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The Ripening of Pineapple Fruits Using Machine Learning Technique

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Abstract

During the Fourth Industrial Revolution, artificial intelligence is being widely applied in a variety of fields. However, in the current agricultural model, humans are still used as the primary labor force, which is costly in terms of both finance and human resources. Furthermore, each region's typical fruits, particularly pineapple, have a rather complicated ripening period. It is difficult to control and manage hundreds of hectares of land. As a result, in this paper, we propose using deep learning models to aid in the identification and detection of ripe pineapple growth stages in order to ensure that care and harvesting are completed on time.

Keywords

Model YOLOv4, Deep Learning, Machine Learning, CNN, R-CNN, GPU, Pineapple.

1. Introduction

Revolution 4.0 is a highly combined physical and digital hyper-connected system with a focus on the Internet, Internet of Things (IoT) and Artificial Intelligence, which creates entirely new production possibilities and has a profound impact on the economic, political and social life around the world. This Fourth Industrial Revolution has four major features, one of which is Artificial Intelligence and Cybernetics, which allows people to control remotely without regard for space or time constraints, as well as interact in a faster and more accurate manner.

Artificial Intelligence (AI) is quickly becoming one of the most anticipated scientific fields, as it has the potential to benefit a wide range of industries. Agriculture is one of the industries where Artificial Intelligence is becoming more widely used and yielding significant results. Unmanned electric tractors, automatic egg harvesters, soil moisture meters, and automatic vegetable irrigation machines are examples of AI applications in this field. In particular, many international studies have shown that the use of AI can greatly increase the accuracy of diagnosis, limit the use of pesticides and ensure food safety, making farming

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more efficient, sustainable and adaptable to climate change. For the reasons stated above, the use of high technology in the pineapple agricultural model is ideal.

A Convolutional Neural Network (CNN) model called YOLO (You Only Look Once) is widely used for object detection. The Yolo algorithm is created by combining convolutional layers with full-connected layers, where convolutional layers extract features from input images, and full-connected layers predict the probability and coordinates of the objects. With this system, high accuracy and speed can almost always be achieved almost in real-time. As a result, we propose using the YOLOv4 model in detecting and identifying the pineapple ripening period.

2. Related Work

Artificial Intelligence in general, and Computer Vision in particular, is one of the key technologies of the Fourth Industrial Revolution that scientists are particularly interested in researching. Some of the most well-known applications of computer vision are as follows: utilizing large data sets accumulated overtime to train recognition models; using machine learning, deep learning techniques to assist in object detection and recognition; developing image classification systems.

Researchers, in particular, are now very interested in the application of high technology in the agricultural industry to assist farmers in their daily work, increase productivity and product quality, and thus promote the sustainable development of agriculture. The following are some notable studies: The paper "Fruit Detection System Using Deep Neural Networks"[1] proposes using Convolutional Neural Network (CNN) algorithm to train a fruit recognition model; Redmon and J.Farhadi propose a method for detecting different growth stages of apple using YOLOv3[2]; Byoungjun Kim1, You-Kyoung Han, Jong-Han Park, and Joonwhoan Lee1 published a paper titled "Improved Vision-Based Detection of Strawberry Diseases Using a Deep Neural Network"[3] in which they propose using Deep Neural Networks (DNN) to improve vision-based strawberry disease detection; Jose Luis Rojas-Aranda, Jose Ignacio Nunez-Varela, JC Cuevas-Tello, and Gabriela Rangel-Ramirez collaborated on a project to classify fruits for retail stores using Deep Learning techniques[4], specifically the Convolutional Neural Network (CNN) algorithm, to improve fruit classification accuracy. A single RGB colour, an RGB histogram, and the RGB centroid from K-means clustering are used as model inputs. According to the findings, the overall classification accuracy for fruit without plastic bags is 95%, while for fruit with plastic bags is 93%. Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi with the paper "You Only Look Once: Unified, Real-Time Object Detection" [5], propose a new approach to object detection. Consider the object detection problem to be a regression problem for spatially separating bounding boxes and associated class probabilities. A single neural network predicts bounding boxes and class probabilities directly from full images in one evaluation. Since the whole detection pipeline is a single network, it can be optimized end-to-end directly on detection performance. Guoxu Liu, Joseph Christian Nouaze, Philippe Lyonel Touko Mbouembe and Jae Ho Kim with paper "YOLO-Tomato: A Robust Algorithm for Tomato Detection Based on YOLOv3" [6, 40, 41] use an improved model based on YOLOv3 to inherit features for more compactness and accuracy. The model replaces the traditional rectangular bounding box (R-Bbox) with a circular bounding box (C-Bbox) for tomato localization. The new bounding boxes can then match the tomatoes more precisely, and thus improve the Intersection-over-Union (IoU) calculation for the Non-Maximum Suppression (NMS).

The proposals and projects listed above demonstrate that, in the current agricultural industry, scientists and researchers are very interested in researching and applying Artificial Intelligence in general and Computer Vision in particular, especially in the field of using algorithms such as CNN to extract image features and attribute descriptors of fruits.

3. System Architecture

The system for recognizing and detecting pineapple fruit ripening is based on computer vision technology and image processing techniques, using a convolutional neural network to identify identification, analyze data, extract image features, enhance data, and process attribute descriptions of input data. In this paper, the authors use the YOLOv4 training model to improve training speed and performance. Following the data collection process, the input images are labeled, and the images' features are extracted by training a deep learning model. As a result of the training process, the trained model will be used to predict images. The analysis and evaluation of pineapple is carried out on the basis of color, shape, size, and texture in order to identify and detect the ripening period of pineapple. The pineapple recognition system's architecture is described below.

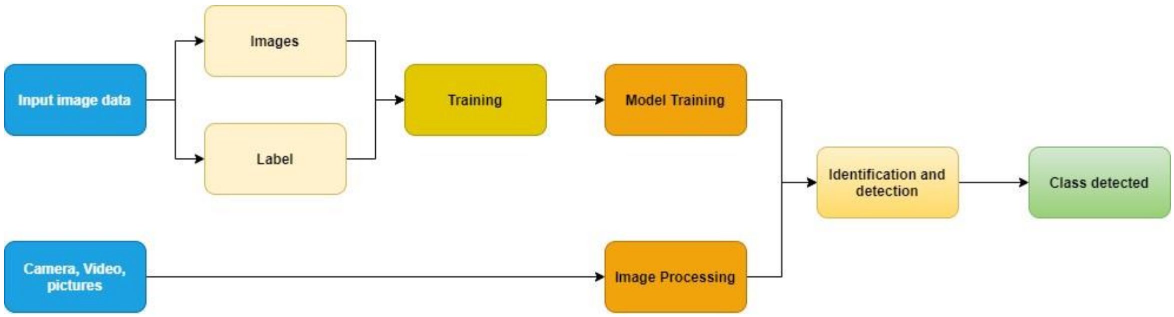

Figure 1 Architecture of the pineapple's growth stages detection system

3.1. Pineapple fruits dataset

Pineapple is a South American tropical fruit tree. Currently, tropical countries and some subtropical countries with relative rivers, such as Hawaii Island, Taiwan, and others, account for 60 percent of the world's pineapple production. Pineapples in Vietnam are classified into three major groups based on morphological characteristics, development, and flavor quality, as shown in Table 1.

Table 1: List of pineapples

Type	The morphological features	Dignity
Queen	Leaves: narrow, hard, with many spines at the leaf's edge, and white veins on the inner surface of the leaf blade. Flowers are pinkish green, fruit eyes are convex, fruit flesh is dark yellow, aroma is distinctive, and the taste is sweet.	High
Cayen	The leaves are dark green, long, and thick, with no or few spines; the flowers are pink, reddish, and cylindrical, with large eyes. Gradually ripening, when ripe, the yellow color changes from the stem to the fruit.	Middle
Spain	The leaves are soft, the dorsal margins are curved, and the spine density is unevenly distributed. Flowers are a light red color. When fully ripe, the fruit is dark red in color with deep eye holes, yellow flesh, a sour taste, and fiber.	Low

Dataset which is used was collected during the research process. We have surveyed and took pictures at some pineapple gardens in Quang Nam - Da Nang. In this paper, the authors perform the identification and detection of the growth stages of the ripe pineapple. Each data contains images divided into one training dataset and one validation dataset. It also contains labels that assign the location to each photo [40,41]. The dataset contains 10,000 photographs of pineapples at various stages of development. Initially, 8,000 images are labelled independently, followed by 2000 images that are evaluated to train the model. Input data is processed by computers to produce results according to instructions.

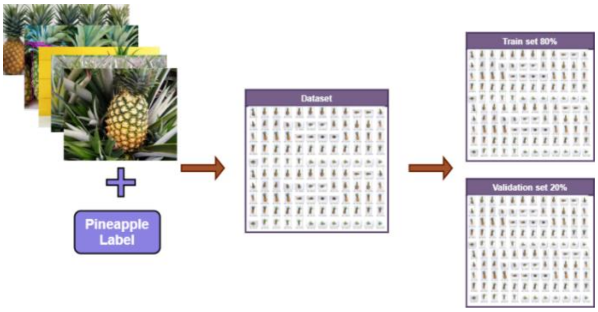

Figure 2: Data collection process

3.2. Annotate Images

Data labelling is the most important step in the training process with correct predictions. After importing the dataset, the authors started labelling each image to extract characteristics of pineapples in this case. The labelling is implemented with a LabelImg tool. labelling is a graphical image annotation tool It is written in Python and uses Qt for its graphical interface. The annotation will be saved as a TXT file and YOLO labelling format used by Image Net. It also contains labels that assign the location to each photo. The dataset has updated attributes such as image name, growth stage, and pineapple position in the image (x_min, y_min, x_max, y_max).

Figure 3: Labeled pineapple

3.3. Data Augmentation

Limited resources make it difficult for local data feeds to take place. Prediction accuracy suffers because of this. Reinforcement learning is used to solve this problem by collecting data in several formats and creating multiple versions based on the data. Using our image processing software, you can transform, detect, identify colours, crop, resize, handle noisy images, and colourize black and white images. Data will be reinforced following these steps.

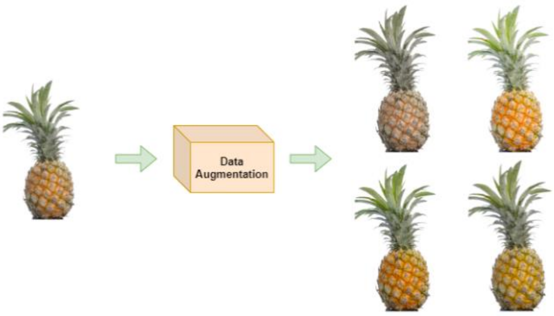

Figure 4: Data Augmentation

3.4. Model Training

Pre-trained model: The YOLOv4 training model is used in this study. This is the most accurate and fastest object detector. Here are some files that are required for the training process:

- For object detection, class files are identified - in this case, the class is pineapple.
- Training files contain the name, format and location of the images.
- Test files contain the name, format, location of the images for the testing process.
- Annotation files contain a dataset of annotations with class identification and image location coordinates.
- Configuration files contain the data and configuration of the YOLOv4 training model.
- Image folder contains the images for the predictive process with YOLOv4.

We are improving the coverage and scale of training by using automatic image collection and labelling. The image resolution is increased to improve accuracy. Higher pixel resolutions allow the model to detect more fine-grained features, which makes removing image borders, image styles, and colours easier. There are patterns on the pineapple based on its outer skin and its defects. As a result of the pineapple's flaws and its outer skin, the patterns appear. Convolutional neural networks are used in the YOLOv4 training model to extract image features. It has been configured. There will be 6000 repetitions of the procedure. The procedure is performed in a collaborative setting.

```
 1: 4175.175293, 4175.175293 avg loss, 0.000000 rate, 6.112641 seconds, 32 images, -1.000000 hours left
Loaded: 10.259133 seconds - performance bottleneck on CPU or Disk HDD/SSD
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 139 Avg (IOU: 0.000000), count: 1, class_loss = 9444.621094, iou_loss = 0.000000, total_loss = 9444.621094
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.177063), count: 1, class_loss = 2244.061035, iou_loss = 0.124023, total_loss = 2244.185059
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU: 0.397271), count: 13, class_loss = 812.275452, iou_loss = 0.332886, total_loss = 812.608337
 total_bbox = 158, rewritten_bbox = 0.000000 %
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 139 Avg (IOU: 0.000000), count: 1, class_loss = 9461.065430, iou_loss = 0.000000, total_loss = 9461.065430
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.280768), count: 1, class_loss = 2235.412842, iou_loss = 0.149658, total_loss = 2235.562500
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU: 0.387248), count: 15, class_loss = 810.291077, iou_loss = 0.555237, total_loss = 810.846313
 total_bbox = 174, rewritten_bbox = 0.000000 %
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 139 Avg (IOU: 0.000000), count: 1, class_loss = 9484.280273, iou_loss = 0.000000, total_loss = 9484.280273
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.000000), count: 1, class_loss = 2242.440430, iou_loss = 0.000000, total_loss = 2242.440430
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU: 0.423764), count: 14, class_loss = 801.962708, iou_loss = 0.431824, total_loss = 802.394531
 total_bbox = 188, rewritten_bbox = 0.000000 %
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 139 Avg (IOU: 0.000000), count: 1, class_loss = 9503.753906, iou_loss = 0.000000, total_loss = 9503.753906
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.000000), count: 1, class_loss = 2225.078369, iou_loss = 0.000000, total_loss = 2225.078369
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU: 0.408941), count: 2, class_loss = 819.981628, iou_loss = 0.029053, total_loss = 820.010681
 total_bbox = 190, rewritten_bbox = 0.000000 %
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 139 Avg (IOU: 0.000000), count: 1, class_loss = 9488.685547, iou_loss = 0.000000, total_loss = 9488.685547
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.000000), count: 1, class_loss = 2246.436768, iou_loss = 0.000000, total_loss = 2246.436768
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 total_bbox = 192, rewritten_bbox = 0.000000 %
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 139 Avg (IOU: 0.000000), count: 1, class_loss = 9471.952148, iou_loss = 0.000000, total_loss = 9471.952148
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.299390), count: 1, class_loss = 2236.439453, iou_loss = 0.169434, total_loss = 2236.608887
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU: 0.415157), count: 9, class_loss = 807.800171, iou_loss = 0.556946, total_loss = 808.357117
 total_bbox = 202, rewritten_bbox = 0.000000 %
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 139 Avg (IOU: 0.000000), count: 1, class_loss = 9436.049805, iou_loss = 0.000000, total_loss = 9436.049805
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.347711), count: 2, class_loss = 2237.659180, iou_loss = 0.568115, total_loss = 2238.227295
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU: 0.372228), count: 10, class_loss = 808.450989, iou_loss = 0.219971, total_loss = 808.670959
```

Figure 5 The summary of the first training epoch

4. Results and Output

4.1. Model training results

The training process will return a set of weights corresponding to the metrics of accuracy, data loss, training time, and so on every 1000 epochs. Finally, it will generate statistics and graphs pertaining to the training process.

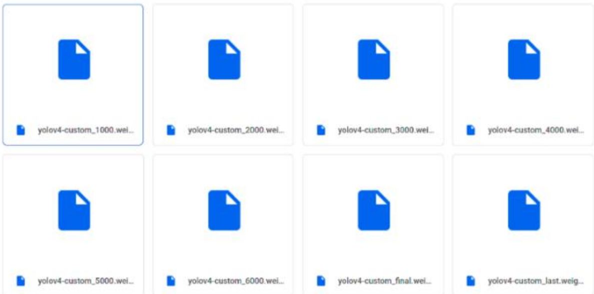

Figure 6 Post-training model

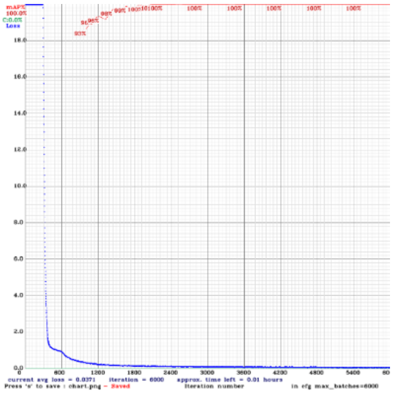

Figure 7 Statistical graph of the training process

4.2. Identification system

Researchers have created a system able to analyze images and videos based on their completed model and evaluation. To construct the system, Python is used. Use Python's Flask WebAPI framework for the system interface. The system imports trained models and compare them with analyzed data. Based on image and video input, the system can identify and detect pineapple images. Objects can be identified and counted with the system.

Figure 8 Pineapple identification system

4.3. Research results

The research team took large-scale photographs at the pineapple garden in Quang Nam - Da Nang. Because there are so many of them, photos were taken in the garden and at the storage facility. More than twenty images with more than 200 discovered pineapples were entered into the system by the team. The system can detect and count objects based on a model that has been trained to provide predictive results. The following two identification results assess the trained model's accuracy. The accuracy of the trained model will be evaluated using two given exported detected results. Detection methods include images and videos. Figure 9(a) depicts the detected results, complete with bounding boxes around the pineapples. The system can identify with between 65% and 85% accuracy. In Figure(b), the researchers experimented with the exportation of collected data using video detection methods. The detection system can recognize and count pineapples. The identification system achieves the correct results allowing use.

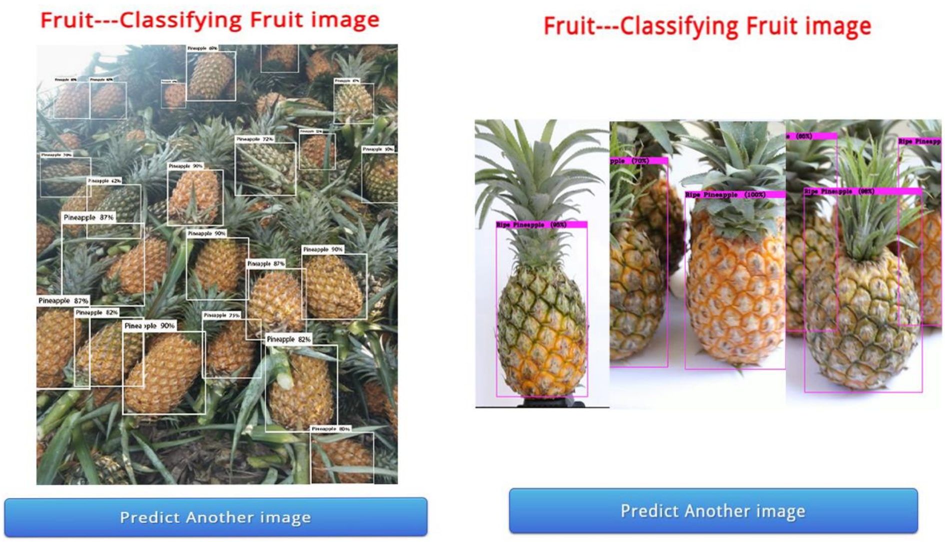

Figure 9 The exported results with image detection

Table 1: System recognition performance statistics

Frame	**Accuracy**	**Number of pineapples**
0-40	70% - 85%	8
40-80	78% - 88%	11
80-150	80% - 89%	12
150-200	80% - 89%	15
Figure 9(a)	62% - 92 %	24

Based on Table 1, there were 85 per cent more pineapples identified in images and videos. Ensure that the identification system is functioning satisfactorily. Researchers expected the findings to meet their expectations. You can see how the number of pineapples and the frames of the camera vary. There are several frames in which pineapples are hidden. The ability of the system to identify is affected by these factors. The factors aforementioned played a role in the detection process. Additionally, the system is capable of performing accurate calculations. This will prevent repetition in one object since the detected pineapples that are numbered will not overlap.

5. Conclusion

Pineapples are detected better by YOLOv4 than in previous versions. Analyzing pineapple development is the subject of this paper. In this study, both the reality and theory of the system and situation were examined. Future research on this topic will be greatly enhanced by the findings. Using the system, farmers can monitor and reduce labour and time spent on the ripening process. System reliability and consistency results indicate a high level of reliability.

Despite this, there were some difficulties encountered in the study. Pineapples are rarely depicted in photographs. Depending on the weather, the detection system will perform differently. A specific geographic area is the focus of this study. There are some drawbacks to the study, along with a lack of advanced technology, so its effectiveness has yet to be determined. Under certain conditions, the system is capable of performing well, laying the foundation for future research, increasing pineapple mass-production productivity, and increasing pineapple surveillance.

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References

[1] Inkyu Sa, ZongYuan Ge, Feras Dayoub, B. Upcroft, Tristan Perez, C. McCool. DeepFruits: A Fruit Detection System Using Deep Neural Networks (2016).

[2] YunongTian, GuodongYang, ZheWang, HaoWang, EnLi, ZizeLiang. Apple detection during different growth stages in orchards using the improved YOLO-V3 model (2012).

[3] Byoungjun Kim, You-Kyoung Han, Jong-Han Park and Joonwhoan Lee1. Improved Vision-Based Detection of Strawberry Diseases Using a Deep Neural Network (2021).

[4] Jose Luis Rojas-Aranda, Jose Ignacio Nunez-VarelaJ. C. Cuevas-TelloGabriela Rangel-Ramirez. Fruit Classification for Retail Stores Using Deep Learning (2020).

[5] Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi. You Only Look Once: Unified, Real-Time Object Detection

[6] Guoxu Liu, Joseph Christian Nouaze, Philippe Lyonel Touko Mbouembe and Jae Ho Kim. YOLO-Tomato: A Robust Algorithm for Tomato Detection Based on YOLOv3 (2020).

[7] Redmon, J.; Divvala, S.; Girshick, R.; Farhadi, A. You only look once: Unified, real-time object detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27 June 2016; pp. 779–788.

[8] Redmon, J.; Farhadi, A. YOLO9000: Better, faster, stronger. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 26 July 2017; pp. 7263–7271.

[9] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun, "Faster R-CNN: Towards RealTime Object Detection with Region Proposal Networks," arXiv:1506.01497v3 [cs.CV], Jan. 2016.

[10] Redmon, J.; Farhadi, A. YOLOv3: An incremental improvement. arXiv 2018, arXiv:1804.02767.

[11] Munera, S., Amigo, J. M., Blasco, J.; Cubero, S.; Talens, P., Alexios, N. (2017). Ripeness monitoring of two cultivars of nectarine using VIS-NIR hyperspectral reflectance imaging. Journal of Food Engineering, 214(3), 29-39.

[12] Optimal deep learning model for classification of lung cancer on CT images, (2019), Lakshmanaprabu S.K., Sachi Nandan Mohanty, Shankar K., Arunkumar N., Future Generation Computer Systems, 19, 1, 374-382.

[13] Lakshmanaprabu S.K., Sachi Nandan Mohanty, Shankar K., Arunkumar N., Optimal deep learning model for classification of lung cancer on CT images, (2019), Future Generation Computer Systems, 19, 1, 374-382.

[14] Tian, Y., Yang, G., Wang, Z., et al., 2019. Apple detection during different growth stages in orchards using the improved YOLO-V3 model[J]. Computers and Electronics in Agriculture 157, 417–426.

[15] A. B. Alexey, "YOLO mark," 2018. [Online]. Available: https: github.com/AlexeyAB/Yolo mark Apple detection during different growth stages in orchards using the improved YOLO-V3 model

[16] P. Rajeshwari, P. Abhishek, P. Srikanth, T. Vinod (2019) Object Detection: An Overview. International Journal of Trend in Scientific Research and Development (IJTSRD), Vol. 3: pp.1663- 1665 \

[17] Xiongwei Wu, Doyen Sahoo, Steven C.H. Hoi, "Recent Advances in Deep Learning for Object Detection," arXiv:1908.03673v1 [cs.CV], Aug. 2019

[18] Yuting Zhang, Kihyuk Sohn, Ruben Villegas, Gang Pan, Honglak Lee, "Improving Object Detection with Deep Convolutional Networks via Bayesian Optimization and Structured Prediction," arXiv:1504.03293 [cs.CV],

Jan. 2016.

[19] Stajnko, Denis and Lakota, Miran and Hoˇcevar, Marko. (2004). Estimation of number and diameter of apple fruits in an orchard during the growing season by thermal imaging. Computers and Electronics in Agriculture. 42. 31-42. 10.1016/S0168-1699(03)00086-3.

[20] Redmon, J., Farhadi, A., 2018. YOLOv3: An incremental improvement. In: IEEE conference on Computer Vision and Pattern Recognition, arXiv:1804.0276.

[21] He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[22] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In ICLR, 2015.

[23] Alexey Bochkovskiy, Chien-Yao Wang, Hong-Yuan Mark Liao. YOLOv4: Optimal Speed and Accuracy of Object Detection.

[24] Van B. Dang, Duy-Dinh Le, Duc A. Duong, Image Filtering Using Visual Information Consistency, Proceedings of the First International Conference on Theories and Applications of Computer Science (ICTACS 2006), Ho Chi Minh City, Vietnam, 2006, pp 51 – 64

[25] Thang B. Dinh, Van B. Dang, Duc A. Duong, Tuan T. Nguyen, Duy-Dinh Le, Hand Gesture Classification Using Boosted Cascade of Classifiers, Proceedings of 4th IEEE International Conference Research, Innovation and Vision of the Future RIVF 2006, Ho Chi Minh City, Vietnam, Feb. 12-16, 2006, pp 138-143

[26] Hoang Van Kiem, Duong Anh Duc, Le Dinh Duy, A Fast Algorithm for Polygon Clipping, Journal of Institute of Mathematics and Computer Sciences, India, Vol. 13, No. 1, 2002.

[27] P. Rajeshwari, P. Abhishek, P. Srikanth, T. Vinod (2019) Object Detection: An Overview. International Journal of Trend in Scientific Research and Development (IJTSRD), Vol. 3: pp.1663- 1665

[28] Xiongwei Wu, Doyen Sahoo, Steven C.H. Hoi, "Recent Advances in Deep Learning for Object Detection, " arXiv:1908.03673v1 [cs.CV], Aug. 2019

[29] Yuting Zhang, Kihyuk Sohn, Ruben Villegas, Gang Pan, Honglak Lee, "Improving Object Detection with Deep Convolutional Networks via Bayesian Optimization and Structured Prediction," arXiv:1504.03293 [cs.CV], Jan. 2016

[30] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In ICLR, 2015.

[31] Dumitru Erhan, Christian Szegedy, Alexander Toshev, Dragomir Anguelov (2014) Scalable Object Detection using Deep Neural Networks. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2147-2154

[32] Yongxi Lu, Tara Javidi, Svetlana Lazebnik, "Adaptive Object Detection Using Adjacency and Zoom Prediction," arXiv:1512.07711 [cs.CV], Apr. 2016

[33] Sun Q., Pfahringer B. (2011) Bagging Ensemble Selection. In: Wang D., Reynolds M. (eds) AI 2011: Advances in Artificial Intelligence. AI 2011. Lecture Notes in Computer Science, vol 7106. Springer, Berlin, Heidelberg

[34] Zhong-Qiu Zhao, Peng Zheng, Shou-tao Xu, Xindong Wu, "Object Detection with Deep Learning: A Review, " arXiv:1807.05511 [cs.CV], Apr. 2019

[35] Keiron O'Shea, Ryan Nash, "An Introduction to Convolutional Neural Networks," arXiv:1511.08458 [cs.NE], Dec. 2015

[36] Munera, S., Amigo, J. M., Blasco, J.; Cubero, S.; Talens, P., Alexios, N. (2017). Ripeness monitoring of two cultivars of nectarine using VIS-NIR hyperspectral reflectance imaging. Journal of Food Engineering, 214(3), 29-39.

[37] Santagapita, P.R., Tylewicz, U. Panarese, V., Rocculi, P, Dalla, Rosa, M. (2016). Nondestructive assessment of kiwifruit physic-chemical parameters to optimize the osmotic dehydration process, A study on FT-NIR spectroscopy. Journal of Biosyst. Eng. 142, (2), 101-129.

[38] S. Kim, Y. Ji and K. Lee," An Effective Sign Language Learning with Object Detection Based ROI Segmentation," 2018 Second IEEE International Conference on Robotic Computing (IRC), Laguna Hills, CA, 2018, pp. 330-333.

[39] Stajnko, Denis and Lakota, Miran and Hoˇcevar, Marko. (2004). Estimation of number and diameter of apple

fruits in an orchard during the growing season by thermal imaging. Computers and Electronics in Agriculture. 42. 31-42.

[40] Nguyen H.H.C., Luong A.T., Trinh T.H., Ho P.H., Meesad P., Nguyen T.T. (2021) Intelligent Fruit Recognition System Using Deep Learning. In: Meesad P., Sodsee D.S., Jitsakul W., Tangwannawit S. (eds) Recent Advances in Information and Communication Technology 2021. IC2IT 2021. Lecture Notes in Networks and Systems, vol 251. Springer, Cham. https://doi.org/10.1007/978-3-030-79757-7_2".

[41] Nguyen, H.H.C., Nguyen, D.H., Nguyen, V.L., Nguyen, T.T.: Smart solution to detect images in limited visibility conditions based convolutional neural networks. In: Advances in Computational Collective Intelligence. ICCCI 2020. Communications in Computer and Information Science, vol. 1287, pp. 641–650. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-63119-2-52.

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