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# Convolutional Neural Network (CNN) Architecture for Pest and Disease Detection in Agricultural Crops

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## Abstract

The ravages of insect pests and plant diseases cause a profound loss in crops. Sometimes, pests and diseases are difficult to identify in the early stages through visual assessment and detection is not possible for larger areas. With the advancement, various technologies have been employed in the agricultural sector for successful crop production. Convolutional Neural Network (CNN) is the deep learning model used to classify the image data into an output variable. This advanced approach is much more practical than human supervision for the detection of insect pests and diseases in crops. It can able to identify pests and diseases with maximum accuracy. The CNN architectures *viz.*, InceptionV3, DenseNet201, ResNet50V2, Visual Geometry Group (VGG19) and Regional Proposal Network (RPN) have been discussed here.

## Introduction

Agriculture plays a significant role in the economic development of the country. The ever-increasing population growth creates the need for sustainable agriculture which is possible through modern tools and technologies. The introduction of high-yielding varieties, changes in climate scenarios, cropping patterns and several anthropological factors have given the way for the emergence of new pests and diseases. Insect pests and diseases cause a huge loss on major crops and significantly affect global crop production. Annually about 20-40% of global crop production was lost due to pests (FAO, 2021). Early detection of pests and diseases is important to prevent further spread and to formulate management practices. In general, continuous monitoring and detection of pests and diseases are challenging task. But it is feasible through different automated techniques, in which deep learning and image processing techniques play a crucial role.

In recent times, Deep Learning (DL) has made breakthroughs in the field of digital image processing and made significant progress through ImageNet Large Scale Visual Recognition Challenge (ILSVRC). ILSVRC is a publicly available dataset having 14 million images and around 21 thousand object classes. During 2012, the CNN named AlexNet achieved a top-5 error of 15.3% on the ImageNet challenge compared to other deep learning networks (Ghesquiere and Ngxande, 2021) in detection. Recently, the CNN models *viz.*, InceptionV3, DenseNet201, ResNet50V2, VGG19 and RPN have outperformed AlexNet on the ILSVRC with a different architectural approach. The logic behind the deep learning technique is data analysis and future learning by employing neural networks.

## Data Set Construction

A wide range of insects and diseases infest crops and vary among each other. There is a necessity to optimize the data set and make it suitable for reading in the train and test set. Considering the interference of the outside environment, the infested leaves are picked outdoors and placed indoors for image shooting and sorting. Images are split into two sets; training and testing sets and the same used for model verification and testing. To improve the calculation efficiency and speed of the model, the oversize part has to be cropped and compressed before training and testing the model. The processed image resolution sizes are quite standard from one network to another, for example, 227 × 227 for AlexNet, 224 × 224 for DenseNet, ResNet, and VGG and 299 × 299 for InceptionV3.

## System Flow

Image detection of insect pests and crop diseases with deep learning mainly includes *viz.,* collection and preprocessing of image data sets, construction, training of CNN models and testing the models with accuracy. The system flow is shown in Figure 1 and later the data will be divided into two parts: the training data set is used to train various CNN models and the testing data set is used for verifying model accuracy. The results include both the classes and the locations of the identified insect pests and plant diseases.

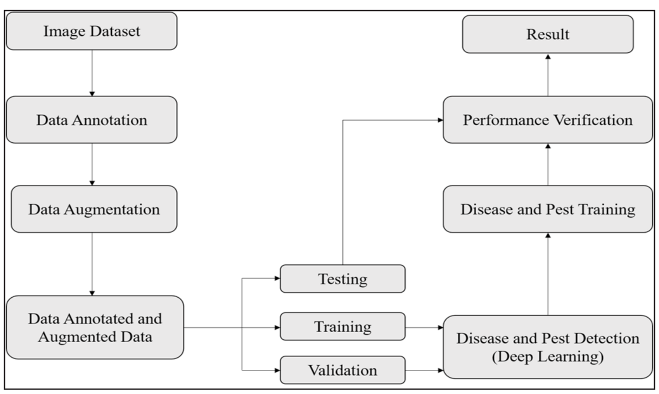


Figure 1: Convolutional Neural Network (CNN) model

## CNN in Plant Disease Detection

The disease can be expressed differently from one plant species to another. It is important to assess the healthiness of crops in the field. Monitoring the condition of each plant is not practical especially on large farms. But, the automatic identification of diseases by imagery does by overcoming the problems with expert assistance tools. The widely used CNN models for plant disease detection are InceptionV3, ResNet50V2 and DenseNet201 which is supported by the Keras framework. Keras framework is a high-level deep learning library with Tensor Flow backend support and also GPU training is possible. It helps in processing of the large datasets.

InceptionV3 is 48 layers with less than 25 million parameters and makes use of inception modules. It is a widely-used image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. This architecture combines a set of convolution and pooling layers, then integrated to capture the features in parallel. It allows CNN to perform on the same level wherein the network gets wider than deeper. Also, the model uses fewer computations methods and a limited amount of parameters.

Resnet50V2 has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer and around 23 million parameters and utilize residual components and contains a skip connection. But, the connection does not have any parameters for bypassing layers. InceptionV3 avoids deeper networks by making them wider rather ResNet does this by utilizing the skipping layers.

DenseNet201 is an extension of ResNet with 201 layers and 20 million parameters. The model connects each layer to each forward layer with skip connections and has a collective knowledge of the previous ones. ResNet uses an additive method (+) that merges the previous layer (identity) with the future layer, whereas DenseNet concatenates the output of the previous layer with the future layer. DenseNet was specially developed to improve the declined accuracy caused by the vanishing gradient in high-level neural networks. DenseNet has less computational complexity than previously proposed networks.

The saliency maps are used to visualize the trained neural network models. The purpose of the saliency map is to find the regions which are prominent and noticeable in every location of the visual field. This can be done by computing the gradient of the output category after inserting the input image. These gradients are used to highlight pixel regions by the Keras Visualization toolkit.

## CNN in Insect Pest Detection

The development of deep learning algorithms has been an excellent solution for image recognition and classification of insects. An improved CNN architecture *viz.*, VGG19 and Regional Proposal Network (RPN) are accurate in distinguishing the different pests. VGG19 and RPN models have outperformed the models like Single Shot Multibox Detector (SSD) and Faster Region-based Convolutional Neural Network (Fast RCNN) (Denan *et al.*, 2018).

VGG19 model is a 19 layer CNN architecture that self-learns the input image and progresses it from low level to high level. The first 16 layers of VGG19 reduce the resolution of the image and extract high-dimensional features. The RPN of 16 layers analyzes the location of insects and removes the unwanted background of the image. RPN architecture is suitable for classifying local features from a complex image dataset. It takes an image of arbitrary size as input and gives a set of proposed boxes as an output, where each box has an object score.

The bilinear interpolation is adopted to fix images to the pixel size of 450 × 750. However, to avoid over-fitting the model, data augmentation can be performed on the training data set. Data augmentation can increase the number of training samples. Salt and Pepper Noise is also added to ensure the validity of data and to change the pixel values of the image. The convolution operation can extract an insect image from a complex background. The region of interest (ROI) is a pooling technique used to convert image regions into required fixed spatial sizes.

The above techniques *viz.*, VGG19 and RPN increase the number of training samples to ten times than original samples. Later, the image feature is inserted into the Softmax layer, which identifies insects and estimates the insect regions. Both RPN and VGG19 architecture are possible to train jointly by fixing the convolutional network layers. It detects the insects with less training time and also have high moving average precision and high accuracy than other existing models.

## Conclusion

Different CNN architectures are designed for the ILSVRC that classify various plant diseases and insect pests. The limitation of CNN architectures is that the models only identify a single object at a time and lack practical production. But, the time required to train the model was much less when compared to other machine learning approaches and has great developmental potential and application value. The CNN models can be adopted instead of traditional selective search techniques to detect insect pests and plant diseases, which can improve detection accuracy and accelerate computations.

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