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X-ray Artificial Intelligence Identification System for Agricultural Products

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The growing trade of agricultural products is accompanied by the increasing challenges for product identification. Due to the mixture of various products in covered baskets or crates, conventional identification heavily relies on manual sorting, in which human operators must open the baskets and recognize internal products one by one. This conventional approach is not only time-consuming, but also suffering an accuracy issues in proper identification of the products, particularly with those with high similarity in appearance. To raise the identification efficiency and avoid careless mistakes, an artificial intelligence-assisted identification system is proposed and investigated. With this new method, the X-ray hardware collects vegetable images from different angles. Then a deep learning-based strategy is developed employing data augmentation, deep neural network, and feature visualization techniques, which formulates an end-to-end scheme for product identification. In the data augmentation stage, automatic type indexing is established mapping X-ray images to the encoded product types, while the collected raw X-ray images are compressed and randomly flipped to increase the processing speed and robustness. After that, an extensible network structure is proposed using the deep residual structure for the image feature extraction and parallel fully connected layers for the type identification. Besides, dropout layers are inserted to prevent the overfitting of the whole deep neural network. Finally, the principal component analysis is leveraged in the feature visualization part to enhance the result reliability and explainability. This integration of hardware and software techniques significantly releases human resources and achieves high detection accuracy, which notably improves the intelligence level of agricultural product identification. Detailed experiments are conducted with various types of agricultural products as well as different combinations. For mixed agricultural products in one basket, the minimum identification accuracy can reach 98.0% in the test dataset and the identification time for one X-ray image is only 0.18 seconds. The 1000-dimensional features extracted by the deep neural network are also visualized as well as the critical features from the convolutional kernel. For the first time, it is disclosed that root parts are core traits inside X-ray images intelligently learned for the type distinguishment.

NOMENCLATURE

TIF = Tagged Image Format
JPEG = Joint Photographic Experts Group

1. Introduction (Times New Roman 10pt)

The trade of agricultural products plays a very important role for each country, especially considering the raising risk in the global supply chain. China proposed “Belt and Road” to strengthen international agricultural cooperation [1]. In Singapore, the land percentage for agricultural products is below 1% [2], which leads to huge demands for agricultural imports. As the neighboring country, Malaysian agriculture is one of its economic growth engines. With sufficient meat and vegetables [3], Malaysian main agricultural export countries include China, European Union, etc.

Because of the product mixture, one main concern during the agricultural trade is type identification. The traditional identification process mainly relies on manual sorting and sampling, which is time-consuming and inaccurate. In [4], the machine version and ultrasonic sensors were used for the citrus fruit identification. For retail applications, video cameras and convolutional neural networks were proposed to estimate the price via weight [5]. Through a garden robot and neural network, the fruit harvesting task was investigated [6]. The above research mainly considers unpacking agricultural products in different conditions, but most products are packed during practical large-scale trades.

To fill this gap, an X-ray artificial intelligence identification system is proposed. At the hardware level, an X-ray scanning module is designed to capture vegetable images from different angles. After that, three other components of the agricultural identification network, digital feature visualization and physical feature determination are developed to achieve effective and automated identification.

2. X-ray Artificial Intelligence Identification System

2.1 X-ray Scanning Module

The structure of the proposed X-ray artificial intelligence system is presented in Fig. 1. In the X-ray scanning module, mixed agricultural products in baskets or crates are sequentially loaded on the conveyor without unpacking. The conveyor automatically transferred agricultural products on a tray. The tray is located between the X-ray source and the detector, which is controlled to rotate the basket during the image capture.

Fig. 2 shows the hardware schematic in the X-ray scanning module. X-ray source, detector, conveyor, and tray are the four core components. The X-ray source is the X-ray vacuum tube that converts electrical input power into X-rays. When it is energized, X-rays are generated penetrating agricultural products. The detector is used to detect the X-ray flux and spatial distribution for the image formulation. The conveyor is used to load product baskets and carry them to the tray. Tray rotates the basket to expose products from different angles.

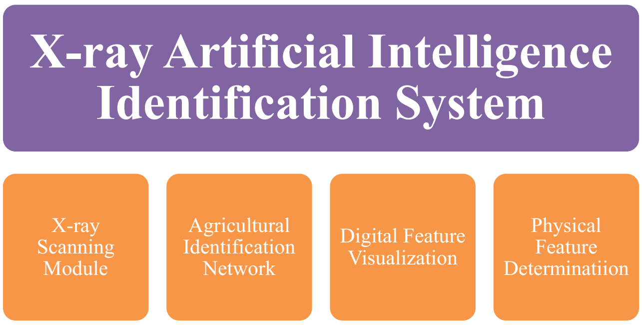

Fig. 1 X-ray artificial intelligence identification system structure.

Fig. 2 Hardware schematic of X-ray scanning module.

2.2 Agricultural Identification Network

In the second module, the agricultural identification network is constituted by the data augmentation stage and identification stage. In the data augmentation stage, automatic type indexing is established mapping X-ray images to the encoded product types, while the collected raw X-ray images are compressed and randomly flipped to increase the processing speed and robustness. It can be seen from Fig. 3, the original TIF image of 8.92M is transferred to JPEG format of 0.39M. After that, the size of 1952 × 1952 is reduced to 224 × 224 for the processing acceleration.

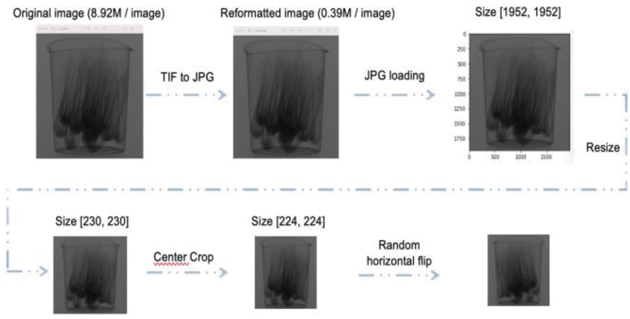

Fig. 3 Data augmentation stage.

Interlinking the data augmentation stage, an extensible network structure is proposed using the deep residual structure for the image feature extraction and parallel fully connected layers for the type identification. Besides, dropout layers are inserted to prevent the overfitting of the whole deep neural network. This deep learning-based agricultural identification network is shown in Fig. 4.

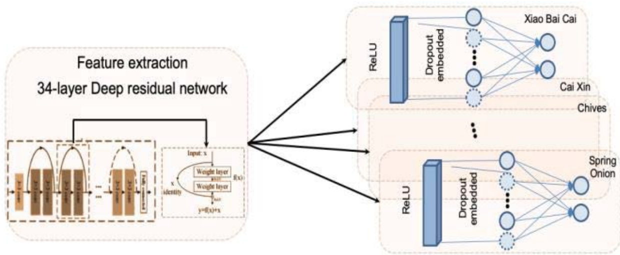

Fig. 4 Agricultural identification network.

With the output from the agricultural identification network, Softmax is deployed to map the input to a real number between 0 and 1, and ensure that the sum is 1, so that the output of each node becomes a probability value:

$$\text{softmax}(y_i) = \frac{e^{y_i}}{\sum_{j=1}^{n} e^{y_i}} \qquad (1)$$

where $y_1, y_2, \ldots, y_n$ are original outputs of the deep network.

Cross entropy is then used in the network loss function to determine the closeness between the actual type and the identified type. Cross entropy in Eq. (2) represents the distance between the actual type probability and the identified type probability. The smaller the cross entropy is, the closer the two probability distributions are:

$$E(p,q) = -\sum_i p_i \log q_i \quad (2)$$

where p_i is the identified probability distribution and q_i is the actual probability distribution.

2.3 Digital Feature Visualization

To guarantee the identification result, the high-dimensional feature before the fully connected layer is visualized through the unsupervised principal component analysis. In the principal component analysis, the singular value decomposition approach is used to transform original data into independent components. Assuming the high-dimensional feature set $\boldsymbol{F} = \{\boldsymbol{f}_1, \boldsymbol{f}_2, \ldots, \boldsymbol{f}_n\}$ for the min-batch data, $\boldsymbol{f}_1, \boldsymbol{f}_2, \ldots, \boldsymbol{f}_n$ indicate the feature vectors for 1 ,…, n samples, respectively. $\boldsymbol{F}$ is normalized to $\boldsymbol{F}_{norm}$ according to the average value of each feature dimension. After that, the covariance matrix of $\boldsymbol{F}$ is calculated:

$$\boldsymbol{C} = \boldsymbol{F}_{norm} * \boldsymbol{F}_{norm}^T \quad (3)$$

With the covariance matrix in (3), its eigenvalue λ_m and corresponding eigenvector $\boldsymbol{v_m}$ are obtained:

$$\boldsymbol{C}\boldsymbol{v_m} = \lambda_m \boldsymbol{v_m} \quad (4)$$

All eigenvalues are sorted from large to small based on their absolute values. The eigenvectors corresponding to the two largest eigenvalues are selected formulating the mapping matrix $\boldsymbol{M}$. In the end, each feature vector is multiplied by $\boldsymbol{M}$ to generate the reduced-order feature.

2.4 Physical Feature Determination

To enhance the identification reliability, the critical kernel feature of the trained agricultural identification network is also visualized. On the hand, the critical physical feature can be figured out. On the other hand, the identification correctness could be double-checked. The pseudocode to extract critical kernel features is given in Algorithm 1.

Algorithm 1 Physical feature determination

```
net_type = torch.load("agricultural_identification_network_model")
new_model = nn.Sequential(*list(net_type.resnet34.children())[:4])
f0 = new_model(inputs)
save_img(f0)
```

3. Experiment and Analysis

3.1 Effectiveness of X-ray Artificial Intelligence Identification System

Four agricultural products of Xiao Bai Cai, Cai Xin, Chives, and Spring Onion are selected here as examples. X-ray images are collected by the proposed X-ray scanning module for type identification. After training the agricultural identification network, the single-type and mixed-type identification results are shown in Table 1 and Table 2, respectively. Under various weights of single-type identification, the minimum identification can reach 95.5% by the proposed system. For the mixed-type identification, the accuracy is around 98%-100%, which notably verifies the proposed strategy.

Table 1 Single-type identification accuracy.

	Xiao Bai Cai	Cai Xin	Chives	Spring Onion
0.25 kg	96% (192/200)	100% (200/200)	100% (200/200)	100% (200/200)
0.50 kg	100% (200/200)	95.5% (191/200)	99.5% (199/200)	99.5% (199/200)
1.50 kg	100% (200/200)	98.0% (196/200)	98.5% (196/200)	100% (200/200)

Table 2 Mixed-type identification accuracy.

	Xiao Bai Cai & Cai Xin	Chives & Spring Onion
0.25 kg	98% (196/200)	100% (200/200)
0.50 kg	98.5% (197/200)	100% (200/200)

3.2 Digital Feature Visualization

During the digital feature visualization, agricultural product features are well separated in Fig. 5. The small overlap between Chives and Spring Onion causes the identification error. When the product weight varies, the visualized features of same type are still closed to each other in Fig. 6, which presents the robustness of X-ray artificial intelligence identification system.

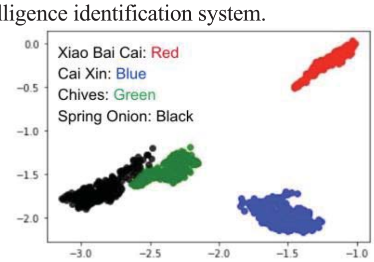

Fig. 5 Digital feature visualization of four agricultural products.

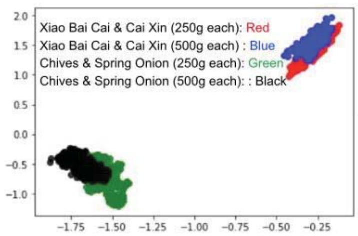

Fig. 6 Digital feature robustness.

3.3 Physical Feature Determination

To verify the results' correctness, critical physical features are presented in Fig. 7 to Fig. 10 for four agricultural products. According to these four figures, root parts are highlighted by the convolutional kernel, which is consistent with our human understanding. It means that the root parts of these agricultural products are unique traits during the identification.

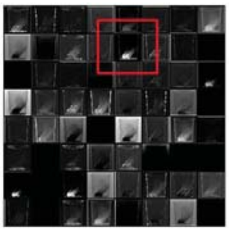

Fig. 7 Xiao Bai Cai critical physical feature.

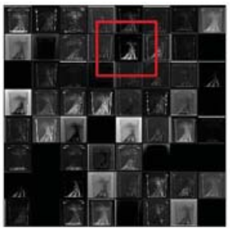

Fig. 8 Cai Xin critical physical feature.

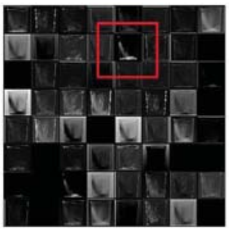

Fig. 9 Chives critical physical feature.

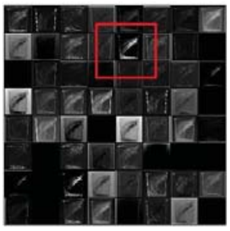

Fig. 10 Spring Onion critical physical feature.

4. Conclusions

An X-ray artificial intelligence identification system is developed by this work for agricultural product trade. Facing the mixture of various products in covered baskets or crates, the proposed X-ray artificial intelligence identification system is made up of four modules: X-ray scanning module, agricultural identification network, digital feature visualization, and physical feature determination.

Without unpacking agricultural products and manual sorting, the proposed X-ray artificial intelligence identification system provides an effective and efficient solution. In the experimental examples of Xiao Bai Cai, Cai Xin, Chives, and Spring Onion, the identification accuracy can reach at least 95.5%. Digital features are well separated by the proposed system and robust to the weight variation. Besides, root parts are also determined by the network verifying the identification correctness.

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