Development of an Intelligent Defect Detection System for Gummy Candy under Edge Computing

Shyh-Wei Chen[1], Chun-Ju Tsai[2], Chia-Hui Liu[3*], William Cheng-Chung Chu[1], Ching-Tsorng Tsai[1]

[1] Department of Computer Science, Tunghai University, Taiwan
[2] Department of Electrical Engineering, Tunghai University, Taiwan
[3] Department of Applied Mathematics, Chinese Culture University, Taiwan
chensw@go.thu.edu.tw, g09360003@go.thu.edu.tw, ljh34@ulive.pccu.edu.tw, cchu@thu.edu.tw, cttsai@go.thu.edu.tw

Abstract

Gummy candies are one of the products of the food industry. It has invested more resources in all aspects of the food production chain to improve production processes. The defective candies cause the unevenness of the product that will cause the appearance, taste and flavor poor. That will lead to economic losses for the company. Most traditional candy companies set up product inspection personnel to eliminate defective product. In this paper, an intelligent defect detection system for gummy candy industry under edge computing environment is proposed. It can replace manual visual inspection, even shorten the processing time to reduce production costs, thereby improving product quality, the efficiency of the production line, and the number of inspections. The system includes: (1) The intelligent defect detection system by deep learning algorithms. (2) The edge computing architecture with AIoT. The proposed system adopted the YOLO deep learning algorithm. The results show that the Precision is 93%, Recall is 87% and the F1 Score is 90. It has certain empirical reference significance for the intelligent defect detection system of candies products. By adopting deep learning algorithm in the detection system, it can reduce the inspection man-power needs and long-term data collection.

Keywords: Defect detection, Deep learning, Artificial Intelligence of Things, Intelligence inspection system

1 Introduction

With the progress of science and technology, people pay more and more attention to food safety. The food industry has also invested more resources in all aspects of the food production chain to improve production processes [1-2]. Gummy candy is one of the products of the food industry. The problem in the production process of gummy candies is the unevenness of the product that will cause the appearance, taste and flavor poor [3-4]. These factors caused economic losses for the company. So far, most of the candy companies set up product inspection personnel to eliminate defective product. The inspector is allowed to visually identify and manually remove the defective hard candy on the conveyor belt [5]. Therefore, the inspection of products in the traditional food industry is quite a waste of human resources. However, eliminating defective products is a very important part of the food industry. The defective products will lead to poor sales of goods and reduce production. The inspectors may be also affected by some factors when visually inspecting food, such as fatigue, drowsiness, or noise, etc. Presently, food industry has developed numerous applications using computer vision to automatic defect inspection. Extracting a lot of external properties, such as the texture, shape, color, and wavelet features from digital images were used to train the classifiers. For example, the random forest method was been used to find the imperfect apples [6]. A multi-hybrid identification method was proposed to identify and remove various foreign in the tobacco packs [7]. The support vector machines were also used in several research to perceive flawed vegetables. In the torrent of the AI digital era, all industries face challenges in the development and application of AI [8-9]. Many industries still need a lot of manpower to invest in production lines, process standardization, quality inspections rely on manpower, and the promotion of traditional marketing methods [10-11]. The artificial intelligence internet of thing, (AIoT) can help companies to optimize the efficiency of internal management and production processes. It not only raises the quality and speed of business decision-making but also improves the production capacity in the factory. The concept of edge computing is practice of capturing, storing, processing and analyzing data near the client, not easily affected by the quality of the network, and is more suitable for time-sensitive applications, making edge computing more suitable for industrial production applications.

According to the above reasons, this paper proposed an intelligent defective detection system for gummy candy factory under edge computing environment. This paper constructs an AIoT intelligent defect detection system for a gummy candy industrial which integrated the IoT device into the edge controller. It directly performed product inspection and control the machine in the factory. The system also uses deep learning algorithms (YOLO) to implement an automated inspection subsystem which can effectively identify the defects of the gummy candies. In additional, the proposed system enables operators to use mobile phones to take the candy's picture to collect training images at the near end. The system continuously learns various product defect categories through automated processes, and continuously optimizes the AI model to accurately identify various defects. It also allows managers to monitor by the monitoring APP in real time,

*Corresponding Author: Chia-Hui Liu; E-mail: ljh34@ulive.pccu.edu.tw
DOI: 10.53106/160792642022092305006

including product management, sampling, real-time production monitoring and related producing statistical reports. The enterprises can improve the production quality of gummy candies to increase revenue through the proposed AIoT intelligent defect detection system.

2 Related Works

The work in this article can be divided into two parts: (1) To research implementing deep learning algorithms into gummy candy defect detection. The proposed system used YOLO as our deep learning algorithm. By applying an automatic selecting system, we pick up defective products quickly. (2) To build gummy candy defect detection equipment with AIoT components. The equipment can be further use in the industry. Deep learning was a branch of machine learning. Many research and development concepts have shown the perspective of machine learning to facilitate the acceleration of the development of deep learning applications [12-13]. Machine learning process can be divided into data preprocessing and feature extraction, model training, prediction, and evaluation [14-15].

These steps were the process cycles of machine learning application development. The results of the performance were used to evaluate and extract more useful features, to modify the parameters of the model, and to produce a better model step by step. In the research and development of machine learning, it was necessary to connect the various steps for the speed-up each cycle and further reduce the development time. Although deep learning can automatically extract features, the pre-processing of data was still an inevitable important task. It was used batch processing for a large amount of data, rich library support, easy to learn and develop, and big data analysis platforms to improve data processing efficiency. Deep learning has been developed many reliable algorithms [16]. Among them, the most famous algorithm used in image recognition was YOLO [17]. YOLO (You Only Look Once: Unified, Real-Time Object Detection) was a neural network-based target detection system. YOLO was a convolutional neural network that can predict multiple Box positions and categories at once [18]. It can achieve end-to-end target detection and recognition. Its biggest advantage is speed. The essence of target detection was regression. Therefore, a CNN that implements the regression function does not require a complicated design process. YOLO did not choose a sliding window or extracting proposals to train the network. It directly selects the whole image to train the model.

AIoT (Artificial Intelligence of Things) is a technology which combines AI with IoT to establish intelligent system. IoT is familiar to our neural system, and AI is familiar to our brain. IoT passes information to AI to deal with it. Compared to IoT, AIoT adds analysis and control functions instead of only data collection, storage, and process. IoT consists of interconnected things with sensors inside and can collect or generate a vast amount of data. When it integrates into a large-scale system with various applications, the collected data could be enormous. Without AI, those data would have limited value. AI could utilize and analyze data to solve a problem or make a decision. This will multiply the value of the data.

The milestone of detection framework present in object detection since deep learning entered the field can be organized into two main categories [18]:

(1) Two-stage detectors divide the detection into two stages, first use a Region Proposal Network (RPN)to generate regions of interests and send the region proposals down the pipeline to do object classification and bounding-box regression. The representative detectors including region proposal-based framework are R-CNN [19], Fast R-CNN [20], Mask R-CNN [21], SPPNet [22], etc.

(2) One-stage detectors treat object detection as a simple regression problem. They don’t require the region proposal stage, directly generate the class probability values and position coordinates of the objects. The representative regression-based one-stage detectors are SSD (Single Shot MultiBox Detector) [23], YOLO.

3 The Proposed Approach

In the traditional industry, the unneccesary human resources consumption and the elimination of non-performing products would recuced the production capacity. This paper constructs an edge comptuting environment and intelligent defect detection system for a gummy candy. This research can assist manufacturers at multiple levels and can figure out a more innovative direction of research through the process. It can replace manual visual inspection, even shorten the processing time to reduce production costs, thereby improving product quality, the efficiency of the production line, and the number of inspections. The Figure 1 shows the proposed system architecture. There are two parts in this system. (1) The intelligent defect detection system by deep learning algorithms. (2) The proposed edge computing architecture with AIoT.

3.1 The Intelligent Defect Detection System

The detection of gummy candy defects is essential in the speed and quality control. The You Only Look Once (YOLO) method is one of the deep learning algorithms and its detection speed reaches 45 pieces per second. The speed advantage makes it an end-to-end leader. Therefore, the system use YOLO deep learning algorithm. By applying an automatic selecting system, the system could pick up defective products quickly. The gummy candy detection system is shown in Figure 2.

In the gummy candy inspection process, the candy is put on a box-type conveying device, and a camera device is set up with the WIFI interface to take real-time images of the candy in each product line. After the candy real-time image is recognized by the intelligent candy defect detection system based on deep learning. It is controlled to blow off the defective candies by an auto blowgun.

3.1.1 Data Collection

By applying IoT devices onto the gummy candy production line, we collected data like humidity and temperature then send it to the database to build a training dataset. For gummy candy defects, we attached a camera to it and took pictures manually. We collected 5000 pictures of defect candies in Figure 4 for our training dataset and used data augmentation to generate around 20000 images.

3.1.2 YOLOv3 Network Algorithm

1. YOLOv3 [24] can be generally divided into two parts: feature extraction layer and processing output layer.
2. It used Darknet-53 as backbone, which incorporates YOLOv2, Darknet-19 [25] and ResNet (Residual Network) [26] like networks. YOLOv3 model can be divided into 106 layers, 75 of them are convolution layers, 23 layers are shortcut layers, 4 are route layers, 3 are yolo layers, rest of the layers are upsampling layers.
3. The system removed maxpooling and fully connected layers, applied 1x1 and 3x3 convolution layers with some shortcut connections. 1x1 convolution layer is for compressing feature representation after 3x3 convolution layer and 3x3 is used to reduce the height and width. Shortcut layer is a ResNet-like network for solving vanishing gradient problem.
4. Aspired by Feature Pyramid Network (FPN) [27], the system used multi-scale fusion prediction to detect large, medium and small objects at three different scales.
5. YOLOv3 makes predictions at three scales, given by downsampling the dimensions of the image by a stride of 32, 16, 8. When we input a 416x416 image, we will get 13x13 (416/32), 26x26 (416/16), 52x52 (416/8) three different feature maps.
6. We used multiple independent logistic regression classifier and binary cross-entropy as loss function. The overall process is shown in Figure 5.
7. Data collection and pre-processing can be divided into three parts: (1) Data collection: we used CCD camera to acquire images as Figure 3. (2) Label images: Using label program to label all of the defect candy images before training. (3) Training test split: we split 80% of data into training data, put rest of them into test data. After training, we tested the proposed model.

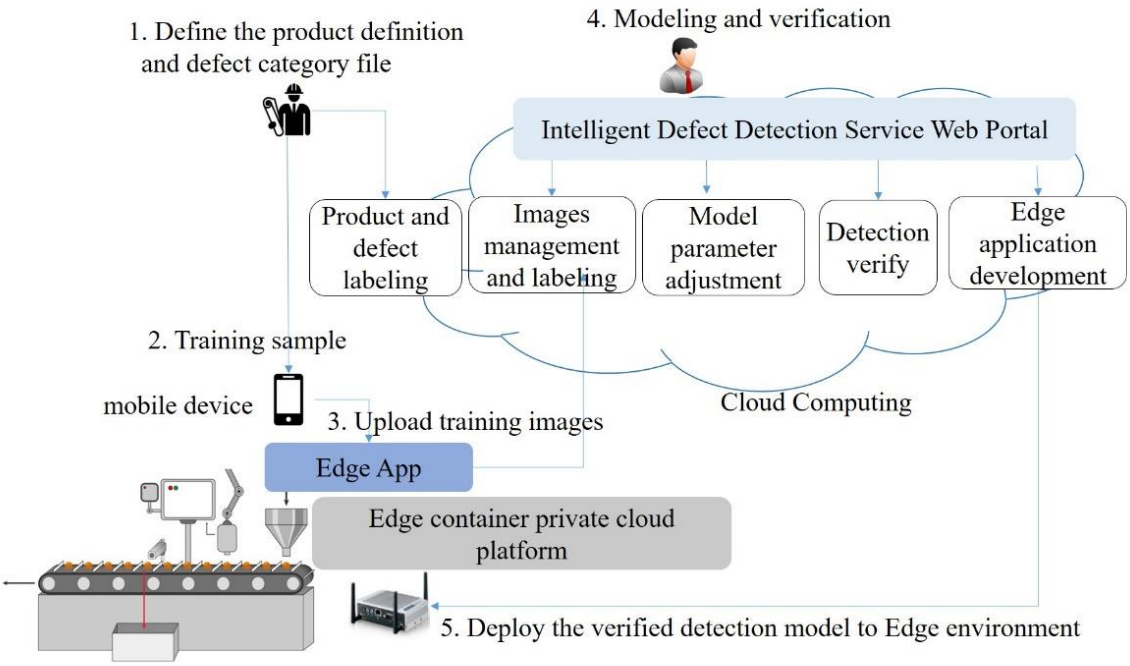


Figure 1. The proposed system architecture

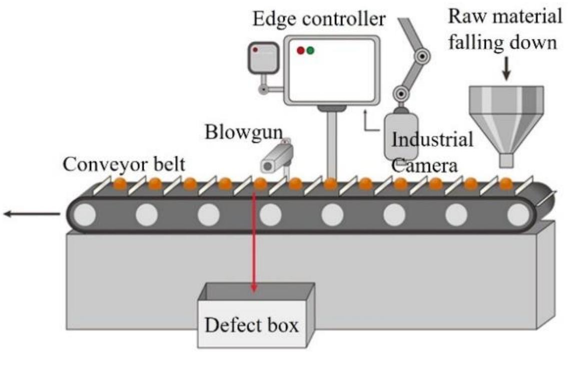


Figure 2. The defect detection system

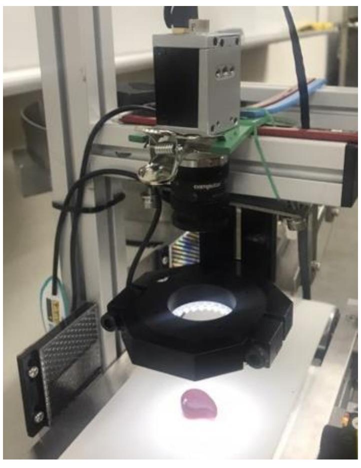


Figure 3. The detection CCD camera

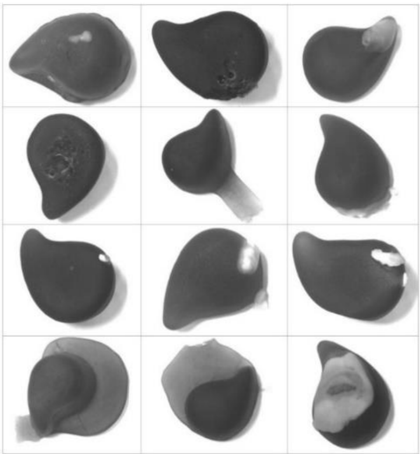


Figure 4. Defect images

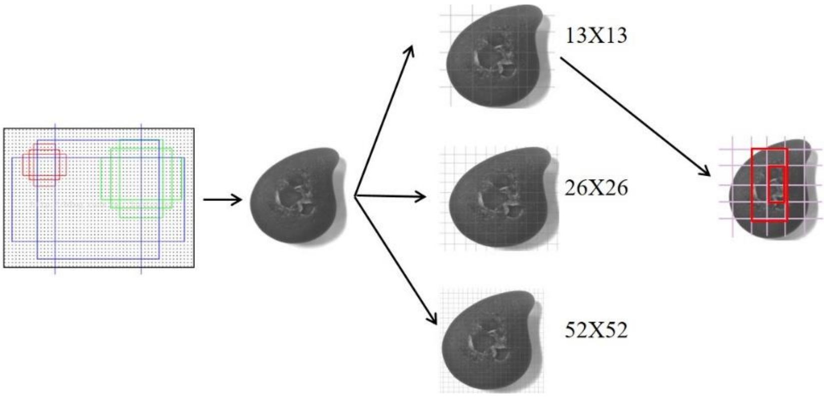


Figure 5. YOLOv3 processing method

3.2 The Proposed Edge Computing Architecture with AIoT

This paper integrated the AIoT into edge controller and developed it in the gummy candy factory as shown in the Figure 6. The proposed system can directly carry out product inspection and control the machine in the factory. The software architecture of the edge controller is shown in the figure: It includes a hardware control module, an image detection module, an image processing module, a process control module, and a real-time monitoring module. Users can conveniently control this system through the monitoring APP developed by this system.

The monitoring APP designed in this paper has the following functions: User authentication, Edge controller viewing, Product management and sampling (classification file creation and pattern sampling upload), Real-time automatic defect image identification and monitoring, and Detection statistical reports. The monitoring APP is shown as Figure 6.

The monitoring APP includes the following features

1. User authentication: In this study, the system used the commonly and convenient authentication mechanism which is password authentication. It established the employees' account names and passwords in the proposed system according their access control privilege. The use can log into the system with their account number and passwords.
2. Product management and sampling: The monitoring APP allows the user to take the gummy images on the production line and upload to the proposed intelligent defect detection system immediately. The images can be used as training test and improve the effecting of the system in time.

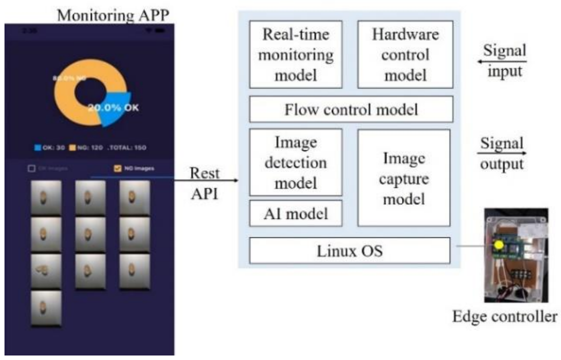


Figure 6. The monitoring APP

4 Experiment Results

4.1 The Experiment Hardware

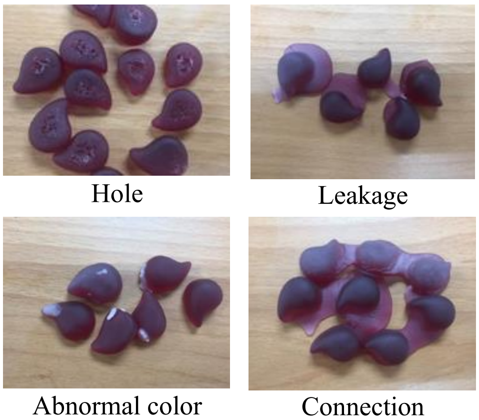
The hardware of the experimental system used Ubuntu 20.04 operating system, equipped with CPU Intel i7-10875H Processor 2.3 GHz, GPU NVIDIA RTX 2080 super and 64 GB running memory, installed CUDA 10.2 and CUDNN 8.0.5 to speed up the GPU computing. However, the detection effect might not be satisfactory due to that the images collected from a general camera. The requirement of image quality in the defect detection system is greatly high. A series of issues such as resolution, frame rate, transmission speed, and economic cost should be taken into consideration in the selection of the camera used in this experimental platform. While selecting the camera used in this study, it should take into consideration about the frame rate, transmission speed, and economic cost. A charge coupled device camera has higher resolution and much less noise than a complementary metal oxide semiconductor cameras of the same size. Therefore, we chooses BASLER series CCD industrial cameras such as ACA2000 in this study.

4.2 Dataset

There are three types of defects: Hole, Abnormal color, Connection and Leakage. Those are shown in Table 1.

In this paper, the gummy candy defect detection system adapted the YOLOv3 to detect the four different kinds of defects. There are 5000 images in total that defect each type has 1250 images in average. For strengthening the training model effect, this study performs data enhancement operations on the dataset to horizontally and vertically flip. It also adjusts the saturation and contrast of the images in all the images. Finally, a new dataset is formed, a total of 20000 images which 80% is for training and others for testing. The proposed system marked the defects on the images. It marked the coordinates of the defect's location and the categories of the defects. The effect of the labeling results is shown in Figure 7.

Table 1. Defect candies



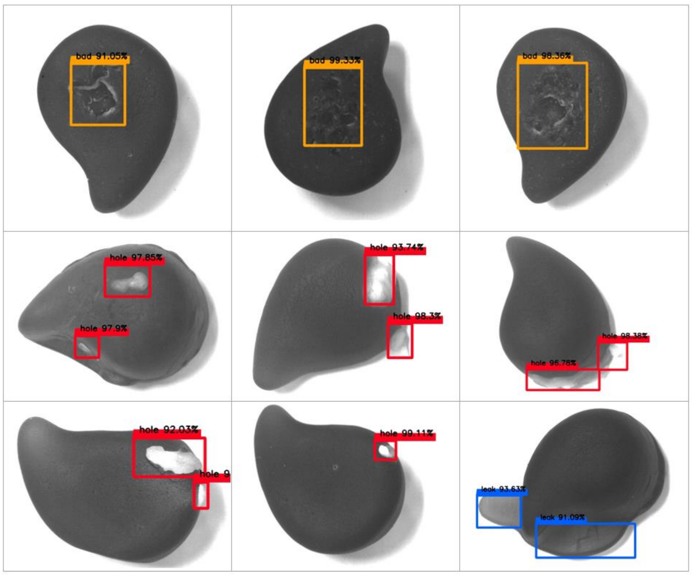


Figure 7. The defect detection result

4.3 Performance Evaluation

YOLOv3 uses multiple independent logistic regression classifiers, which can perform multi-class prediction on multiple labels. It uses binary cross entropy as the loss function and maintain good accuracy. The metrics can be dereived from the confusion matrix such as Precision, Recall and F1 score.

- Precision: It is the proportion of correct positive predictions and the ability of a classifier to identify only relevant objects.
- Recall: It measures the ability of a classifier. This metric is the proportion of true positive detected among all ground truths.
- F1 score: It is a harmonic mean of precision and recall.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

$$\text{F1 score} = 2 * \left(\frac{Precision*Recall}{Precision+Recall}\right) \tag{3}$$

TP: True positive is a positive example that is correctly predicted.

FP: False positive is a negative example that is incorrectly predicted as a positive example.

FN: False negative is a positive example that is incorrectly predicted as a negative example

TN: True Negatives is an outcome where the model correctly predicts the positive class.

The confusion matrix is shown in Table 2.

Table 2. Confusion matrix

	Truth 1	Truth 0
Predicting 1	True Positive (TP)	False Positive (FP)
Predicting 0	False Negative (FN)	True Negative (TN)

The experiment results in this paper, the measured candies are 20000 normal and 20000 flaws which detection speed is 3.2 per second. The 18600 candies were picked out as normal (TP), and 1400 candies were not picked out (FP), 17300 candies's defects were picked out (TN) and 2700 candies's defects were not picked out (FN). Therefore, the Precision is 93%, Recall is 87% and the F1 Score is 90. The performance results is shown in Table 3. The proposed system detects the defect gummy from the 2D images. The defect information of the gummy is not only showed on the surface. It required the use of 3D defect detection method. Therefore, the limitation of this study is that to detect the 3D surface characteristics of the gummy warrants further research.

$$\text{Precision} = 93\% \tag{4}$$

$$\text{Recall} = 87.3\% \tag{5}$$

$$\text{F1 score} = 90\% \tag{6}$$

Table 3. The performance results

	P	R	F1-score
The intelligent defect detection system	0.93	0.873	0.9

5 Conclusion

In the traditional industry, the production was reduced due to human resources consumption and the elimination of non-performing products. This paper constructs an edge comptuting environment and intelligent defect detection system for a gummy candy. This research can assist to replace manual visual inspection, even shorten the processing time to reduce production costs, thereby improving product quality, the efficiency of the production line, and the number of inspections. The proposed system included: (1) The intelligent defect detection system by deep learning algorithms. The detection of gummy candy defects is essential in the speed and quality control. The speed advantage makes You Only Look Once (YOLO) method an end-to-end leader. Therefore, the system use YOLO deep learning algorithm. By applying an automatic selecting system, the system could pick up defective products quickly. (2) The proposed edge computing architecture with AIoT. It integrated the AIoT into Edge controller and developed it in the gummy candy factory. The proposed system can directly carry out product inspection and control the machine in the factory. This research collected 5000 pictures of defect candies for the training dataset which used data augmentation to generate around 20000 images and 80% pictures is for training and others for testing. The proposed system continuously learns various product defect categories through automated processes, and continuously optimizes the AI model to accurately identify various defects. It also allows managers to monitor by the monitoring APP in real time, including product management, sampling, real-time production monitoring and related statistical reports. The results showed that the Precision is 93%, Recall is 87% and the F1 Score is 90. The enterprises can improve the production quality of gummy candies to increase revenue through the proposed AIoT intelligent defect detection system. This study can reduce the inspection man-power needs. Also, the long-term data collection has certain empirical reference significance for the intelligent defect detection system of candies products.

References

[1] D. Watson, S.-P. Nyarugwe, R. Hogg, C. Griffith, P.-A. Luning, and S. Pandi, The Exotropia Food Safety Cultural Conundrum: A Case Study of A UK Fish High-Risk Processing Company, *Food Control*, Vol. 131, Article No. 108431, January, 2022.

[2] E.-J. Frankish, G. McAlpine, D. Mahoney, B. Oladele, P.-A. Luning, T. Ross, J.-P. Bowman, H. Bozkurt, Review Article: Food Safety Culture from The Perspective of the Australian Horticulture Industry, *Trends in Food Science & Technology*, Vol. 116, pp. 63-74, October, 2021.

[3] D. Toudert, N.-L. Bringas-Rábago, Interest In Food, Food Quality, Satisfaction, and Outcomes In a Border Context: Gender, Country of Residence and Born Moderation, *International Journal of Gastronomy and Food Science*, Vol. 25, Article No. 100394, October, 2021.

[4] F. Canio, E. Martinelli, EU quality Label vs Organic Food Products: A Multigroup Structural Equation Modeling to Assess Consumers' Intention to Buy In Light of Sustainable Motives, *Food Research International*, Vol. 139, Article No. 109846, January, 2021.

[5] M. Siegrist, A. Bearth, C. Hartmann, Food Disgust Sensitivity Influences the Perception of Food Hazards: Results from Longitudinal and Cross-Cultural Studies, *Appetite*, Vol. 153, Article No. 104742, October, 2020.

[6] Y. Lu, R. Lu, Detection of Surface and Subsurface Defects of Apples using Structured-illumination Reflectance Imaging with Machine Learning Algorithms, *Transactions of the ASABE*, Vol. 61, No. 6, pp. 1831-1842, September, 2018.

[7] M. Chao, K. Chen, Z. Zhang, Research on Tobacco

Foreign Body Detection Device Based on Machine Vision, *Transactions of the Institute of Measurement and Control*, Vol. 42, No. 15, pp. 2857-2871, November, 2020.
[8] M.-S. Iraji, Comparison between Soft Computing Methods for Tomato Quality Grading using Machine Vision, *Journal of Food Measurement and Characterization*, Vol. 13, No. 1, pp. 1-15, March, 2019.
[9] M. Khojastehnazh, H. Ramezani, Machine Vision System for Classification of Bulk Raisins using Texture Features, *Journal of Food Engineering*, Vol. 271, Article No. 109864, April, 2020.
[10] G. Iymen, G. Tanriver, Y.-Z. Hayirlioglu, O. Ergen, Artificial intelligence-based Identification of Butter Variations as a Model Study for Detecting Food Adulteration, *Innovative Food Science & Emerging Technologies*, Vol. 66, Article No. 102527, December, 2020.
[11] V. Kakani, V.-H. Nguyen, B.-P. Kumar, H. Kim, V. R. Pasupuleti, A Critical Review on Computer Vision and Artificial Intelligence in Food Industry, *Journal of Agriculture and Food Research*, Vol. 2, Article No. 100033, December, 2020.
[12] E.-A. Boasiako, S. Zhou, Y. Liao, Q. Liu, Y. Wang, K. Owusu-Agyemang, Privacy Preservation in Distributed Deep Learning: a Survey on Distributed Deep Learning, Privacy Preservation Techniques Used and Interesting Research Directions, *Journal of Information Security and Applications*, Vol. 61, Article No. 102949, September, 2021.
[13] Z. Bai, X.-L. Zhang, Speaker Recognition based on Deep Learning: an Overview, *Neural networks*, Vol. 140, pp. 65-99, August, 2021.
[14] S.-D. Kumar, S. Esakkirajan, S. Bama, B. Keerthiveena, A Microcontroller based Machine Vision Approach for Tomato Grading and Sorting using SVM Classifier, *Microprocessors and Microsystems*, Vol. 76, Article No. 103090, July, 2020.
[15] T. Czimmermann, G. Ciuti, M. Milazzo, M. Chiurazzi, S. Roccella, C. M. Oddo, P. Dario, Visual-based Defect Detection and Classification Approaches for Industrial Applications - A SURVEY, *Sensors*, Vol. 20, No. 5, Article No. 1459, March, 2020.
[16] G. Ciaburro, Sound Event Detection in Underground Parking Garage using Convolutional Neural Network, *Big Data and Cognitive Computing*, Vol. 4, No. 3, Article No. 20, September, 2020.
[17] J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You Only Look Once: Unified, Real-Time Object Detection, *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Las Vegas, NV, USA, 2016, pp. 779-788.
[18] L. Liu, W. Ouyang, X. Wang, P. Fieguth, J. Chen, X. Liu, M. Pietikäinen, Deep Learning for Generic Object Detection: a Survey, *International Journal of Computer Vision*, Vol. 128, No. 2, pp. 261-318, February, 2020.
[19] R. Girshick, J. Donahue, T. Darrell, J. Malik, Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation, *IEEE Conference on Computer Vision and Pattern Recognition* (*ICVPR*), Columbus, OH, USA, 2014, pp. 580-587.
[20] S. Ren, K. He, R. Girshick, J. Sun, Faster R-CNN: towards real-Time Object Detection with Region Proposal Networks, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 39, No. 6, pp. 1137-1149, June, 2017.
[21] K. He, G. Gkioxari, P. Dollar, R. Girshick, Mask R-CNN, *IEEE International Conference on Computer Vision* (*ICCV*), Venice, Italy, 2017, pp. 2980-2988.
[22] K. He, X. Zhang, S. Ren, J. Sun, Spatial pyramid Pooling in Deep Convolutional Networks for Visual Recognition, *Proceedings of the European Conference on Computer Vision* (*ECCV*), Zurich, Switzerland, 2014, pp. 346-361.
[23] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, A. C. Berg, SSD: Single Shot Multibox Detector, *Proceedings of the European Conference on Computer Vision* (*ECCV*), Amsterdam, The Netherlands, 2016, pp. 21-37.
[24] J. Redmon, A. Farhadi, *YOLOv3: An Incremental Improvement*, April, 2018, https://arxiv.org/abs/1804.02767.
[25] J. Redmon, A. Farhadi, YOLO9000: Better, Faster, Stronger, *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Honolulu, HI, USA, 2017, pp. 6517-6525.
[26] K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Las Vegas, NV, USA, 2016, pp. 770-778,.
[27] T.-Y. Lin, P. Dollar, R. Girshick, K. He, B. Hariharan, S. Belongie, Feature Pyramid Networks for Object Detection, *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Honolulu, HI, USA, 2017, pp. 936-944.

Biographies

Shyh-Wei Chen received the Ph.D. degrees in Graduate Institute of Biomedical Electronics and Bioinformatics from the National Taiwan University in 2019, and M.S. degree from the Department of Computer Science from Tunghai University, Taiwan, in 2010. He is currently an assistant professor in the Department of Computer Science at Tunghai University. His main areas of research are Artificial Intelligent Techniques and its Application, Machine Learning, Smart Manufacturing and Medical Informatics.

Chun-Ju Tsai is currently a graduate student in the Department of Electrical Engineering at Tunghai University. His research interests include artificial Intelligent techniques and its application.

Chia-Hui Liu received her Ph.D. degree in Department of Electrical Engineering from National Taiwan University in 2011. She is currently an associate professor at the Department of Applied Mathematics, Chinese Culture University, Taiwan. Her research interests include big data, machine learning, wireless sensor network, and information security.

William Cheng-Chung Chu is a Life time distinguished professor of the Department of Computer Science, and the Director of Software Engineering and Technologies Center of Tunghai University. He had served as the Dean of Research and Development office from 2004 to 2007, and the dean of Engineering College of Tunghai University from 2008 to 2011, He was a research scientist at the Software Technology Center of the Lockheed Missiles and Space Company, Inc., where he received special contribution awards in both 1992 and 1993 and a PIP award in 1993. In 1992, he was also a visiting scholar at Stanford University. He received ACM Recognition of Service Award in 2011, IEEE Computer Society Gold Core member Award and IEEE Computer Society Outstanding Contribution Award in 2010. He is now serving as associate editor for IEEE Transaction on reliability. He had served as the associate editor for Journal of Software Maintenance and Evolution (JSME) and Journal of Systems and Software (JSS). His current research interests include Aim big data, cloud computing, gerontology and geriatrics health care. Dr Chu received his MS and PhD degrees from Northwestern University in Evanston Illinois, in 1987 and 1989, respectively, both in computer science. He has edited several books and published over 200 referred papers and book chapters.

Ching-Tsorng Tsai is currently a professor of the Department of Computer Science of Tunghai University. He received the Teaching Innovation Award of Tunghai University in 2008, the Administrative Services Innovation Awards of Tunghai University in 2010 and 2012, the best paper award in Intelligent Living Technology Conference in 2005. Dr. Tsai received several grants on the research from the National Science Council of Taiwan and industrial application. He received the Ph.D. degree from the Department of Electrical Engineering, National Cheng-Kung University, Tainan, Taiwan, in 1994. Since 1994, he has published over 30 journal papers and over 100 conference papers, as well as participating in many academic activities, including serve as guest editor of Journal of computer (JOC) 2015, the conference chair of the CVGIP 2012 and publicity chair on IEEE 2015 International Computers, Software & Applications Conference (COMPSAC 2015), general chair on TANET 2016, and financial chair on WWW 2020.