Internet of Things 21 (2023) 100649

Contents lists available at ScienceDirect

Internet of Things

journal homepage: www.sciencedirect.com/journal/internet-of-things

# Knowledge graph and deep learning based pest detection and identification system for fruit quality

DingJu Zhu [a,b,c,*], LianZi Xie [a,#], BingXu Chen [d,#], JianBin Tan [a], RenFeng Deng [b], Yongzhi Zheng [a], Qi Hu [a], Rashed Mustafa [e], Wanshan Chen [f], Shuai Yi [a], KaiLeung Yung [g], Andrew W.H.IP [h]

[a] School of Computer Science, South China Normal University, Guangzhou, Guangdong Province, 510631, China
[b] School of Software, South China Normal University, Guangzhou, Guangdong Province, 510631, China
[c] Guangdong Provincial Industrial College for Artificial Intelligence and Robotics Education, Guangzhou, Guangdong Province, 510631, China
[d] Institute of Plant Protection, Guangdong Academy of Agricultural Sciences, Guangdong Province, 510640, China
[e] Computer Science and Engineering, University of Chittagong, Chittagong-4331, Bangladesh
[f] National S&T Innovation Center for Modern Agricultural Industry (Guangzhou), Guangzhou, Guangdong Province, 510520, China
[g] Department of Industrial and Systems Engineering, Hong Kong Polytechnic University; Hong Kong, 999077, China
[h] Department of Mechanical Engineering, University of Saskatchewan, M4Y1M7, Canada

ARTICLE INFO

*Keywords:*
Pests detection and identification
Knowledge graph
Raspberry PI
Image classification

ABSTRACT

Fruit usually plays a vital role in people's daily life. Many kinds of fruits are rich in vitamins and trace elements, which have high edible value. Pests and diseases are a considerable problem in the process of fruit planting. The quality and quantity of fruit can be effectively improved by the detection and preventing pests and diseases. However, suppose in the process of fruit growth, it is always necessary to manually identify and detect pests and diseases. In that case, it will inevitably consume a lot of workforce and material resources. Therefore, it is advisable to have an automated system to save unnecessary time and effort. This article introduces the detection and identification system of pests and diseases based on Raspberry Pi to identify and detect the pests and diseases of fruit such as Longan and lychee. Firstly, we constructed a knowledge graph of pests and diseases related to lychee and longan. Then, we used the Raspberry Pi to control the camera to capture the pests and diseases images. Next, the system processed and recognized the images captured by the camera. Finally, the Bluetooth speaker broadcasted the results in real-time. We constructed the knowledge graph through data collection, information extraction, knowledge fusion and storage. We trained the vgg-16 model, which achieves 94.9% accuracy in the pests identification task, and we deployed it on a Raspberry Pi.

## 1. Introduction

We took Lychee and Longan as examples of fruit. Lychee and Longan are produced in southern China and are two prevalent fruits. Lychee is a subtropical fruit tree with more than one million tons of annual content. Lychee in Guangdong is the most widely distributed among them, with planting area and output accounting for more than 50% of the country. Countries such as Vietnam and

* Corresponding author:zhudingju@m.scnu.edu.cn
*E-mail address:* zhudingju@m.scnu.edu.cn (D. Zhu).
# co-first author

https://doi.org/10.1016/j.iot.2022.100649
Available online 28 November 2022

Thailand also produce lychees, and the countries where lychees have been introduced include the United States, Australia, India, South Africa and Mexico. Longan is a cultivated fruit tree, which, together with lychee, banana and pineapple, is known as the Four Treasures of South China. Longan is also grown in Vietnam and Indonesia. Early-ripening lychee generally mature in March, and lychees develop from May to July. The maturity period of Longan varies according to regions and varieties. Usually, the maturity period of Thai Longan is in late May, and the maturity period of Chinese Longan is from July to August.

Lychee has the effect of tonic the spleen and liver, promote the production of body fluid to quench thirst, reduce swelling and pain, and moisten the lung to arrest cough. The Longan fruit tree can be used as a landscape and protective forest, and its wood is strong and durable. Its nectar is known as "Longan honey". Longan Honey is the best quality honey with golden color. Longan has various effects such as aphrodisiac, blood tonic, heart, and spleen tonic, nourish the blood, calm the mind, and moisturize and beautify the skin.

Lychee and Longan are often cultivated in the same geographical areas and many pests are common to both crops [1]. Based on the great value and high yield of lychee and Longan, pests and diseases cause substantial economic losses to the lychee and Longan cultivation industry. In addition, damage caused by pests and diseases can pose a severe threat to food safety, thus reducing the availability and capacity of food and increasing food costs. Pests and diseases can also reduce the taste of food and change people's preferences and habits for food.

The technology industry is one of the most important industries in a country [2]. If the technology industry is combined with the agricultural sector, it will not only bring convenience but also bring economic growth [3, 4]. Just like our system can not only reduce workforce and material resources by automatic detection and identification of pests but also get more economic benefits. It is well known that electronic technologies and applications have contributed to the growth of several economic activities such as agriculture and industry [5].

In this paper, we introduce the pests detection and identification system based on Raspberry Pi. Took the detection and identification of pests and diseases of lychee and longan as an example. Firstly, we constructed a knowledge graph of pests and diseases of longan and lychee. Then, we used the Raspberry Pi to control the camera to capture the pests and diseases images. Next, the system processed and recognized the images captured by the camera. Finally, broadcasted the results in real-time through Bluetooth speaker.

### *1.1. Knowledge graph*

The knowledge graph is a large-scale semantic network, as shown in Fig. 1. It is a graph-based data structure, which consists of nodes and edges. "Entities" are represented by nodes, and each bite is a "relationship" between entities. Things in the real world, such as people, animals, companies, place names, and telephones, can be represented by entities. A relation can express a specific connection between different entities. It originated from Google's purpose of optimizing its search engine.

### *1.2. Raspberry PI*

Raspberry PI has all the basic functions of PC. It is a microcomputer motherboard based on an arm. It can process the images collected by the camera in real-time to complete collection and identification. Most robots currently use the raspberry PI as the master, because of the high computing speed and low price of raspberry PI. Our system also chooses raspberry PI as the system master. Knowledge data is stored inside and image recognition modules are deployed on Raspberry PI. Fig. 2

## 2. Related works

Plant diseases and insect pests are a great challenge, especially in the agriculture. The accurate and efficient detection of plant diseases and insect pests is conducive to early blocking treatment and it also reduce a lot of economic losses. Recently, methods for identifying and detecting plant diseases and insect pests in the field of agriculture have emerged. Researchers have proposed many methods for identifying plant diseases and insect pests in agriculture. This section will discuss various methods of plant pest identification and management methods.

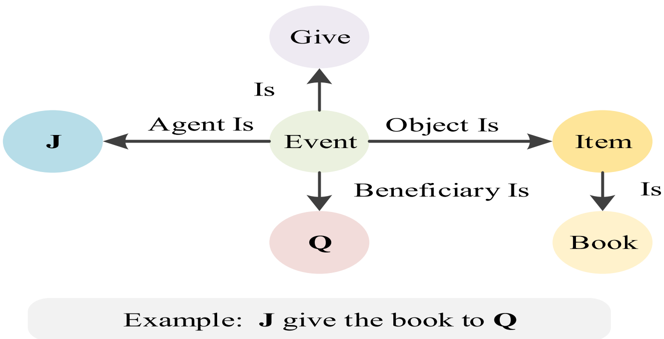


**Fig. 1.** An example of the semantic web.

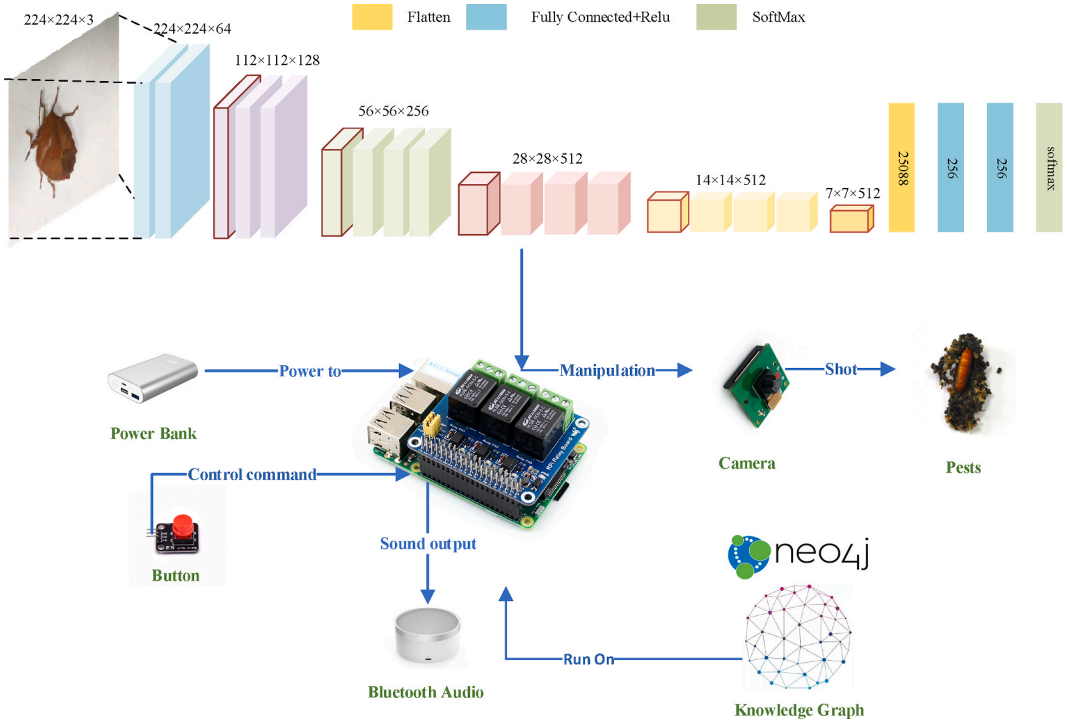


**Fig. 2.** Our system architecture diagram.

First, we can understand that Integrated Pest Management (IPM) is a pest control method. The goal is to maintain the pests tolerably and keep the number of problems below the economic damage level. In this regard, the early identification of pests and diseases is very essential. The author used the semantically enhanced and very mature IPM decision support system to finally establish a complete agricultural knowledge base (by collecting data from multiple and different sources), and developed a plan that can help farmers make pest control decisions [6]. Similarly in the literature [7], the author introduced a knowledge-based plant disease diagnosis system in this article. With the help of experts in related fields, the system built a rule-based engine. If the symptoms described by the farmer trigger the rule, then it diagnoses and provides appropriate treatment and advice. It was unclear how signs enter the system, but it relies on the farmer's perception. Techniques like this one developed to help farmers diagnose pests and diseases are often based on knowledge, and knowledge technologies are widely used in agriculture. Plant diseases and pests have a vertical industry knowledge graph, which is one of the most widely used fields. The vertical domain knowledge graph has the advantages of high precision and fine granularity, which can effectively support knowledge reasoning and knowledge retrieval applications [8]. The development of pest expert systems based on knowledge graphs has promoted the transformation of agricultural technology achievements and made great contributions to the development of high-yield, efficient and high-quality agriculture [9]. The knowledge graph technology of plant diseases and pests had been widely used in agricultural production and application, such as fertilization, drainage and irrigation [10], greenhouse control [11], and agricultural information integration framework [12]. Furthermore, the characteristics of knowledge graphs combined with machine learning or deep learning algorithms that can rapidly organize and process massive amounts of information to enable intelligent applications such as smart search, question, and answer, and decision support play a crucial role in agriculture. In literature [13], a grain worm knowledge graph was constructed. Firstly, the acquired data were pre-processed and entities and relationships were extracted from the processed data. The extracted data were linked and merged with entities through knowledge fusion, and the grain worm knowledge graph was evaluated and visualized for grain worm mapping applications. In the literature [14], this study proposed a deep learning-based knowledge graph construction method for crop pests and diseases, which performed semi-automatic extraction of semi-structured and unstructured knowledge based on domain ontology according to the corpus characteristics of the crop pest and disease domain, and stored the knowledge graph in the Neo4j graph database to realize the visual display of entity interaction relations and knowledge inference. In [15], a deep neural network model of fruit tree disease and insect pest diagnosis based on agricultural knowledge graph was proposed, which enables the disease and insect pest diagnosis not only to be associated with the disease and insect pest image but also to be combined with the disease and insect pest description text. And the experimental results showed that for apple ring rot, apple scab and apple disease, the accuracy of the model in this paper is higher than that of the traditional deep neural network model. Therefore, the full integration of agricultural knowledge map and deep learning technology will play a positive role in improving the accuracy of fruit tree pest diagnosis. In addition to these methods, there are other equally advanced and effective methods of identifying and managing plant pests. For example, the combination of remote sensing technology and spectral technology [16], the use of wireless sensor networks to monitor and detect pests [17], and the use of artificial intelligence nose (or electronic nose) as a fast and non-invasive method to diagnose insects and diseases attacking vegetables and fruit trees [18], etc.

## 3. Raspberry Pi-based disease detection and identification system

Methods for identifying and managing plant pests and diseases are endless, the most common of which is image processing using sophisticated artificial intelligence techniques such as deep learning. In some cases, image processing is complemented with information retrieved by sensors or other inputs [6].

Kumar [19] focused on image processing techniques to analyze the captured images through acquisition, preprocessing, segmentation, and clustering steps. The system in that paper captured leaf images. It identified them through a Raspberry Pi connected to a camera, whose main feature is that the crops are continuously monitored and the data are transmitted in real-time. However, in many projects, their main feature lies in the continuous monitoring of crops and real-time data transmission. For these projects, most of their cutting-edge devices are Raspberry Pi. The Raspberry Pi encourages learning, innovation, and a vibrant community to support the purpose of experimental research and introduces relatively low development costs. Compared with other common PC platforms, Raspberry Pi can provide IO pins, and the provided IO pins can directly control other underlying hardware functions. In addition, Raspberry Pi is small and low-cost. Some applications and PC tasks can be completed. The literature [20] presented a system for rice leaf disease detection based on lightweight artificial intelligence techniques, which applied the concept of edge computing and processed all the data in a cutting-edge device, the Raspberry Pi. The authors of the paper used sharp images of healthy and infected rice leaves against a white background. After necessary pre-processing, the necessary features were extracted from the pictures. Then based on these features, image classification models were built using various machine learning algorithms.

With the continuous development of deep neural networks, researchers can significantly improve the accuracy of object detection and identification. The literature [21] introduced a method based on deep learning. The equipment used is cameras with different resolutions to detect pests and diseases in tomato plants. Three leading families of detectors were considered in this paper: faster region-based convolutional neural networks (Faster R-CNN), region-based fully convolutional networks (R-FCN), and single multi-box detectors (SSD), which were referred to as "deep learning meta-architectures". These meta-architectures were combined with "deep feature extractors" (e.g., VGG nets and ResNet). The authors presented the capabilities of feature extractors and deep meta-architectures and proposed a method for global and local class annotation and data augmentation that reduced the number of false positives during train and improved accuracy. With the continuous development of machine learning, the principle of CNN has been widely applied to the disease identification of different crops. CNN used different foci to identify diseases in plants. It is of great importance in research [22]. For example, in the literature [23], CNN-based LeNet and image processing were used to identify two leaf diseases from healthy leaves. The literature [24] described a deep convolutional neural network-based method for the real-time identification of maize leaf diseases. The performance of the deep neural network was improved on a GPU system by tuning a combination of hyperparameters and tuning pools. Further, optimized the number of model parameters to make it more suitable for timely inference. The Intel Movidius Neural Compute Stack deploys pre-trained deep CNN models on the Raspberry pi 3, which consists of specialized CNN hardware blocks. The results also demonstrated the feasibility of the approach. The proposed maize disease identification model could run on standalone intelligent devices like Raspberry Pi, smartphones, and drones. Four state-of-the-art convolutional neural network models were presented in the literature [25] for the training and evaluation of tomato leaf disease classification. A subset of 18,160 RGB images from the Plantvillage dataset was divided into ten classes for migration learning. The selected models have a deeply separable convolutional structure for low-power devices. Quantitative metrics and saliency maps performed the quantitative and qualitative evaluation. Finally, a graphical user interface was implemented on a Raspberry Pi 4 microcomputer.

In the literature [26], plant health monitoring based on NDVI (Normalized Vegetation Index) calculation was designed to identify the differences between healthy and non-healthy plants by calculating NDVI values. The images of such plants were taken by a near-infrared camera connected to a Raspberry Pi. The Raspberry Pi was written in python to capture the images and calculated the NDVI. Then the results were sent to the user via the VNC viewer software to help them distinguish between healthy and non-healthy plants.

## 4. Fruit pest and disease knowledge graph

In the pest detection and identification system, the knowledge graph was constructed through the following four steps: Data Acquisition, Information Extraction, Knowledge Fusion, and Knowledge storage.

### *4.1. Data Acquisition*

Data acquisition was the first step to establishing a knowledge graph of lychee pests and diseases. Unlike open-domain knowledge graphs such as DBpedia and xlore, vertical domain knowledge graphs are usually constructed based on industry data, emphasising the depth of knowledge. The top-level ontology design of ontology is generally inseparable from the assistance of domain experts. Therefore, to ensure the quality of learning, in the data acquisition stage, the industry's internal data was used with the aid of domain experts, and a crawler was written to crawl Wikipedia and other data.

**Table 1**
Entity types.

| Entity types | Examples |
|---|---|
| Diseases | sooty blotch |
| Pests | Hypitima Longanae Yang et Chen |
| Pathogenic bacteria | Colletotrichum spp. |

**Table 2**
Entity relationship types.

| Entity relationship types | Examples |
|---|---|
| Genera_is | Conopomorpha sinensis Bradley => Lepidoptera |
| Pathopoiesia | Triposporiopsis spinigera (Höhn.) Yamam. => sooty blotch |
| Family_is | Dasychira thwaitesi Moore => Lymantridae |

### 4.2. *Information extraction*

In this process, obtaining information from data sources to obtain candidate knowledge units is critical. The knowledge in the pests and disease field is relatively simple and the relationship is relatively short, so observing and classifying directly through structured data is appropriate. For unstructured data, we used manual methods and the Hanlp toolkit to extract relevant information units to ensure the quality of knowledge.

As shown in Table 1, entities are obtained as nodes of the graph through data sorting, mainly including diseases, pests, and pathogenic bacteria. The obtained relational data are shown in Table 2.

### 4.3. *Knowledge fusion*

The duplication of expert internal knowledge data and Wikipedia knowledge data leaded to inconsistent entity attribute names and data type conflicts. In this process, we needed to take a series of steps, for example, entity disambiguation and entity link. Therefore, we considered the data volume this system and used text similarity combined with manual methods to carry out knowledge fusion. To eliminate ambiguity, entity words or attribute words were vectorized here. For example, after vectorized by the BERT model vectorizes the word A and word B, cosine similarity as shown in Formula (1) was used to evaluate the similarity between vectors in vector space to achieve the purpose of knowledge fusion. To ensure efficiency, accuracy and reliability, the method adopted in this study is that similar entity words are selected by the program, and then submitted to manual review. In this way, compared with manual screening of similar entity words, the efficiency is improved. Compared with the method of program screening similar entity words, manual review is added to enhance the accuracy and reliability of knowledge.

$$cos(\theta) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i-1}^{n} B_i^2}} \tag{1}$$

### 4.4. *Knowledge storage*

Combined with the actual situation of the project, to achieve better read and write performance and scalability, the mainstream

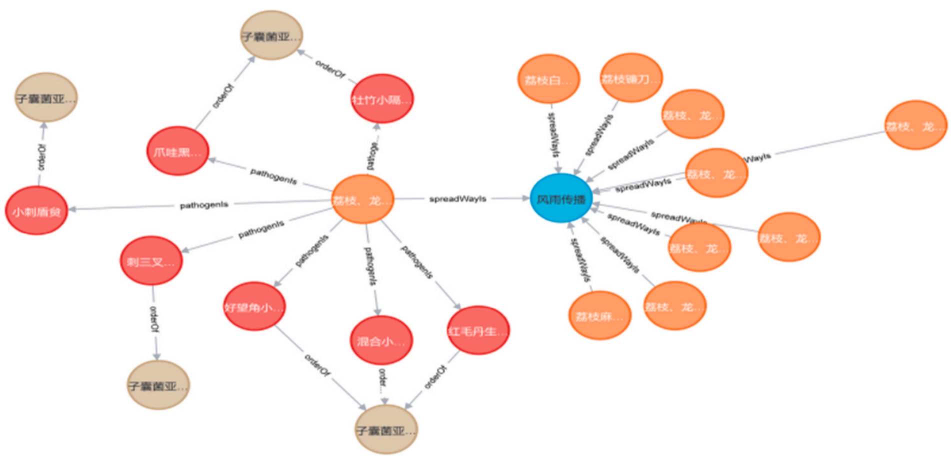


**Fig. 3.** Representation of knowledge graph.

Neo4j graph database was adopted. Entities and relationships were obtained from what was imported into Neo4j. For data queries, Cypher query language was used for efficient retrieval. The visual interface of Neo4j is shown in Fig. 3.

## 5. Image classification

In the pest detection and identification system, identifying pest species is essential for protecting crops and increasing yield. We used the VGGNet [27] model to identify different bugs. The model has high accuracy in image classification tasks. We conducted experiments on the Pest dataset to verify their accuracy. The deep network structure can extract more advanced features. We deployed the trained model to the Raspberry Pi, and identify the type of bug through the input photos.

### 5.1. Model architecture

VGG16 comprises five convolutional blocks, two fully connected layers and one output layer. Every Convolutional block include 2 or 3 convolutional layers and a max-pooling layer [28]. The deep network architecture with 3 × 3 convolution filters can extract subtle feature, significantly improving image classification. The Vgg-16 model architecture is shown in Fig. 4.

### 5.2. Loss function

$$L = \frac{1}{N}\sum_i L_i = \frac{1}{N}\sum_i - [y_i \cdot log(p_i) + (1 - y_i) \cdot log(1 - p_i)] \tag{2}$$

We used cross-entropy as the loss function for multi-classification tasks [29], often used in classification problems. The last layer of the model usually used the softmax function to output the probabilities of each category and combines the loss function to help train the model. The formula is shown above: N is batch size, $y_i$ is the sample label, $p_i$ is the probability that the prediction is an upbeat class.

### 5.3. Our dataset

We evaluated the effectiveness and accuracy of the models on the Pest dataset.

Pest Dataset: The pest dataset contains ten types of pictures, a total of 1093 images, from the D0 dataset, a high-quality large-scale data set marked by agricultural experts. Besides, we used data augmentation to expand the dataset and enhance the robustness of the model. We resized the image to 224 × 224, and randomly flipped, cropped, and normalized the training images before feeding these images to model. The dataset sample is shown in Fig. 5.

## 6. Result

This section will first introduce the quality metrics to be used. Then we will show the predicted result of model and each class, as well as examples classification, to obtain quantitative and qualitative overview of the model. Finally, we will give the overall metric of the model on Pest dataset.

### 6.1. Quality criteria

The results of the model are shown and compared, and the following evaluation indicators need to be considered [30]: Accuracy is the ratio of correctly labelled images to the total number of samples, as shown in (3). Precision is the probability of a given positive label, describing how many of them are positive (4). Recall is the accuracy of positively predicting instances, explaining how many markers are correct (5). The F1 score is used as an additional measure of the accuracy of the classifier, taking accuracy and recall into account (6).

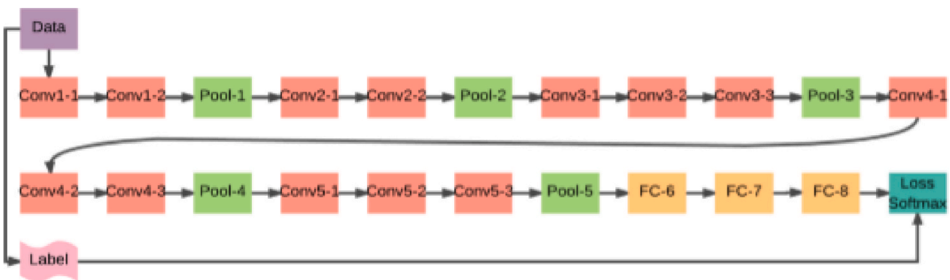


**Fig. 4.** VGG-16 model architecture.


**Fig. 5.** Example images of pest dataset.

**Table 3**
Hyperparameter table.

| Hyperparameters | Values |
|---|---|
| Epochs | 100 |
| Classes | 10 |
| Batch size | 4 |
| Optimizer | SGD |
| Learning | 0.0001 |

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{6}$$

In experiments, we used VGG-16 to identify particular pests. The models have good performance in image classification tasks. We randomly divided the dataset. 70% of the dataset was used for training and 30% was used for testing. The experiment hyperparameters are set in Table 3.

### 6.2. Evaluation result

To evaluate the effect of the model, we used vgg-16 model to experiment on the pest dataset. The loss and accuracy results of the training set and test set are displayed in Fig. 6, Fig. 7, Fig. 8, Fig. 9.

As Figs. 6–9 showed, the loss was reduced to 0.2 and the accuracy rate reached 94.9% after the model was trained for 100 epochs. We set the learning rate to 0.0001 and used SGD optimizer to optimize model parameters for reducing loss and reaching high accuracy.

Table 4 shows the evaluation indicators of the test set. The dataset contains ten species of insects, and the VGG-16 model had high precision and recall on our test set. Overall, our model achieves high accuracy on the pest identification task.

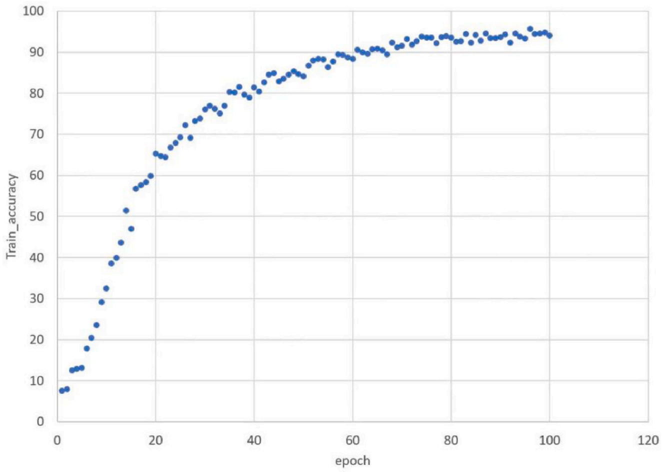


**Fig. 6.** Accuracy results of the training set.

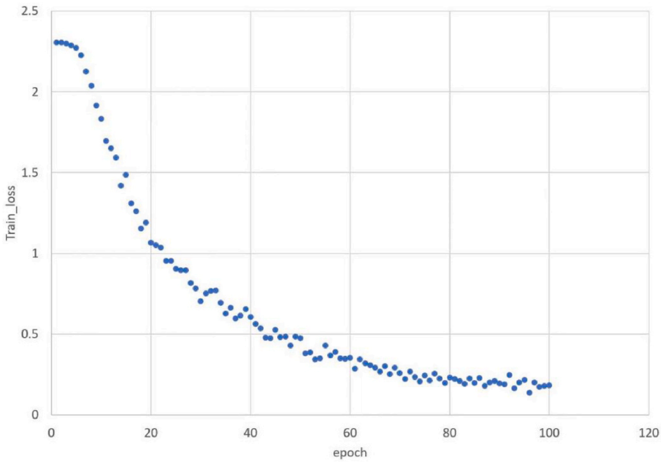


**Fig. 7.** Loss results of the training set.

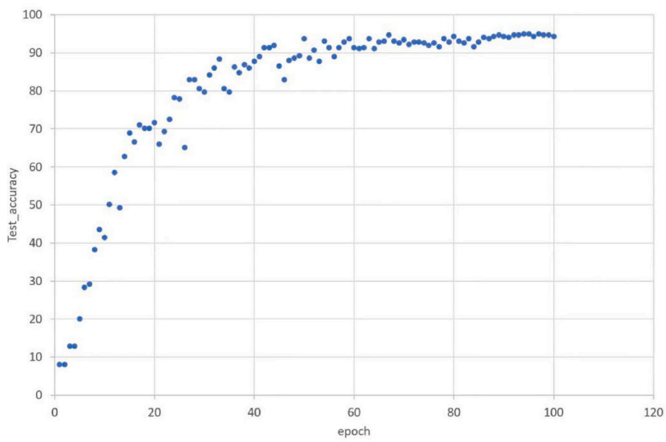


**Fig. 8.** Accuracy results of the test set.

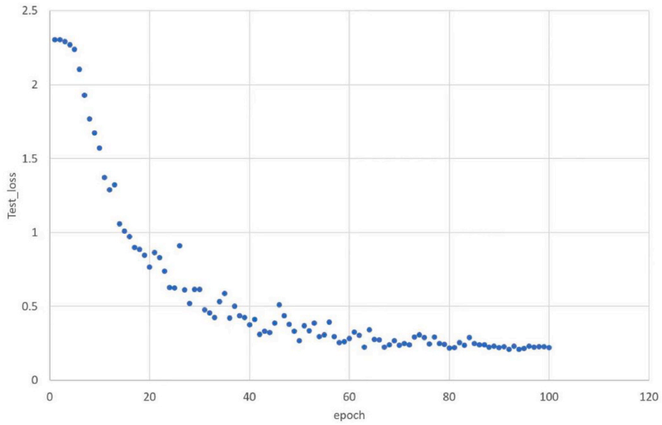


**Fig. 9.** Loss results of the test set.

**Table 4**
Evaluation result for pest classes base on vgg-16 model.

| VGG-16 | Precision | Recall | F1-score | Samples |
|---|---|---|---|---|
| Test set | 0.95 | 0.95 | 0.95 | 1093 |

### *6.3. Hardware implement*

We used Intel(R) Xeon(R) Gold 6330 CPU @ 2.00GHz CPU to train and evaluate our model with 16RAM.And for training the vgg-16 model, RTX 3090 and 24GB GDDR6X memory were used. Our programming language is python3.8, and we select pycharm as the development environment. Our model is mainly based on tensorflow-2.5.0, opencv-4.5.3.56, keras-2.6.0. Simultaneously, we built a deep learning environment on the Raspberry Pi and deployed the model so that the Raspberry Pi can identify pests.

## 7. Conclusion

The resource variety, cultivation area and production in China of Lychee and Longan are the largest in the world. However, with the acceleration of urbanization, modernization, industrialization, climate change, and environmental pollution, wild and semi-wild Lychee Longan's native environment has been universally destroyed. The loss of fantastic resources is severe, and there is even a risk of complete extinction. National, local, and research units have been built to preserve the limited capacity of the Lychee Longan resource nursery, backward facilities, primitive means, and the lack of backup nursery construction. Even if the germplasm resources have been preserved, there is still a risk of damage and loss [31]. Therefore, early pest or disease outbreaks detection becomes critical so that preventive measures.

Due to the small area of cultivated land per capita and the lack of concentration of land, the combination of traditional intensive farming and modern agricultural machinery technology has produced semi-traditional and semi-modern agriculture. On the other hand, in the development of agriculture in the world today, developed countries in Europe and America such as the United States and Canada have large-scale high-tech modern agriculture. Some Asian countries such as South Korea and Japan also have high-tech sophisticated modern agriculture [32], it is not difficult to find that to find that high-tech sophisticated, intelligent agricultural machinery systems are a great helper in improving the level of agricultural development.

This paper describes the Raspberry Pi-based Lychee Longan pest and disease detection system. We used raspberry Pi as a whole to deploy our system. This project's core goal is to detect Lychee Longan plants' pests and diseases. Accurate identification of pests and diseases would prevent and improve yields. And our system can not only be used for the cultivation of Lychees and Longan but also can be extended to similar vegetables such as tomatoes. We hope our work can have a positive effect on agricultural development. I even think that to promote rural agriculture development better: we can combine the application of mobile information systems in rural areas [33]. First, the information on pests and diseases is collected at the information center or information point, and then the data is transmitted to the gateway. Such as SMS, MMS and voice, and other information terminals and enable farmers and enterprises, and other relevant personnel to receive and use the information to create more value.

## Informed Consent Statement

Any research article describing a study involving humans should contain this statement. Please add “Informed consent was obtained from all subjects involved in the study.” OR “Patient consent was waived due to REASON (please provide a detailed justification).” OR “Not applicable.” for studies not involving humans. You might also to exclude this statement if the study did not include humans.

Written informed consent for publication must be obtained from participatss who can be identified (including by the patients). Please state “Written informed consent has been obtained from the patient(s) to publish this paper” if applicable.

### Data availability statement

We confirm that this manuscript has not been published elsewhere and is not under consideration by any other journal. All authors agree with the submission.

We deeply appreciate your consideration of our manuscript.

### Declaration of Competing Interest

We have no conflicts of interest to declare.

**Authors' Contributions**

Dingju Zhu proposed and conceptualized the study and were responsible for methodology; Dingju Zhu, Lianzi Xie, Yongzhi Zheng, Qi Hu,Jianbin Tan investigated the data and were responsible for software and system; Lianzi Xie, Yongzhi Zheng, Qi Hu,Jianbin Tan validated the study,visulized the study;Bingxu Chen,Yongzhi Zheng, Qi Hu,Jianbin Tan; Lianzi Xie were involved in data curation; Andrew W.H.IP and KaiLeung Yung help to promote our study and other authors help to promote our manuscript.

### Data availability

Data will be made available on request.

### Acknowledgements

This work was supported by a Special project of "Research on teaching reform and practice based on first-class curriculum construction" of the China Association of Higher Education (2020JXD01), a Special Project in the critical field of "artificial intelligence" in Colleges and universities in Guangdong Province (2019KZDZX1027), Provincial Key platforms and scientific research projects of Guangdong Universities (major scientific research projects - Characteristic Innovation) (2017KTSCX048), Scientific research project of Guangdong Bureau of traditional Chinese medicine (20191411) and Project of Collaborative Innovation Center of Guangdong Academy of Agricultural Sciences (XTXM202202) and Project of Guangdong Provincial Department of Agriculture and rural Affairs (Guangzhou) (2021KJ383) .

### References

[1] Waite, G. K., and J. S. Hwang. "Pests of litchi and Longan." Tropical fruit pests and pollinators: biology, economic importance, natural enemies and control (2002): 331-359.
[2] A Alnoor, K W Khaw, H Al-Abrrow, et al., The hybrid strategy on the basis of Miles and Snow and Porter's strategies: An overview of the current state-of-the-art of research[J], Int. J. Engi. Bus. Manage. 14 (2022), 18479790221080214.
[3] I Charania, X. Li, Smart farming: Agriculture's shift from a labor intensive to technology native industry[J], Internet Things 9 (2020), 100142.
[4] L Zhu, P. Spachos, Support vector machine and YOLO for a mobile food grading system[J], Internet Things 13 (2021), 100359.
[5] Alshubiri F, Jamil S A, Elheddad M. The impact of ICT on financial development: Empirical evidence from the Gulf Cooperation Council countries[J]. Int. J. Eng. Bus. Manage., 2019, 11: 1847979019870670.
[6] Miguel Ángel Rodríguez-García, Francisco García-Sánchez, Rafael Valencia-García, Knowledge-based system for crop pests and diseases recognition, Electronics 10.8 (2021) 905.
[7] Katty Lagos-Ortiz, et al., An ontology-based decision support system for the diagnosis of plant diseases, J. Inform. Technol. Res. (JITR) 10.4 (2017) 42–55.
[8] L Xiaoxue, B Xuesong, W Longhe, et al., Review and trend analysis of knowledge graphs for crop pest and diseases[J], IEEE Access 7 (2019) 62251–62264.
[9] B Stewart-Koster, N D Anh, M A Burford, et al., Expert based model building to quantify risk factors in a combined aquaculture-agriculture system[J], Agric. Syst. 157 (2017) 230–240.
[10] Yi W, Ying W, Ye Y, et al. A decision support system for fertilization and irrigation management of citrus based on semantic ontology[J]. Transactions of the Chinese Society of Agricultural Engineering, 2014, 30(9).
[11] Walczuch D, Nitzsche T, Seidel T, et al. Overview of Closed-loop control systems and artificial intelligence utilization in greenhouse farming[C]//2022 IEEE International Conference on Omni-layer Intelligent Systems (COINS). IEEE, 2022: 1-6.
[12] Sun X, Wu H, Hao P, et al. Research on information integration method of agricultural products producing and managing based on knowledge graph[C]// International Conference on Computer and Computing Technologies in Agriculture. Springer, Cham, 2017: 232-243.
[13] DUAN Meng-shi,XIAO Le.Review of Knowledge Graph and Its Application in the Field of Food Worm[J].Softw. Guide,20(08):241-246.
[14] Wu Saisai, Zhou Ailian, Xie Nengfu, et al. Construction of visualization domain-specific knowledge graph of crop diseases and pests based on deep learning[J]. Transactions of the Chinese Society of Agricultural Engineering (Transactions of the CSAE), 2020, 36(24): 177-185.
[15] L Guan, J Zhang, C. Geng, Diagnosis of Fruit Tree Diseases and Pests Based on Agricultural Knowledge Graph[C]//, J. Phys. Confer. Series. IOP Publishing 1865 (4) (2021), 042052.
[16] F Martinelli, R Scalenghe, S Davino, et al., Advanced methods of plant disease detection. A review[J], Agron. Sustain. Dev. 35 (1) (2015) 1–25.
[17] S Azfar, A Nadeem, A B Alkhodre, et al., Monitoring, detection and control techniques of agriculture pests and diseases using wireless sensor network: a review [J], Int. J. Adv. Comput. Sci. Appl. 9 (12) (2018).
[18] S Cui, P Ling, H Zhu, et al., Plant pest detection using an artificial nose system: a review[J], Sensors 18 (2) (2018) 378.
[19] Kumar, Dinesh, et al. "Image processing based leaf disease detection using raspberry Pi." (2021).
[20] SM Shahidur Harun Rumy, et al., An IoT based system with edge intelligence for rice leaf disease detection using machine learning, in: 2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS), IEEE, 2021.

[21] Alvaro Fuentes, et al., A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition, Sensors 17.9 (2017) 2022.
[22] G.Rama Mohan Reddy, Nettam Sai Sumanth, N. Sai Preetham Kumar, Plant leaf disease detection using cnn and raspberry Pi, Int J 5.2 (2020).
[23] Amara, Jihen, Bassem Bouaziz, and Alsayed Algergawy. "A deep learning-based approach for banana leaf diseases classification." Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband (2017).
[24] Sumita Mishra, Rishabh Sachan, Diksha Rajpal, Deep convolutional neural network based detection system for real-time corn plant disease recognition, Procedia Comput. Sci. 167 (2020) 2003–2010.
[25] Victor Gonzalez-Huitron, et al., Disease detection in tomato leaves via CNN with lightweight architectures implemented in Raspberry Pi 4, Comput. Electron. Agric. 181 (2021), 105951.
[26] Jyotirmayee Dash[a], et al., Plant health monitoring system using raspberry Pi, Expo Math. 119.15 (2018) 955–959.
[27] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition, arXiv:1409.1556, 2014.
[28] Islam S, Khan S I A, Abedin M M, et al. Bird species classification from an image using VGG-16 network[C]//Proceedings of the 2019 7th international conference on computer and communications management. 2019: 38-42.
[29] P T De Boer, D P Kroese, S Mannor, et al., A tutorial on the cross-entropy method[J], Ann. Oper. Res. 134 (1) (2005) 19–67.
[30] V Gonzalez-Huitron, J A León-Borges, A E Rodriguez-Mata, et al., Disease detection in tomato leaves via CNN with lightweight architectures implemented in Raspberry Pi 4[J], Comput. Electron. Agric. 181 (2021), 105951.
[31] Hu Guibing, Zheng Shaoquan, Xiang Xu, Wang Jiabao, Peng Hongxiang, Zhao Jietang, Huang Xuming, Zhu Jianhua, Li Hongli, Liu Chengming, Shi Shengyou, Chen Jiezhen, Deng Chaojun, Jiang Fan, Xu Qizhi, Chen Houbin."14th Five-Year Plan" Development Ideas of Litchi and Longan Seed Industry [J]. China Tropical Agriculture,2020(03):4-6+16.
[32] Li Meng, Zhai Yunxia, Application of intelligent agricultural machinery system in precision agriculture based on satellite technology [J], Agricult. Eng. 5 (S2) (2015) 37–39.
[33] J Cao, C. Liu, Applications of Mobile Information System in Rural Area of China[M]//Research and Practical Issues of Enterprise Information Systems II, Springer, Boston, MA, 2008, pp. 1395–1400.