare system on the cloud. The VegeCare tool is a mobile application of the Android terminal that predicts the object and manages the plant growth for farmers. The VegeCare tool’s functions have a plant disease classification, vegetable classification and insect pest classification. The VegeCare system on Cloud-AI has three functions: computing module, data management and job scheduler.

Based on corn disease classification characteristics, we consider the accuracy and loss, which are computed by a high-level API of TensorFlow (tf.keras).

![Fig. 1. Model of the proposed system.](image)

3.2 Corn Disease Classification

Corn/maize prefers hot and sunny conditions. When the rainy season, corn often becomes disease affected by fungus and infectious disease by pests. VegeCare tool considers four classes of typical corn diseases: gray leaf spot, common rust, health and northern leaf blight. The samples of each class are shown in Fig. 2.
Gray Leaf Spot. Corn gray leaf spot is a type of infection caused by *Cercospora zeae-maydis*. The disease is usually first noticed in the lower leaves. The lesions initially become small dots with yellow halos. Then, the lesions become pale brown to gray and rectangular shapes parallel to the leaves’ veins. Finally, the lesions merge and kill the leaves.

Common Rust. Corn common rust is a type of infection caused by *Puccinia sorghi*. The disease creates multiple spore prints on both surfaces of leaves. The spore prints become orange to brown, slightly slender, 2–5 mm long and 1–2 mm wide. Then, the spore prints are slightly blackened. Finally, the surface skin breaks and the spores are spread by flying around.

Northern Leaf Blight. Corn northern leaf blight is a type of infection caused by *Setosphaeria turcica*. The disease increases in cold and humid conditions. The massive outbreak of the disease will spread to the whole field. The disease becomes large lesions on the surface of leaves with yellow-brown to gray, spindle-shaped and 3–10 cm long. When the lesions become old, the center of lesions becomes black and like musty, and can easily split vertically from the center.

4 Evaluation Results

4.1 Evaluation of Setting

In this paper, we use the dataset of PlantVillage [11] to collect the corn disease classification images. The dataset contains 9,245 images belonging to 4 classes. We show a list of hyperparameters of the proposed CNN in Table 1. To create a training model, we used a maximum of 400 epochs and the batch size is 32. The image size is $256 \times 256$. The network is based on the sequential model, which consists of four convolutional layers, four pooling layers and four fully connected layers. We consider dropout layers to prevent the model from over-fitting and use Rectified Linear Unit (ReLU) as the activation function to improve the representation of the model. In the output layer, softmax as an activation function is used to split the final result into multiple diseases.
An Intelligent VegeCare Tool for Corn Disease Classification

Table 1. List of hyperparameters.

| Function                        | Values          |
|---------------------------------|-----------------|
| Epoch                           | 100, 200, 400   |
| Batch size                      | 32              |
| Filter sizes for convolution layer | $3 \times 3$     |
| Activation function             | ReLU            |
| Loss function                   | Categorical cross-entropy |
| Optimizer                       | RMSprop         |
| Dropout                         | 0.5             |

4.2 Training and Validation Results

The dataset contains 9,245 images belonging to 4 classes of corn diseases. Because of the imbalanced data distribution, we split the dataset to 7,316, 1,829 and 100 images. The training, validation and testing sets are split at the sub-class level. The dataset should be diverse to prevent over-fitting and improve classification results. We use various images of corn leaves, which are converted from original images by using rotation, re-scale, random zooming and shear conversion.

From Fig. 3 to Fig. 5 are shown the results of accuracy and loss for different epochs. For 100 epochs (see Fig. 3), the validation accuracy results are increased with the increase of epochs. The training and validation loss is quite low. For 200 epochs (see Fig. 4), the accuracy after 100 epochs starts to decrease. Due to this effect, the loss results are also increased. For 400 epochs (see Fig. 5), the training accuracy is less than 90%. After 360 epochs, there are some oscillations.

![Fig. 3. Training and validation results for 100 epochs.](image-url)
4.3 Classification Results

We used a total of 100 images (25 images for each class) to evaluate the proposed VegeCare tool and investigate the accuracy of corn disease classification. The results of corn disease classification for different epochs are shown in Table 2. For both common rust and healthy leaves, the classification results show that the proposed tool has a good accuracy regardless of the number of epochs. For the gray leaf spot, the accuracy of the proposed tool is more than 96% for 100 and 200 epochs. While the accuracy for 400 epochs is less than 72%. For northern leaf blight, the accuracy of the proposed tool for 100 epochs has a good accuracy, but the accuracy decreases with increased epochs.

From these results, we found that our proposed tool classified common rust disease correctly considering that the spore is smaller and looks different from the other diseases. For 400 epochs, the proposed tool sometimes classified gray leaf spot and northern leaf blight leaves as health leaves. This is because of the over-fitting problem.
Table 2. Testing results for classification.

| Class                  | Epoch | Class #1 | Class #2 | Class #3 | Class #4 | Accuracy |
|------------------------|-------|----------|----------|----------|----------|----------|
| 1: Gray leaf spot      | 100   | 24       | 0        | 0        | 1        | 96       |
|                        | 200   | 24       | 0        | 0        | 1        | 96       |
|                        | 400   | 18       | 0        | 3        | 4        | 72       |
| 2: Common rust         | 100   | 0        | 25       | 0        | 0        | 100      |
|                        | 200   | 0        | 25       | 0        | 0        | 100      |
|                        | 400   | 0        | 25       | 0        | 0        | 100      |
| 3: Healthy             | 100   | 0        | 0        | 25       | 0        | 100      |
|                        | 200   | 0        | 0        | 25       | 0        | 100      |
|                        | 400   | 0        | 0        | 25       | 0        | 100      |
| 4: Northern leaf blight| 100   | 0        | 0        | 0        | 25       | 100      |
|                        | 200   | 2        | 0        | 1        | 22       | 88       |
|                        | 400   | 1        | 0        | 6        | 18       | 72       |

5 Conclusions

In this paper, we proposed a corn disease classification tool called VegeCare. We evaluated the performance for corn diseases considering accuracy and loss. From the evaluation results, we found that our training data for 100 epochs have a good performance.

In the future work, we will implement an all-in-one tool with multiple crop classification for improving the flexibility of our proposed tool.

References

1. Kaggle: Data science community. https://www.kaggle.com/
2. Ahmed, N., De, D., Hussain, I.: Internet of things (IoT) for smart precision agriculture and farming in rural areas. IEEE Internet Things J. 5(6), 4890–4899 (2018)
3. Bacco, M., Berton, A., Gotta, A., Caviglione, L.: IEEE 802.15.4 air-ground UAV communications in smart farming scenarios. IEEE Commun. Lett. 22(9), 1910–1913 (2018)
4. Castellanos, G., Deruyck, M., Martens, L., Joseph, W.: System assessment of WUSN using NB-IoT UAV-aided networks in potato crops. IEEE Access 8, 56823–56836 (2020)
5. Daskalakis, S.N., Goussetis, G., Assimonis, S.D., Tentzeris, M.M., Georgiadis, A.: A uW backscatter-morse-leaf sensor for low-power agricultural wireless sensor networks. IEEE Sens. J. 18(19), 7889–7898 (2018)
6. Elijah, O., Rahman, T.A., Orikutimi, I., Leow, C.Y., Hindia, M.N.: An overview of internet of things (IoT) and data analytics in agriculture: benefits and challenges. IEEE Internet Things J. 5(5), 3758–3773 (2018)
7. Faria, F.A., dos Santos, J.A., Rocha, A., da Torres, R.S.: Automatic classifier fusion for produce recognition. In: Proceedings of the 25th International Conference on Graphics, Patterns and Images (SIBGRAPI-2012), pp. 252–259 (2012)
8. Geetharamani, G., Pandian, A.J.: Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Comput. Electr. Eng. 76, 323–338 (2019)
9. Hinton, G.E., Osindero, S., Teh, Y.W.: A fast learning algorithm for deep belief nets. Neural Comput. 18(7), 1527–1554 (2006)
10. Hokkaido Agricultural Research Center N: HARC brochure (2017). http://www.naro.affrc.go.jp/publicity_report/publication/files/2017NARO_english_1.pdf
11. Hughes, D.P., Salathé, M.: An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowdsourcing. Computing Research Repository (CoRR) (2015)
12. Kang, L., Kumar, J., Ye, P., Li, Y., Doermann, D.: Convolutional neural networks for document image classification. In: Proceedings of 22nd International Conference on Pattern Recognition 2014 (ICPR-2014), pp. 3168–3172, August 2014
13. Le, Q.V.: Building high-level features using large scale unsupervised learning. In: Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing 2013 (ICASSP-2013), pp. 8595–8598, May 2013
14. Lee, H., Grosse, R., Ranganath, R., Ng, A.Y.: Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In: Proceedings of the 26th Annual International Conference on Machine Learning, pp. 609–616, June 2009
15. Mattihalli, C., Gedefaye, E., Endalamaw, F., Necho, A.: Plant leaf diseases detection and auto-medicine. Internet Things 1–2, 67–73 (2018)
16. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., Hassabis, D.: Human-level control through deep reinforcement learning. Nature 518, 529–533 (2015)
17. Ruedeeniraman, N., Ikeda, M., Barolli, L.: Performance evaluation of VegeCare tool for tomato disease classification. In: Proceedings of the 22nd International Conference on Network-Based Information Systems (NBiS-2019), pp. 595–603, September 2019
18. Ruedeeniraman, N., Ikeda, M., Barolli, L.: Performance evaluation of VegeCare tool for potato disease classification. In: Proceedings of the 23rd International Conference on Network-Based Information Systems (NBiS-2020), August 2020
19. Sardogan, M., Tuncer, A., Ozen, Y.: Plant leaf disease detection and classification based on CNN with LVQ algorithm. In: Proceedings of the 3rd International Conference on Computer Science and Engineering (UBMK-2018), pp. 382–385, September 2018
20. Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., Hassabis, D.: Mastering the game of Go with deep neural networks and tree search. Nature 529, 484–489 (2016)
21. Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., Chen, Y., Lillicrap, T., Hui, F., Sifre, L., van den Driessche, G., Graepel, T., Hassabis, D.: Mastering the game of Go without human knowledge. Nature 550, 354–359 (2017)