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***Abstract* – Less than 250 words. Manual trimming garlic root and evaluating the clearness the root condition are tedious tasks in postharvest processing of garlic production. The evaluation is still solely depended on the human naked eye. A garlic root trimming machine is currently not available, and we are trying to develop an autonomous machine to assist the root trimming routine. In this study, we introduce numerical models that utilize traditional computer vision algorithm and the most recent algorithm of a deep convolutional neural network to automatically recognize and classify the root trimming images. The final model achieves a classification accuracy of 96%. It can stream and classify garlic root images on a real-time monitoring camera. The model can be integrated into a mechanical machine for autonomous root trimming and real-time evaluation in postharvest processing of garlic. Its application can be extended to other agricultural products.**

***Keywords*: garlic root trimming, deep learning, convolutional neural network**

I. INTRODUCTION

Garlic (*Allium sativum*) originated from Central Asia, has been popularly cultivated and consumed throughout the world. It is widely used as a common seasoning because of its special taste and flavor in food production [1]. It is also used as a traditional medicine to treat various human diseases in many countries for thousands of years [1]–[3]. According to FAOSTAT (2018), there

are 76 countries having garlic production greater than 1000 tons in 2016 [4]. China is the world largest garlic producers with 21 million tons annually that accounts for 80 % of world production, followed by India with 1,4 million tons about 5% of world production. The United States ranked 10th and Japan ranked 37th in the global production of garlic with 167,370 and 20,623 tons, respectively [4]. However, Japan is one of the leading countries in providing high-grade garlic. The most famous brand is Aomori garlic. In 2016, Aomori prefecture accounted for 67.5% of total national garlic production [5]. Garlic production in Japan has gradually increased by 10.5 % from 2006 to 2016 [5].

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Together with the global 4.0 industrial revolution, Japan heads to Society 5.0 or super smart society where the application of artificial intelligence in smart agriculture is one of the important tasks to overcome the Japanese aging population and dealing with the shortage of labors in the agricultural sector. Therefore, there is a great demand for a smart system that could automatically and intelligently handle postharvest garlic processing.

Many computer vision algorithms have been developed for decades to understand image content toward automation in agricultural machinery. Recently, the application convolutional neural network (CNN or ConvNet) in deep learning is considered as a modern technique for image analysis. It has been successfully applied in various disciplines and achieved breakthroughs in many computer vision tasks such as concrete crack detection [6], skin lesion detection [7] and tomato crop disease classification [8]. Deep learning extends the traditional machine learning model to more complexity. It well extracts the important features of the data and represents them in a hierarchical way to improve prediction accuracy [9].

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II. Materials and methods

○ A. *Garlic and image preparation*

Garlic (*Allium sativum*) originated from Central Asia, has been popularly cultivated and consumed throughout the world. It is widely used as a common seasoning because of its special taste and flavor in food production [1]. It is also used as a traditional medicine to treat various human diseases in many countries for thousands of years [1]–[3]. According to FAOSTAT (2018), there

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○ B. *Model development*

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Model 3

We utilized the pre-trained VGG16 model [10] and transfer its convolution base parameters to our ConvNet model. VGG16 model was pre-trained with 14 million images of 1000 classes from ImageNet, a public image library. It consists of 16 layers from 5 convolution blocks and a fully connected classifier block. The model was first loaded, and only its convolution base was used. A flatten layer and two dense layers are added to classify garlic classes. The convolution base parameters were frozen during training. After the model was trained with garlic data set for 30 epochs. The parameters at convolution block 5 was un-frozen and re-trained again for fine-tuning all parameters in another 15 epochs.

All the model developments and result visualization were programmed in R statistical computing language version 3.5.2 and Python 3.5. ConvNet computation and model structure implementation were built in Keras 2.2.4 framework with TensorFlow 1.12 backend. The model was trained in a Windows 10 computer, Intel® Core™ i7-8700K CPU @ 3.70GHz (12 CPUs), NVIDIA GeForce GTX 1080 Ti GPU, RAM 64 GB.

III. Results and discussion

○ A. *Models and their classification performances*

Model 1:

Model 1 classification performance is presented in Fig. 1. The model demonstrates a fast computation speed. The classification is almost instant on a normal computer. It required only a few representative garlic images to develop the model. It can distinguish most of the garlic root image that has a clean outer sheath. Parameters for image processing need manual adjustment to achieve high classification accuracy during the model development stage. Although image brightness was pre-adjusted, the model has difficulties to distinguish between muddy soil in garlic outer sheath and root areas. Regarding model integration into a trimmer robot, this model has an advantage since it requires less computation power. The root clearness threshold such as the allowed root residue percentage can be easy to re-setup or input without modifying the model. However, the model is very sensitive to image lighting condition and image background. To achieve a high classification performance, image capturing condition should be well controlled.

Figure 1. Garlic root recognition performance of model 1

Model 2:

The model architecture and parameters are presented in Fig. 2 and Table I. It needs to be trained through label images. The computation is much slower than model 1. It required a large number of garlic images to achieve a stable and high classification accuracy. However, it performs well in both clean garlic and garlic with muddy soil in the surface (before polishing). The accuracy is 83% after 45 epochs. The model uses ConvNets thus spatial root pattern is trained that improve classification accuracy and prevent the interference of image background and muddy soil in garlic outer sheath. The use of image augmentation significantly prevents overfitting problem with our limited dataset.

TABLE I. CONVNET MODEL ARCHITECTURE AND PARAMETERS (MODEL 2)

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_1 (MaxPooling2D)	(None, 74, 74, 32)	0
flatten_1 (Flatten)	(None, 175232)	0
dense_1 (Dense)	(None, 512)	897192 96
dense_2 (Dense)	(None, 1)	1
Total params: 89,720,705 Trainable params: 89,720,705 Non-trainable params: 0		

Model 3:

Model 3 (or the final model) architecture and parameters are presented in Fig. 3, 4 and Table II. The model used VGG16 transfer learning and fine-tuning appeared to have the highest validation accuracy as compared to model 1 and model 2. Model 3 accuracy is 91 % after the first 30 epochs during transfer learning and reaches 96 % after 15 epochs more in parameter fine-tune training (Fig. 4).

TABLE II. TRANSFER LEARNING MODEL ARCHITECTURE AND PARAMETERS (MODEL 3)

Layer (type)	Output Shape	Param #
vgg16 (Model)	(None, 4, 4, 512)	147146 88
flatten_1 (Flatten)	(None, 8192)	0
dense_1 (Dense)	(None, 256)	209740 8
dense_2 (Dense)	(None, 1)	257

Total params: 16,812,353 Trainable params: 16,552,193 Non-trainable params: 260,160

Although it took 20 – 30 minutes to train the model in a powerful computer with GPU, the prediction was fast and almost instant in a real-time monitoring camera. Its prediction in a normal laptop computer without GPU was about 0.2 – 0.3 seconds per image. Thus, its integration in a mechanical root trimming machine is possible. The model is not so sensitive to image background, image capturing condition as compared to model 1, however, the model may need to be adjusted or calibrated when a new image capturing condition is used as reported by Guo et al (2018) [11].

○ *B. Advantages and disadvantages of deep learning model*

As compared to traditional computer vision model, the deep learning models that used ConvNets has certain advantages in image recognition and classification. The deep learning model can significantly improve classification performance. It reduces effort in feature engineering by automatically search for good features from the data. The model was trained with a large number of input images thus it has a high degree of generalization, and robust to illumination, complex background and complex image. Although the training is computation expensive but the testing time is quite fast as compared to other machine learning algorithms as reported by Kamilaris and Prenafeta-Boldú (2018) [9].

Besides its advantages, deep learning model also has disadvantages. It requires large dataset thus data collection may be laborious and expensive. For example, garlic root trimming image collection is usually not available in any public domain. Data labeling needs the involvement of expert since the garlic image labeling is conducted in each individual image in train and validation dataset. With the current ConvNet models, if user would like to change root residue threshold, it requires to re-train the model from beginning, and the training requires powerful computer with a high-class GPU.

IV. Conclusions

This study presents different computer vision approaches to solve the garlic root image recognition problem. While traditional computer vision algorithms are applicable with fast computation speed, deep learning used convnets appears to be robust and achieves a higher accuracy. However, each method has its own advantages and disadvantages, there is no best method for every computer vision problem.

It is possible to train a ConvNet from scratch with limited image data, and the model still provides decent results. Overfitting is the main issue and data augmentation is a powerful tool fighting it. Transfer learning model that utilized a pre-trained model has a high feature abstraction ability, and it can improve the model prediction performance. The final model achieved an accuracy of 96%.

The classification performance could be improved when more generalized garlic root images were collected. Additionally, the model algorithm may be improved by considering object detection model such as YOLO [12] architecture to localize garlic root image region then perform classification or utilizing the semantic image segmentation Mask R-CNN [13]. Mask R-CNN may make the garlic root residue threshold being more flexible. However, these architectures require more efforts on image labeling and semantic segmentation at pixel levels, as well as more computation power.

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