How to Cite:
Kalambe, K., Awachat, S., & Raipure, S. (2022). Design of deep recursive CNN model for detecting and classifying peston plant. *International Journal of Health Sciences*, *6*(S1), 10537–10545.
https://doi.org/10.53730/ijhs.v6nS1.7540

Design of deep recursive CNN model for detecting and classifying peston plant

Kavita Kalambe
Department of Computer Science and Engineering, Shri. Ramdeobaba College of engineering and Management, India
Corresponding author email: kalambekb@rknec.edu

Snehal Awachat
Department of Computer Science and Engineering, Shri. Ramdeobaba College of engineering and Management, India

Shwetal Raipure
Department of Computer Science and Engineering, Shri. Ramdeobaba College of engineering and Management, India

Abstract---Automatic pest on plant detection in early stage is very essential for food quality control in the agriculture industry. However, the visual method to identify pest on every plant by human is a cumbersome process and cannot be well suited in the agriculture field, because it is time consuming, less accurate and labor intensive. Pest on Plant and plant leaf disease are the major factors responsible for reducing the quality and quantity of food production. Detection at the earlier stage of pest growth and its killing would result in reducing its effect on plant and enhance the quality of food production. Various existing ways have been used to identify and classify pest on plant, but issues have not been resolved, and there is still a scope for improvement. This paper proposes a Deep Recursive Convolutional Neural Networks (DR-CNN) to improve the average running time and achieve high accuracy. DR-CNN model is integrating the convolution, ReLU and Max pooling Layer into single unit and call recursively. Initially, the pest images are fed as input to the DR-CNN model, to extract feature pyramid networks (FPN) for detecting the image with pest and without pest and if pest is detected then classify pest into pest category for further analysis. The final result will shows the location and classification of pest on plant in the input.

Keywords---pest on plant detection, Deep Recursive-CNN, ReLU, Max pooling, feature pyramid networks (FPN).

Manuscript submitted: 27 March 2022, Manuscript revised: 18 April 2022, Accepted for publication: 9 May 2022

Introduction

Modern technologies have been used extensively in the agriculture industry which supports the farmers to produce enough food to fulfill the requirement of more than 10 million people. Even so, food security remains endangered due to various factors affected on healthy crops including uncertain climatic condition [1], floods, earthquake, pest on plants and diseases, and many others. Every farmer takes various efforts to enhance the quality and quantity of food production whose livelihoods mainly depends on foods. Most of the food loss is mainly caused by plant diseases and pest on plant that damage the food at the global level [2], Various types of diseases appeared on plant leaves — especially bacteria, leaf spot, mosaic, mildew, yellow curved, and many other diseases [3]. Similarly various pest such as worm, insects, etc. appeared on plant. These diseases and pest have a fatal impact on the growth of plant and also degraded the quality and quantity of food, and hence, affect the economic benefits of the agriculture industry. Prior detection of these diseases and its diagnosis would result in reducing the disease's effect on plant and enhance the quality of food production.

At present, the plant leaf disease detection mostly adopts the manual method of visualization by expert. Most of the farmers don't have the knowledge of plant diseases. This method is not affordable to smallholder farmers as they need to travel long distance to meet experts which is time consuming process. Moreover, low accuracy, and poor reliability. Therefore, it is necessary to design the system of automatic real-time detection of plant leaf disease and its diagnosis at the prior stage. Recently, many researchers have used a variety of image processing, machine learning, artificial intelligence and deep learning techniques to detect diseases on plant leaves. One of the most promising methods is based on deep learning, particularly Convolutional Neural Network (CNN). Deep learning includes various convolutional layers that represent learning image features.

The pest and disease detection by manual method is inefficient and also costly. Therefore, there is a need to provide automated solutions to farmers based on image processing using deep learning. Sample image datasets are used for detecting disease and pest in machine vision system due to appropriate tools and software packages are available. These tools helps to process image using AI based image processing algorithm which provides greater efficiency, low cost and increase accuracy of the image recognition[4]. According to the Food and Agriculture Organization (FAO), food production needs to be increased by 70% by 2040 to fulfil the global demands of food (https://www.tomatonews.com/). Famers used chemicals such as pesticide and fungicides to prevent crops from disease and pest. But these chemicals negatively affect the agricultural ecosystem. Hence, early and accurate pest and disease detection technique will help the agricultural ecosystem. Nowadays, artificial neural network and Deep Learning techniques are the most prominent technique used for detection of pest at the prior stage of its growth. Early identification and its diagnosis can reduce processing costs; reduce chemical quantity and thereby reducing its negative impact on environment [5]–[7]. Various techniques have been proposed with the advancement of technology. Here in this paper, the real field images of plants are processed using recursive deep convolutional neural network to recognize pest on plant and after detecting a precision amount of chemical apply to destroy pest, so this method can significantly improve food quality and production efficiency.

Related Work

Many researchers have used deep learning convolutional neural network architectures for automatic disease detection and classification systems like googleNet, mobileNet, InceptionV3, VGG16, EfficientB0 and SqueezeNet, as discussed below in [8], [9].

Chai *et al.* analyzed tomato leaf diseases consisting leaf spot, early and late blight leaf mildew, and extracted different characteristic features like size, color, texture of leaf spot disease of tomato using stepwise discriminant and Bayesian discriminant principal component Analysis(PCA) respectively. They achieved accuracy of these methods were 94.71% and 98.32%, respectively. Transfer learning and image processing technique has been proposed for classifying and identifying tomato leaf disease having 94–95% accuracy [10][9].

Li and He proposed BP neural network model for detecting and classifying apple leaf disease with accuracy 92.6%. They studied five different kinds of disease on apple leaf (Yellow leaf disease, rust disease, round spot disease, speckled deciduous disease, and mosaic disease). Guan *et al.* studied 3 kinds of rice diseases such as stripe blight, blast, and bacterial leaf blight and extracted 63 feature parameters including size, texture, morphology, color features, etc. using Bayesian discriminant method and applied step-based discriminant analysis with the maximum detection accuracy of 97.2%.

Many authors used pre-trained CNN model architecture to detect diseases on different datasets and compared their accuracy. In the paper [11], AlexNet and VGG 19 models have been used to detect tomato crops diseases using a samples of 13,262. Accuracy achieved by this model is 97.49%. In the paper [12], transfer learning and Convolutional Neural Network model have been used to detect dairy crops diseases accurately with achieving accuracy 95%.

In the paper [13], the author used image processing and classification algorithm to identify and classify leaf disease, here, they collected sample data using 8 mega pixel camera and divide it into two categories 50% healthy and 50% unhealthy samples. Though image processing algorithm provides high accuracy but it also has some limitations. 1. It requires more processing time. 2. It performs complex operation for extracting features. 3 It is sensitive to location of object in an image and it is expensive also.

K. Thenmozhi et. al. 2019 [14] proposed an efficient deep CNN model for classification of pest image on crop using deep CNN and transfer learning approach. They used the NBAIR, Xie1, and Xie2 datasets which contains 40, 24, and 40 classes of field crop insect images respectively. They achieved classification accuracy of 96.75, 97.47, and 95.97% for these three classes of insect datasets.

Denan Xia et. al. 2018[15] proposed CNN model for solving multi-classification problem of insect images and they adopted region proposal network to generate smaller number of proposal windows for improving prediction accuracy and computation speed. They had used “Mpest” dataset and 24 common images of Xie dataset. There are some issues such as target detection error, classification task, the classification of insects needs to be more detailed, the periods of insect growth should be divided. Different pest control measures according to the period of insect growth is not implemented.

Sk Mahmudul Hassan et al. (2021) [16] used depthwise separable convolution instead of traditional convolution layer, which reduces the number of parameter in the layers and computation cost. They used plantVillage datasets and compares proposed model using four pre-trained model InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, they achieved the best accuracy 99.56% in EfficientNetB0 model. On average, in the MobileNetV2 and EfficientNetB0 architectures to train the images less time was required.

Materials and Methods

In this part, pest and disease detection methodology, build models, and datasets that are relevant to our model are discussed.

Insect Dataset Collections: Data Pre-processing And Augmentation

In this paper, for experimentation we have collected a real field pest images and NBAIR datasets which contain 40 classes of pest images [14]. These images undergoes into data cleaning where certain amount of data pre-processing is done on the data which includes color filtering, conversion of RGB into grey scale image, canny edge detection, extreme outer contours detection, bounding box and resize image. If the pest image size in the bounding box is small, then Region of Interest (ROI) of pest image is extracted from original image and finally we will get the cropped pest image as shown in Fig.1.

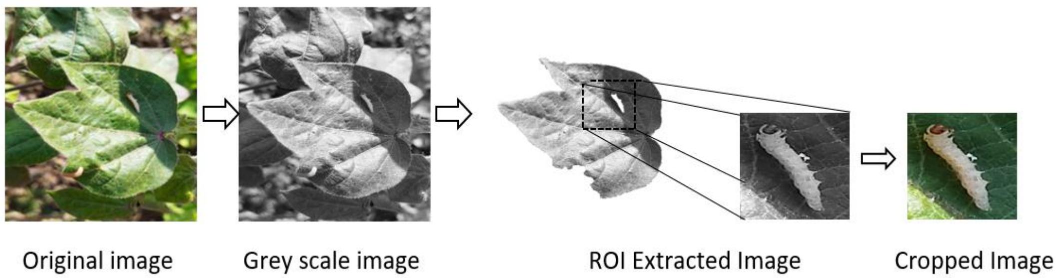

Fig. 1: Data Pre-processing Operations on Original Image a) Original RGB Image of Pest On Plant b) Grey Scale Image c) Region of Interest is Extracted And Cropped

Deep Learning

Deep learning is the sub part of machine learning. It uses feed-forward artificial neural network architectures that contain many processing layers. Deep learning technology is best known technology for the recognition of image and voice [17]. In agriculture sector, Deep learning plays an important role for detection and classification. The neural network has millions of neurons which are connected to each other through the adjacent layers of the network. Inputs are fed to these neurons, processed there and activate the corresponding output. Convolutional Neural Network (CNN) of deep learning consist of multi-layered neural network [18]. Basic implementation of deep Learning is illustrated in fig.2. First, dataset is gathered which undergoes division into training and testing datasets, then train a model using deep learning model architecture such as AlexNet, ResNet, GoogleNet, VGGNet, etc.[18] and their training and validation plots are generated to understand the efficiency of the model. After that performance metrics and Visualization techniques are used for the classification and detection of images.

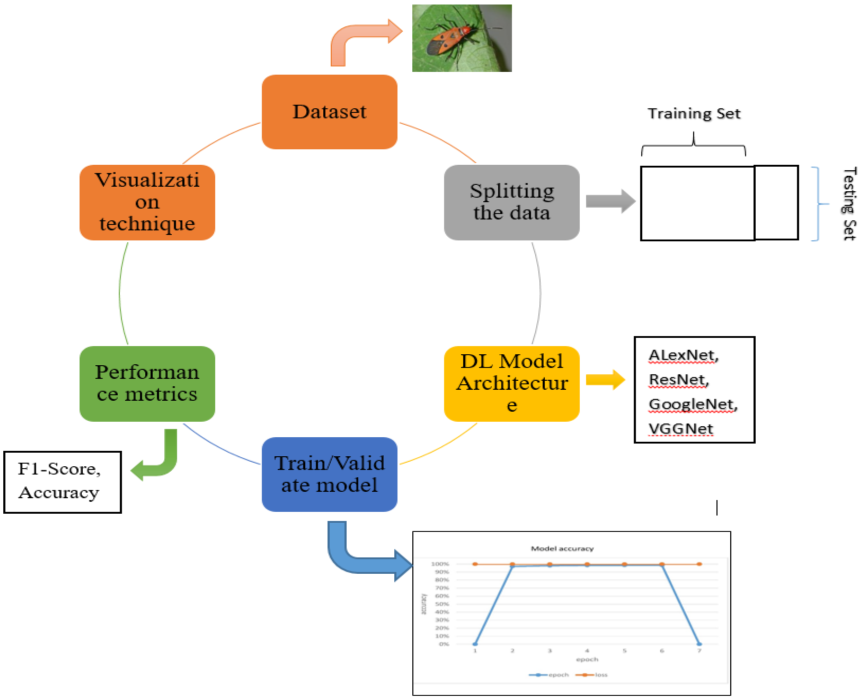

Fig. 2: Implementation of Basic Deep Learning Model

Convolutional Neural Network

The Convolutional Neural Network is a type of deep, feed forward neural network, mostly used for visual imagery. CNN has multiple layers including convolution, pooling, max pooling or average pooling, Relu activation function, flattening layer and fully connected layers as shown in fig. 3. Number of layers, size of image and its parameters differ according to different CNN model architecture such as AlexNet, ResNet, GoogleNet, VGGNet, InceptionNet, [15] etc. Several CNN model architectures are designed for different image processing such as face detection, object detection, OCR, handwritten digit recognition etc.

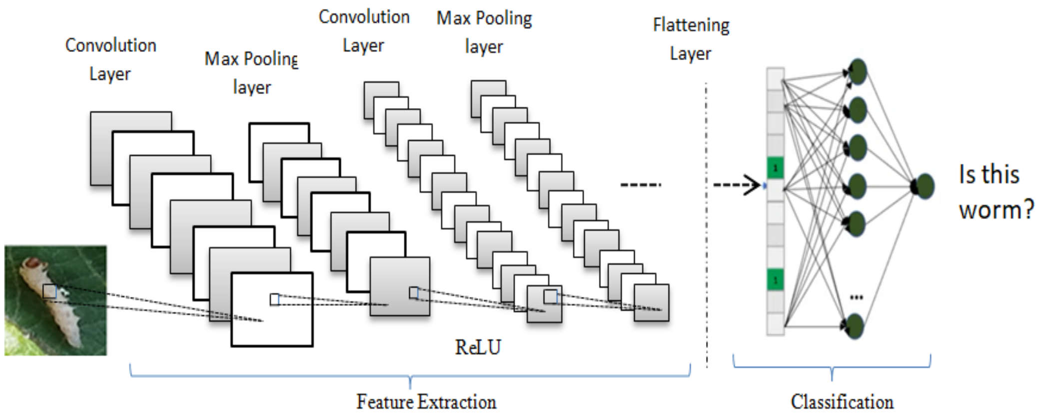

Fig. 3: Convolutional Neural Network

Image is inputted to the convolutional layer with the dimension (h x w x r). Where h is the height and width of the image and r is the number of channels. For example, image size (227 x 227 x 3) when the image is RGB image. The image is given as an input in the convolution layer; the layer extracts the features of the image by applying various filters. It produces the feature maps at each convolution layer in the model. A filter is nothing but a feature detector in the form of matrix of values, known as weights, which strides over the image matrix to detect particular features of the input image [7]. Convolution operation is a mathematical operation consists of sum of product of corresponding weights of weight matrix with element in the input matrix which stores the value in the corresponding cell of the resultant matrix after passing filter over entire image matrix.

If the resultant matrix contains the value lesser than 0 then Rectified Linear Unit ReLU activation function, replace all negative values with 0. This increases the non-linear properties of the model. This resultant matrix is the feature map which undergoes to the polling layer. Pooling layer reduces the dimension of the feature map which helps to overcome the problem of overfitting[19].Fully connected layer sum up all extracted features to learned high-level features by the model and softmax classifier is used for classifying the input images into predefined classes [20].

Proposed Deep Recursive-CNN model for pest detection

We proposed a Deep Recursive CNN model for the classification of pest images. This model has convolutional layer followed by ReLU activation function, and max pooling layer which performs recursively 6 times with different output size and different filters to generate deep feature map and also reduce the number of parameters. Parameters used in the proposed model such as output image size, number of filters, filter size and stride after performing every convolution and max pooling layer are mentioned in the fig. 4. ReLU (Rectified Linear Unit) activation function helps to increase the non-linearity of the model. A dropout ratio of 0.2 is used after two convolution to increase the learning speed of the model [15]. All feature maps are summed up by using two fully connected layer and classify the images with softmax classifier as shown in fig. 4. The results of the proposed deep recursive CNN model is compared with pre-trained model of deep learning architecture using transfer learning.

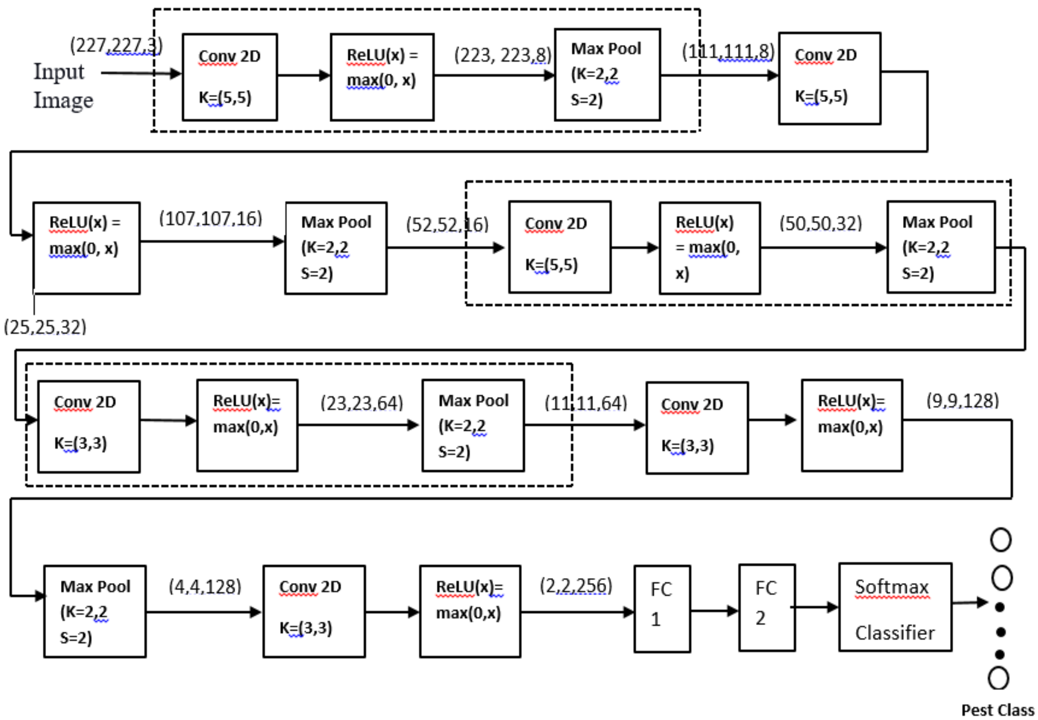

Fig. 4: Proposed Deep Recursive CNN Model for Pest Detection and Classification

In this paper, for implementing proposed deep recursive CNN algorithm, an open source tool python and its libraries such as PyTorch, Tensorflow, Numpy, Open CV, Pandas, etc. can be used. We have collected a real field pest images and NBAIR datasets which contain 40 classes of pest images.The proposed model shows the output of sample without pest if it has very low probability. Otherwise, further it processed the input samples through proposed CNN, which calls recursively to the convolutional layer, ReLU and Max pooling layer with depth separable convolution layer to reduce the number of parameters.

Conclusion

In this paper, we have review on basic knowledge of deep learning techniques, its general implementation, Convolution Neural Network, various deep learning architecture model for detection and classification of plant leaf disease and pests on plant. However, several performance metrics such as accuracy is measured of these architectures. Many DL model proposed in the related work have shown good accuracy on used datasets that was divided into training and testing datasets, but the accuracy on other datasets are not good. We have proposed a Deep Recursive CNN model capable for detecting and classifying pest on plants with high accuracy. Moreover, we have considered real field datasets, for a practical scenario. Hence, this model presents the better robustness to adapt diverse pest datasets.

This DR-CNN model processes the images of pest that occur on anywhere on the plant like upper and lower side of the leaf, on root, on stem, on flower images. Also this will detect pest at any stage of its growth such as early, middle and adult stages. For the future work, implementation of the proposed method specified in this paper will be performed. The primary task is to work on the one crop and verify the performance of the proposed work.This work contributes for aiding the farmers and agronomists to detecting the disease and pests and ultimately helps to increase production in the field of agriculture.

References

[1] A. P. K. Tai, M. V. Martin, and C. L. Heald, "Threat to future global food security from climate change and ozone air pollution," *Nat. Clim. Chang.*, vol. 4, no. 9, pp. 817–821, 2014, doi: 10.1038/nclimate2317.

[2] C. A. Harvey *et al.*, "Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar," *Philos. Trans. R. Soc. B Biol. Sci.*, vol. 369, no. 1639, 2014, doi: 10.1098/rstb.2013.0089.

[3] N. K. Trivedi *et al.*, "Early detection and classification of tomato leaf disease using high-performance deep neural network," *Sensors*, vol. 21, no. 23, 2021, doi: 10.3390/s21237987.

[4] R. Wang, M. Lammers, Y. Tikunov, A. G. Bovy, G. C. Angenent, and R. A. de Maagd, "The rin, nor and Cnr spontaneous mutations inhibit tomato fruit ripening in additive and epistatic manners," *Plant Sci.*, vol. 294, no. February, p. 110436, 2020, doi: 10.1016/j.plantsci.2020.110436.

[5] J. Basavaiah and A. Arlene Anthony, "Tomato Leaf Disease Classification using Multiple Feature Extraction Techniques," *Wirel. Pers. Commun.*, vol. 115, no. 1, pp. 633–651, 2020, doi: 10.1007/s11277-020-07590-x.

[6] H. Ali, M. I. Lali, M. Z. Nawaz, M. Sharif, and B. A. Saleem, "Symptom based automated detection of citrus diseases using color histogram and textural descriptors," *Comput. Electron. Agric.*, vol. 138, pp. 92–104, 2017, doi: 10.1016/j.compag.2017.04.008.

[7] H. Kibriya, R. Rafique, W. Ahmad, and S. M. Adnan, "Tomato Leaf Disease Detection Using Convolution Neural Network," *Proc. 18th Int. Bhurban Conf. Appl. Sci. Technol. IBCAST 2021*, pp. 346–351, 2021, doi: 10.1109/IBCAST51254.2021.9393311.

[8] S. Zhao, Y. Peng, J. Liu, and S. Wu, "Tomato leaf disease diagnosis based on improved convolution neural network by attention module," *Agric.*, vol. 11, no. 7, 2021, doi: 10.3390/agriculture11070651.

[9] M. Hasan, B. Tanawala, and K. J. Patel, "Deep Learning Precision Farming: Tomato Leaf Disease Detection by Transfer Learning," *SSRN Electron. J.*, pp. 1–5, 2019, doi: 10.2139/ssrn.3349597.

[10] S. Vetal and K. R.S., "Tomato Plant Disease Detection using Image Processing," *Ijarcce*, vol. 6, no. 6, pp. 293–297, 2017, doi: 10.17148/ijarcce.2017.6651.

[11] A. K. Rangarajan, R. Purushothaman, and A. Ramesh, "Tomato crop disease classification using pre-trained deep learning algorithm," *Procedia Comput. Sci.*, vol. 133, pp. 1040–1047, 2018, doi: 10.1016/j.procs.2018.07.070.

[12] S. Coulibaly, B. Kamsu-Foguem, D. Kamissoko, and D. Traore, "Deep neural networks with transfer learning in millet crop images," *Comput. Ind.*, vol. 108, pp. 115–120, 2019, doi: 10.1016/j.compind.2019.02.003.

[13] M. H. F. R. Syafiqah Ishaka, S. N. Aqmariah, and H. S. Mohd Kanafiahb, "Jurnal Teknologi LEAF DISEASE CLASSIFICATION ARTIFICIAL NEURAL NETWORK," *J. Teknol.*, vol. 17, pp. 109–114, 2015.

[14] K. Thenmozhi and U. Srinivasulu Reddy, "Crop pest classification based on deep convolutional neural network and transfer learning," *Comput. Electron. Agric.*, vol. 164, no. June, p. 104906, 2019, doi: 10.1016/j.compag.2019.104906.

[15] D. Xia, P. Chen, B. Wang, J. Zhang, and C. Xie, "Insect detection and classification based on an improved convolutional neural network," *Sensors (Switzerland)*, vol. 18, no. 12, pp. 1–12, 2018, doi: 10.3390/s18124169.

[16] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, "Identification of plant-leaf diseas[1] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, 'Identification of plant-leaf diseases using cnn and transfer-learning approach,' Electron., vol. 10, no. 12, 2021, doi: 10.3390/electronics101213," *Electron.*, vol. 10, no. 12, 2021.

[17] L. Li, S. Zhang, and B. Wang, "Plant Disease Detection and Classification by Deep Learning - A Review," *IEEE Access*, vol. 9, no. Ccv, pp. 56683–56698, 2021, doi: 10.1109/ACCESS.2021.3069646.

[18] P. P. Patel and D. B. Vaghela, "Crop Diseases and Pests Detection Using Convolutional Neural Network," *Proc. 2019 3rd IEEE Int. Conf. Electr. Comput. Commun. Technol. ICECCT 2019*, pp. 1–4, 2019, doi: 10.1109/ICECCT.2019.8869510.

[19] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Front. Plant Sci.*, vol. 7, no. September, pp. 1–10, 2016, doi: 10.3389/fpls.2016.01419.

[20] M. Khanramaki, E. Askari Asli-Ardeh, and E. Kozegar, "Citrus pests classification using an ensemble of deep learning models," *Comput. Electron. Agric.*, vol. 186, no. October 2020, p. 106192, 2021, doi: 10.1016/j.compag.2021.106192.