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Indian Vegetable Image Classification Using Convolutional Neural Network

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Abstract – ***This paper represents a method of recognition and classification of vegetable images based on deep learning. Using the open source deep learning framework, the improved CNN network model was used to train the vegetable image data set. The classification accuracy of the CNN network is improved due to the hyperparameter tuning and layer addition. This study introduces a new, high-quality, dataset of images containing vegetables. This study also presents the results of some numerical experiments for training a neural network to detect vegetables. The methods surveyed in this paper can distinguish different kinds of vegetables in terms of their color and texture. In the future same experiment is going to be done and we will predict different types of vegetable disease. Along with local feature detection techniques, computer vision and pattern recognition are developing quickly. In this study, we extracted and learned the object to train the Deep Neural Network (DNN) for object category recognition. To recognize vegetable objects, we used deep learning and investigated the convolutional neural network (CNN). According to the evaluation findings, 3 million iterations were sufficient for the CNN vegetable identification learning process. The recognition rate was 97.50 %.***

Keywords - ***Deep learning, object identification, computer vision, vegetable dataset, image processing***

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1.0 Introduction

Some common procedures, from vegetable production through distribution, are carried out a hand. similar to picking and organizing vegetables. We, therefore, decided to use deep neural architecture to resolve this issue by developing a model that can identify and categorize veggies.

2. Proposed Methods

The mannequin statistics and techniques applied in the learn about are thoroughly explained in the sections that follow.
In the past loads of research have been finished on vegetable classification and the use of CNN for deep learning. They have succeeded a lot(Steinbrener, J., Posch, K., & Leitner, R. (2019).

2.1. Creating and Processing a Vegetable Image Dataset

To create the data set of vegetable images, elevated it into 15k images. One of them is the education set constituted 80% of the total, and the check set was 20% of the total. Some of the shots were taken by myself while others were obtained through the website. This study skilled fifteen
Vegetable classes are broccoli, cauliflower, cucumber, cabbage, tomato, beans, bitter gourd, bottle gourd, brinjal, capsicum, papaya, potato, pumpkin, radish plus carrots. Due to the measurement of every photograph in the vegetable of each photograph dataset being distinct, the picture measurement is scaled down to 224*224. The dataset of vegetable images included in this study has an equal variety of each picture of each veggie category (15000). There isn't much variety in the photographs; thus, the vegetable photograph statistics Set rotates 90 degrees tiers by way of the technique of statistics expansion, instruction means of By using this technique, the picture records were four times magnified, and Figure shows the results of rotating vegetable photographs.

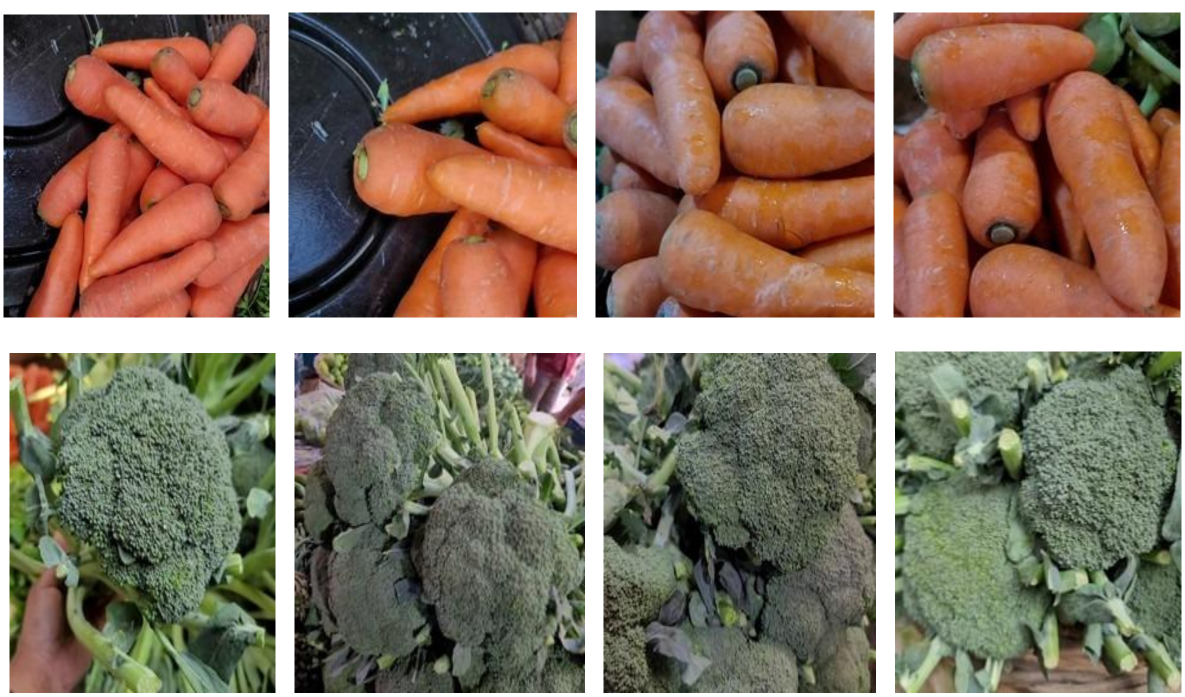

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Figure 1- A portion of the expanded vegetable data.

Figure 1 shows an image of the original, rotated 90 degrees, for each type of vegetable. picture size is extraordinary in the vegetable photograph records set, to neatly organize the image, the photograph is processed into the equal measurement in Figure 1 (224*224). The information growth method is appropriate for training and checking out images. In the education phase, the increased information can produce extra training samples, thereby decreasing the effect of overfitting. In the test phase, the expansion in information helps to enhance the classification accuracy rate.

2.2. Enhancing the CNN Model

The improved CNN network model and the traditional CNN network model are shown in Table 1.

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 98, 98, 32)	896
dropout_4 (Dropout)	(None, 98, 98, 32)	0
conv2d_4 (Conv2D)	(None, 96, 96, 64)	18496
dropout_5 (Dropout)	(None, 96, 96, 64)	0
conv2d_5 (Conv2D)	(None, 94, 94, 128)	73856
dropout_6 (Dropout)	(None, 94, 94, 128)	0
flatten_1 (Flatten)	(None, 1131008)	0

dense_2 (Dense)	(None, 128)	144769152
dropout_7 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 15)	1935

Table 1:Table of CNN Parameters

In neural networks, a Convolutional neural network (ConvNets or CNNs) is one of the main categories to do image recognition and image classifications. Object detection recognition faces, etc., are some of the areas where CNNs are widely used.
Like a typical multi-layer perceptron, the backpropagation model is used in CNN's learning process. The weighting filter and coupling coefficient are then updated by CNN using stochastic gradient descent. By utilizing convolutional and pooling procedures, CNN can identify the optimal feature in this manner. Rectified Linear Units (ReLU) are employed in CNN to expedite training for the category recognition job. CNN offers a comprehensive toolkit with well-documented examples for training, testing, fine-tuning, and deploying models. CNN has been used to recognize objects with success. In Fig. 2, a typical CNN is displayed. There are several layers in the network, and each layer has one or more nodes. A typical convolutional neural network is shown. Vegetable category, Figure 1.
Technically, deep gaining knowledge of CNN fashions to educate and test, each entered photo will ignore via a sequence of convolution layers with filters (Kernals), Pooling, thoroughly related layers (FC), and apply Softmax feature to classify an object with probabilistic values between 0 and 1.

The first layer to extract features from an input image is convolution. Convolution learns visual features from small input data squares, preserving the link between pixels. An image matrix and a filter or kernel are only two examples of the two inputs that go into this mathematical operation. Applying filters to the convolution of an image allows for the performance of operations like edge detection, blur, and sharpening. The example below displays multiple convolution images after using various filters (Kernels).
Rectified Linear Unit, or ReLU, refers to a non-linear operation. The result is x = max (0,x). The goal of ReLU is to add nonlinearity to our ConvNet. Because the real-world data would need our ConvNet to learn non-negative linear values

There are other non-linear functions such as tanh or sigmoid that can also be used instead of ReLU. Most of the data scientists use ReLU since performance wise ReLU is better than the other two.

The pooling layers section would reduce the number of parameters when the images are too large. Spatial pooling also called subsampling or downsampling which reduces the dimensionality of each map but retains important information.

Maximum pooling, or max pooling, is a pooling operation that calculates the maximum, or largest, value in each patch of each feature map. The results are down-sampled or pooled feature maps that highlight the most present feature in the patch, not the average presence of the feature in the case of average pooling.

In the layer we call as FC layer, we flattened our matrix into the vector and feed it into a fully connected layer like a neural network.

3. Result

Name	precision	recall	f1-score	support
Bean	0.88	0.96	0.92	200
Bitter_Gourd	0.96	0.92	0.94	200
Bottle_Gourd	0.89	0.98	0.93	200
Brinjal	0.95	0.8	0.87	200
Broccoli	0.97	0.89	0.93	200
Cabbage	0.79	0.97	0.87	200
Capsicum	0.95	0.99	0.97	200
Carrot	0.99	0.98	0.99	200
Cauliflower	0.94	0.89	0.91	200
Cucumber	0.95	0.94	0.95	200
Papaya	0.92	0.92	0.92	200
Potato	0.97	0.96	0.97	200
Pumpkin	0.97	0.9	0.93	200
Radish	0.91	0.99	0.95	200
Tomato	0.92	0.83	0.88	200

Figure 2: Table of Accuracy

accuracy			0.93	3000
macro avg	0.93	0.93	0.93	3000
weighted avg	0.93	0.93	0.93	3000

Epoch 1/10
750/750 [==============================] - 1270s 2s/stop - loss: 2.1305 - Accuracy: 0.2927 - val_loss: 1.4206 - val_accuracy: 0.5397
Epoch 2/10
750/750 [==============================] - 3534s 5s/step - loss: 0.8514 - accuracy: 0.7245 - val_loss: 0.5218 - val_accuracy: 0.8277
Epoch 3/10
750/750 [==============================] - 3089s 4s/step - loss: 0.3979 - accuracy: 0.8769 - val_loss: 0.3409 - val_accuracy: 0.8870
Epoch 4/10
750/750 [==============================] - 1583s 2s/step - loss: 0.2390 - accuracy: 0.9262 - val_loss: 0.2672 - val_accuracy: 0.9220
Epoch 5/10
750/750 [==============================] - 1553s 2s/step - loss: 0.1828 - accuracy: 0.9452 - val_loss: 0.3865 - val_accuracy: 0.8947
Epoch 6/10
750/750 [==============================] - 1373s 2s/step - loss: 0.1558 - accuracy: 0.9537 - val_loss: 0.2818 - val_accuracy: 0.9140
Epoch 7/10
750/750 [==============================] - 1317s 2s/step - loss: 0.1029 - accuracy: 0.9660 - val_loss: 0.3278 - val_accuracy: 0.9253
Epoch 8/10
750/750 [==============================] - 1341s 2s/step - loss: 0.0876 - accuracy: 0.9713

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- val_loss: 0.1972 - val_accuracy: 0.9517
Epoch 9/10
750/750 [==============================] - 1345s 2s/step - loss: 0.0956 - accuracy: 0.9728
- val_loss: 0.3061 - val_accuracy: 0.9330
Epoch 10/10
750/750 [==============================] - 1393s 2s/step - loss: 0.0896 - accuracy: 0.9750
- val_loss: 0.3541 - val_accuracy: 0.9270

Val loss: 0.33727145195007324
Val accuracy: 0.9269999861717224

Test loss: 0.32879751920700073
Test accuracy: 0.9290000200271606
Classification Report
precision recall f1-score support

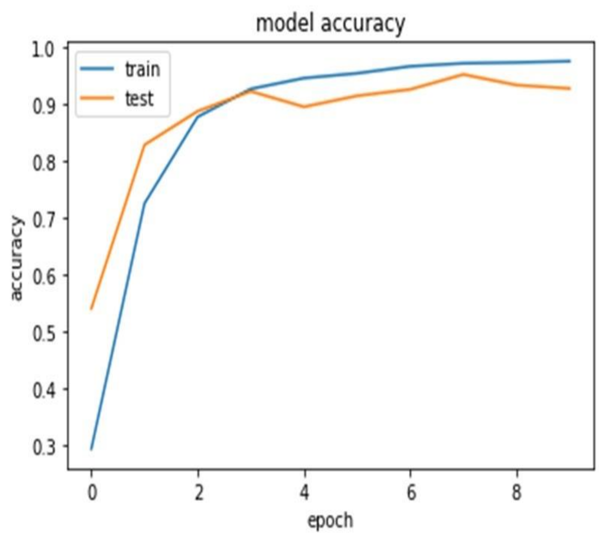

Figure 3:Graph of Accuracy

We can observe that accuracy rises as epoch size increases. In addition, greater Epoch can enhance memory utilization effectiveness and speed up processing. The larger the Epoch, the more precise the reduction direction, and the smaller the training shock. Figure 3 shows that the Epoch setting not only has a significant impact on accuracy but also on how quickly the network converges. The network converges fastest when Epoch is 8.

Epoch	1	2	4	6	8	10
Accuracy(%)	29.27	72.45	87.69	95.37	97.13	97.50

Table 2: Epoch experimental result

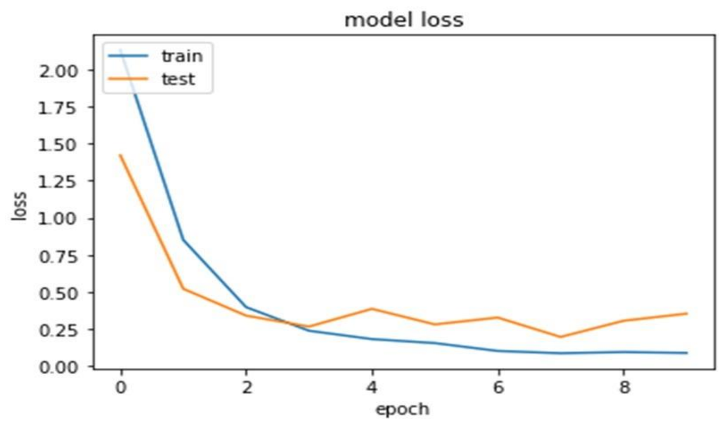

Figure 4:Graph of Evaluated losses by epoch on both training and testing set in a CNN model.

Epoch	1	2	4	6	8	10
Loss	213.05	85.14	23.90	15.58	8.76	8.96

Table 3:Loss of training and testing dataset

We can find that the Loss decrease with the increase of Epoch. Decrease of Epoch shows that the loss of the training dataset decreases continuously while the loss of the testing set decreases at early steps and starts to increase after a certain point.

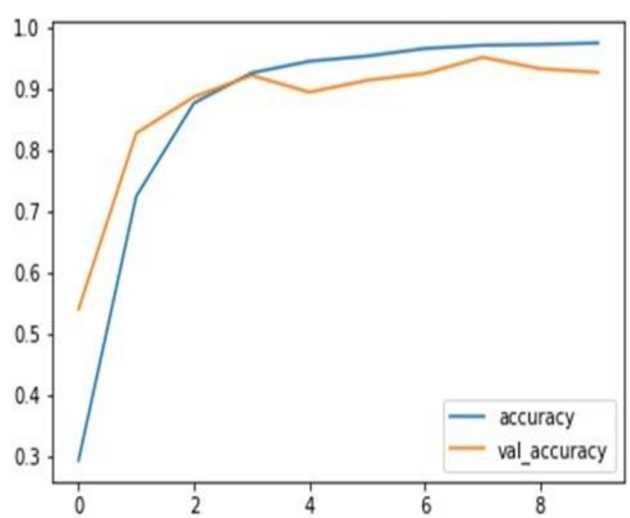

Figure 5:Graph of Val_accuracy

Epoch	1	2	4	6	8	10
Validation Accuracy(%)	53.97	82.77	92.20	91.40	95.17	92.70

Table 4: Table of Validation Accuracy

It is clear that the figure's val accuracies have grown with the number of epochs. The epoch's maximum val accuracy is 92.70 percent.

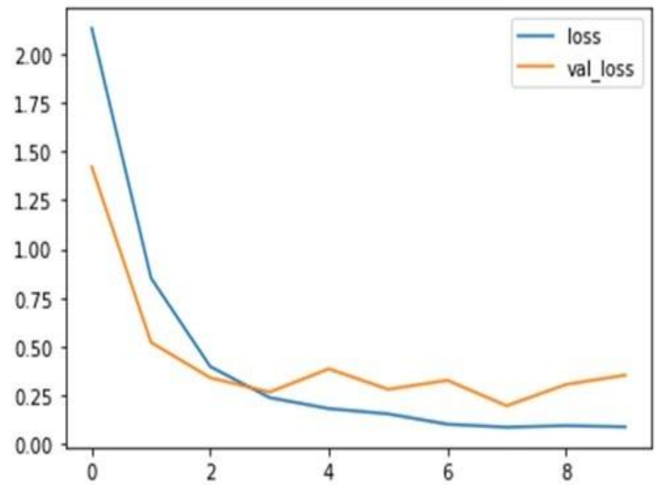

Figure 6:Graph of Val_loss

Epoch	1	2	4	6	8	10
Validation loss(%)	142.06	52.18	26.72	28.18	19.72	35.41

As the epoch increases, we observe that the Val_ Loss decreases. The training dataset's Val loss reduces constantly, according to Decreased of Epoch, whereas the testing set's loss initially decreases and then gradually increases at a given point.

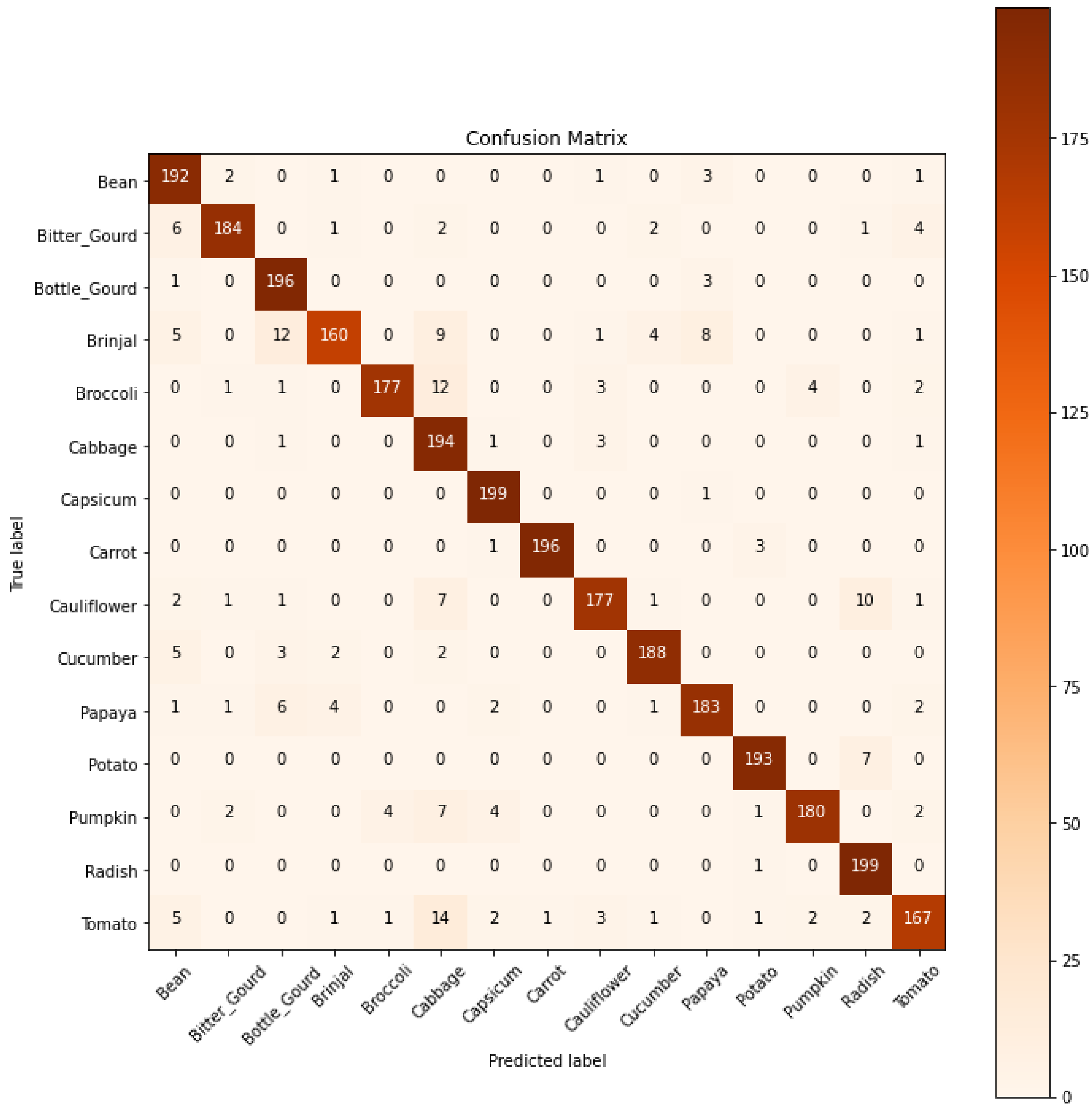

Figure 7:Confusion Matrix

Conclusion

In this paper, we present a CNN framework for object category recognition. We used picture data from the fifteenth category of vegetables to evaluate. According to the evaluation's findings. In this instance, the algorithm picks up on background items in some files as veggies. Future research will focus on additional applications including object tracking and object motion using DNN. This study motivates us to carry on with our research and identify other vegetable groups. The food industry is growing daily, and producing these raw materials is important for human development. There are various studies have been done on the identification of vegetables. We have successfully proposed a deep neural network model like a proposed convolution neural network. It was tested on this number of images along with this number of types. The study also faces challenges of high competition and cost for predicting different classes of vegetables. And this also involves a large number of time for computation. The proposed model has been tested on different items of vegetables and has an accuracy of 97.5%. This model could be applied to large-scale manufacturing and production of vegetable houses. The automatic vegetable isolation, as well as packaging, is needed for large-scale production. This study will help mankind to have more control over food which is a daily need for survival.

Reference

Álvarez-Canchila, O. I., Arroyo-Pérez, D. E., Patiňo-Saucedo, A., González, H. R., & Patino-Vanegas, A. (2020, May). Colombian fruit and vegetables recognition using convolutional neural networks and transfer learning. In Journal of Physics: Conference Series (Vol. 1547, No. 1, p. 012020). IOP Publishing.

Femling, F., Olsson, A., & Alonso-Fernandez, F. (2018, November). Fruit and vegetable identification using machine learning for retail applications. In 2018 14th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS) (pp. 9-15). IEEE.

Hussain, Dostdar, Israr Hussain, Muhammad Ismail, Amerah Alabrah, Syed Sajid Ullah, and Hayat Mansoor Alaghbari. "A Simple and Efficient Deep Learning-Based Framework for Automatic Fruit Recognition." Computational Intelligence and Neuroscience 2022 (2022).

Jana, S., Parekh, R., & Sarkar, B. (2021). Detection of Rotten Fruits and Vegetables Using Deep Learning. In Computer Vision and Machine Learning in Agriculture (pp. 31-49). Springer, Singapore.

Sakai, Y., Oda, T., Ikeda, M., & Barolli, L. (2016, July). A vegetable category recognition system using deep neural network. In 2016 10th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS) (pp. 189-192). IEEE.

Sharpe, S. M., Schumann, A. W., Yu, J., & Boyd, N. S. (2020). Vegetation detection and discrimination within vegetable plasticulture row-middles using a convolutional neural network. Precision Agriculture, 21(2), 264-277.

Steinbrener, J., Posch, K., & Leitner, R. (2019). Hyperspectral fruit and vegetable classification using convolutional neural networks. Computers and Electronics in Agriculture, 162, 364-372.

Ulloa, C. C., Krus, A., Barrientos, A., del Cerro, J., & Valero, C. (2022). Robotic fertilization in strip cropping using a CNN vegetables detection-characterization method. Computers and Electronics in Agriculture, 193, 106684.

Zheng, Y. Y., Kong, J. L., Jin, X. B., Su, T. L., Nie, M. J., & Bai, Y. T. (2018, November). Real-time vegetables recognition system based on deep learning network for agricultural robots. In 2018 Chinese Automation Congress (CAC) (pp. 2223-2228). IEEE.

Zeng, G. (2017, October). Fruit and vegetables classification system using image saliency and convolutional neural network. In 2017 IEEE 3rd Information Technology and Mechatronics Engineering Conference (ITOEC) (pp. 613-617). IEEE.