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Smart Fruit Quality Evaluation Using AI Algorithms

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Fruit quality classification in the consumer market has become a considerable burden following the decrease in the young adult population engaged in agriculture in Taiwan owing to its labor-intensiveness. We propose a system to identify the external quality of fruit, which utilizes a camera as an image sensor and an artificial intelligence algorithm as a classifier. This application is suitable for real operating environments. Fruits are mainly detected by the “you only look once” (YOLO)-V3 algorithm, with the designated fruit continuously tracked using the characteristics of the image, such as size, height, width, etc., and the quality of fruit is detected during the tracking process. Finally, the switching gap of the application distinguishes fruits of different quality. The proposed application detects round fruit such as apples, oranges, and lemons using our newly developed process. We also provide a graphical user interface to control and collect data, evaluate models, and monitor the entire system operation to improve the efficiency of the proposed application. The experimental results show that the proposed application achieves an accuracy rate of up to 88% after testing on 6000 fruit images.

1. Introduction

In recent years, the miniaturization of chips and the technological advancement of image sensors have proceeded. Artificial intelligence algorithms have also been rapidly developed and applied in various fields. Among them, machine learning and deep learning have been extensively used in image processing as their pattern recognition capabilities are compatible with human vision. In machine learning and deep learning, features can be captured from data through training. We can apply feature operations in fruit detection and recognition to implement automatically controlled gateways for fruit quality classification with supervised learning.

We have been investigating deep learning applications in machine learning and their application to fruit quality classification, which is an essential but labor-intensive process in agriculture because human vision and manual screening are often required. Hence, we have designed a classification application for automatically sorting fruits according to their quality to help farmers. Furthermore, we aim to implement the system with a reduced hardware cost.

2. System overview

The proposed system combines appropriate equipment and technologies, such as the YOLO object detection algorithm, an STM32 micro processor, a graphical user interface, and an MG996R servomotor, to recognize and classify the quality of fruit. The system's functions include fruit detection, quality recognition, and fruit tracking and control.

The system is coupled with a graphical user interface to display the current location of the fruit and the classification status. Cameras are integrated to perform fruit image detection and image preprocessing. By using the YOLO algorithm for fruit detection, overlapping objects can be separated and the detected fruit image can be tracked continuously. A fruit recognition model is designed to recognize the quality of the fruit and perform classification. Another model is then used to determine whether the quality of the fruit is satisfactory.

Software architecture

The fruit quality classification system is divided into four parts. The first part consists of the software control of the front and back gateways. The second part is the network model built by the CNN method, where Model-A uses Tiny-YOLO to detect fruit on the conveyor platform and Model-B recognizes the type of fruit and checks for defects. The third part consists of the comparison and elimination algorithm used to eliminate the repeated bounding boxes. The fourth part is the tracking algorithm used to track the fruit on the conveyor platform. Finally, Tensor RT is applied to compress the model. Figure 2 shows a software diagram of the fruit quality classification system.

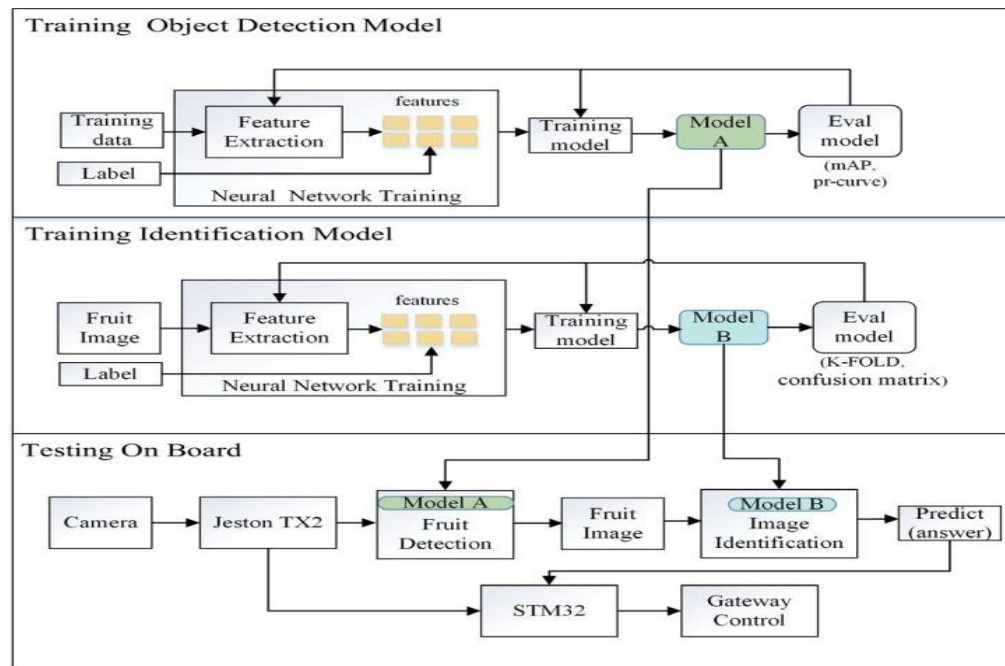


Fig.1. (Color online) Structure diagram of fruit quality classification system.

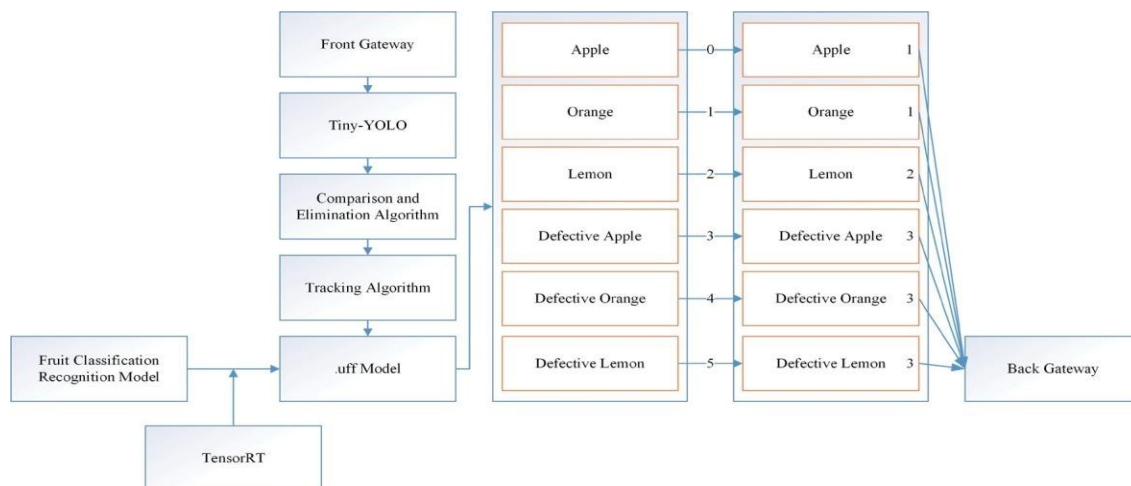


Fig.2. (Color online) Software diagram of fruit quality classification system.

Comparison and elimination algorithm We have implemented an algorithm to compare

Type	Filters	Size	Strides	Padding	Output
Convolution(BN)	16	3x3	1x1	Same	416x416
Maxpooling	16	2x2	2x2	Same	208x208
Convolution(BN)	32	3x3	1x1	Same	208x208
Maxpooling	32	2x2	2x2	Same	104x104
Convolution(BN)	64	3x3	1x1	Same	104x104
Maxpooling	64	2x2	2x2	Same	52x52
Convolution(BN)	128	3x3	1x1	Same	52x52
Maxpooling	128	2x2	2x2	Same	26x26
Convolution(BN)	256	3x3	1x1	Same	26x26
Maxpooling	256	2x2	2x2	Same	13x13
Convolution(BN)	512	3x3	1x1	Same	13x13
Maxpooling	512	2x2	1x1	Same	13x13
Convolution(BN)	1024	3x3	1x1	Same	13x13
Convolution(BN)	256	1x1	1x1	Same	13x13
Convolution(BN)	512	3x3	1x1	Same	13x13
Convolution(BN)	21	1x1	1x1	Same	13x13
Convolution(BN)	128	1x1	1x1	Same	13x13
UpSampling2D	128	Upsampling layer Size=2			26x26
Concatenate	128+256	Merge Layer			26x26
Convolution(BN)	256	3x3	1x1	Same	26x26
Convolution(BN)	21	1x1	1x1	Same	26x26

SCALE1

SCALE2

YOLO detection

the distance of each box and the nearest bounding box one by one, which eliminates repeated boxes and reduces error sin object tracking due to fruit defects being occluded by the good parts. The elimination principle is to eliminate the object bounding box without defects when both an object bounding box with defects and an object bounding box without defects appear simultaneously, as shown in Fig. 4.

Fig.3. (Color online) Complete Tiny-YOLO architecture.

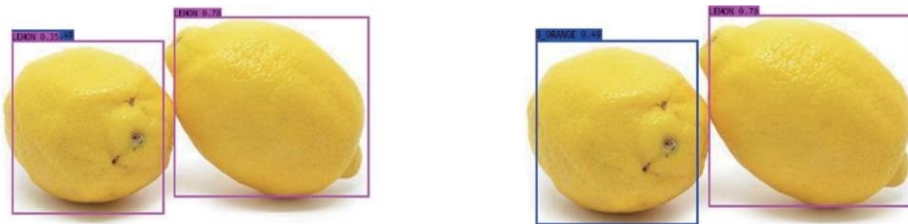


Fig.4. (Color online) Example of eliminating repeated boxes.

3. Experimental Results

Recognition model evaluation and training

The fruit identification model uses the YOLO algorithm to process the dataset. The YOLO object detection algorithm circles the fruit and crops out the part containing the fruit from an image or video, similar to the region of interest (ROI) method. The photos are classified into six categories. The training and verification picture ratios are both set to 0.2. The classification method assigns labels of 0 to 5 for apples, oranges, lemons, defective apples, defective oranges, and defective lemons, respectively, as shown in Table 1. The two trained recognition model architectures are configured with a batch size of 256 and 50 epochs. The first architecture is the fully connected architecture and the second is the auto encoder architecture. Categorical cross-entropy is used as the loss function, and Adam is used as the learning optimizer. The initial established default learning rate α is 0.001.

4. Conclusion

In this research, we applied the Tiny-YOLO neural network model to perform object detection and compared several other models in terms of structural performance. We developed a system by building the model architecture with the Tensor Flow and Keras frame works. In addition, we acquired the images used in the data set by using a camera as an image sensor.

With a four-layer convolution network for object detection, the fruit recognition model for classification of the fruit quality achieved an accuracy of 88%. In an experiment, the complete system was implemented with a graphical user interface for user-friendly operation. In this work, a relatively large model was used to classify the three types of fruit. If the model is applied to a more compact development board, then a single classification model can be used for each type of fruit.

References

- 1 A. Krizhevsky, S. Ilya, and E. H. Geoffrey: Commun. ACM **60**(2017)84. <https://doi.org/10.1145/3065386>
- 2 A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam: Comput. Sci. (2017). <https://arxiv.org/abs/1704.04861>
- 3 F. Chollet: Proc. Conf. Computer Vision and Pattern Recognition (IEEE, 2017) 1251. <http://doi.org/10.1109/CVPR.2017.195>
- 4 M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen: Proc. Conf. Computer Vision and Pattern Recognition (IEEE, 2018) 4510. <http://doi.org/10.1109/CVPR.2018.00474>

- 5 Y.Chen,H.Fan,B.Xu,Z.Yan,Y.Kalantidis,M.Rohrbach,Y.Shuicheng,andJ. Feng: Proc. Int. Conf. ComputerVision(IEEE,2019)3435.<http://doi.org/10.1109/ICCV.2019.00353>
- 6 M. Apte,S.Mangat,andP.Sekhar:StanfordUniversity(2017).
<http://cs231n.stanford.edu/reports/2017/pdfs/135.pdf>
- 7 F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer: Computer Science (2016). <https://arxiv.org/abs/1602.07360>
- 8 J.RedmonandA.Farhadi:ComputerScience(2018).<https://arxiv.org/abs/1804.02767>
- 9 T.Santad,P.Silapasupphakornwong,W.Choensawat,andK.Sookhanaphibarn: Proc.IEEEGlobalConf.Consumer Electronics Conf. (IEEE, 2018) 157.
<https://doi.org/10.1109/GCCE.2018.8574819>
- 10 Yogesh and A. K. Dubey: Proc. Int. Conf. Reliability, Infocom Technologies and Optimization (IEEE, 2016) 590.<https://doi.org/10.1109/ICRITO.2016.7785023>
- 11 Z.M.Khaing,Y.Naung,andP.H.Htut:Proc.IEEENWRussiaYoungResearchersin Electrical and Electronic EngineeringConf.(IEEE,2018)1805.<https://doi.org/10.1109/EIConRus.2018.8317456>
- 12 H.J.Jeong,K.S.Park,andY.G.Ha:Proc.Int.Conf.BigDataandSmartComputing (IEEE, 2018) 635. <https://doi.org/10.1109/BigComp.2018.00113>
- 13 HendryandR.C.Chen:ImageVisionComput.**87**(2019)47.
<https://doi.org/10.1016/j.imavis.2019.04.007>
- 14 C. Sachin, N. Manasa, V. Sharma, and A. A. Nippun Kumar: Proc. Int. Conf. Cutting- edge Technologies in Engineering (IEEE, 2019)