Research Article

Protecting the Farming Land from Insects Damage to Growing Crops using Deep Convolutional Neural Network

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Abstract: Rice cultivation is one of the most important economic sectors for Indian economy. With the increase in world population, the demand for the rice cultivation is also increasing. In order to increase the growth of rice crop, it is necessary to detect the pests in an earlier stage to minimize the pest growth. But our farmers are still struggling to protect the crops from external threats particularly from insects in agricultural lands. To overcome this problem, we are providing a solution to protect the crops in the farming lands using deep networks. Hence, the lives of farmers are saved from their struggle. In this paper, we proposed a system that will help the farmers in detecting rice crop pest using deep convolutional neural network with VGG16 architecture. Then, the proposed model is compared with the existing models GoogleNet and AlexNet.

Keywords: Convolutional Neural Network, Deep Learning, Pest Detection, VGG16 Model.

1. Introduction

Agriculture plays a major role in the development of economy and it will directly affect the people life. Preventing the pest from the crops and also the economy. Rice is being cultivated in more than 50 countries. Rice plays a major role in human food cycle. There are more than 200 insects species are identified in rice crop. In that 42 insect species are damaging the rice crop. Pest damage the entire crop easily and it will directly affect the productivity. Accurate and early detection of pest helps the farmers to treat their plants before the pest damaging the entire crop field. Recognizing the pest in an earlier stage controls the spread of pest in the entire crop fields. This will lead us to improve the crop production. In this paper we proposed an automatic pest detection system is developed using deep convolutional neural network. Insect classification is a hard task due to its complex structure. Using some latest technologies like machine learning, artificial intelligence, and deep learning pest can be detected by using image processing techniques. Now a days deep learning models are used to solve various problems in agriculture particularly for pest and disease detection.

2. Related Work

The author Alfarisy, A. A et.al. discussed about preventing the paddy production loss in Indonesia due to pest and diseases in rice crop. The proposed system identifies the pest in earlier stage and an alert message is sent to farmer smartphone. They used 4511 images to train the pretrained model CaffeNet and they achieved the higher accuracy of 87% in 30,000 iteration.

The author Mique, E. L et.al. developed an android application to provide the details about the detected pest. They collected the information for dataset by conducting interview to Regional Crop Production Center staff and it is used to train the pre trained model Google Inception v3. The trained model is used as a library in the developed android application. They achieved 90.9% accuracy.

The author Wu, J et.al. used GoogleNet and AlexNet to identify the pest and disease using machine learning technique. The dataset is constructed with the help of images in plant village website. They used 20,000 images to train the model since they are using machine learning technique it requires large amount of data to learn effectively. The proposed model achieves 98.48% accuracy.

The author Rahman et.al, proposed a model to increase the crop production by identifying the pest in earlier stage. They used keras framework with tensorflow backend to train the VGG16 and Inception v3 architectures. The trained model is compared with MobileNetv2, NasNet Mobile and SqueezeNet. Among all the model fine-tuned VGG16 achieves higher accuracy of 97.12%.

The author Thenmozhi, K et.al. proposed a model to detect the pest using canny edge detection method with the help of three different datasets i.e. National Bureau of Agricultural Insect Resource, Xie1, Xie2. Matlab2018 framework is used to develop the deep learning model. NBAIR dataset achieves 96.75% accuracy, Xie1 dataset achieves 97.47% accuracy and Xie2 dataset achieves 95.97% accuracy.

3. Comparison

Table 1. Comparison

Reference	Objective	Framework	Advantage	Future Work	Accuracy
Alfarisy, A. A et.al.	Prevent Paddy Production loss in Indonesia	Caffe	Better Accuracy	Improve Machine Specification	87%
Mique, E. L et.al.	Detect rice crop pest and diseases	Google Inception v3	Satisfy user requirement even late in life cycle.	Faster Retrieval of information.	90.9%
Wu, J et.al.	Detect rice crop pest and diseases	AlexNet and GoogleNet	Data expansion is used to increase the amount of data so that the machine can learn effectively.	Shorter time of training is required.	98.48%
Rahman et.al.	Detect rice crop pest and diseases in earlier stage to prevent loss in Bangladesh	Keras Framework with tensor flow	High precision	Segmentation can be used to make a system more effective.	97.12%
Thenmozhi, K et.al.	Classify Insect Species	ResNet, GoogleNet, VGGNet	Better Performance	More number of classes to improve computation speed.	NBAIR-96.75%, Xie1 - 97.47%, Xie2 - 95.97%

4. Proposed Work

The pest dataset is collected from National Bureau of Agricultural Insect Resource (NBAIR) that contains 57 different types of pest particularly for rice crop field. In this paper, 57 categories of rice crop insects are used which is around 1000 pest images. Those images are collected and used as a dataset to train the deep learning model. Among several deep learning models, we are use VGG16 pre trained model. VGG16 is an improvement of AlexNet by changing the large kernel sized filters into 3x3 kernel sized filters. It was previously trained with ImageNet dataset in NVIDIA Titan Black GPU for one week. The VGG16 model has 16 layers, 13 convolutional layers and 3 fully connected layers. After each maxpool layer, convolutional layers are doubled in VGG16. The collected datasets are divided into two parts. 80% of the images are used training the model and the remaining 20% of the images are used for the testing purpose. Keras framework with tensorflow backend is used to train the VGG16 model with NBAIR dataset. Later the trained model is tested with image and video input. Our proposed model is compared with the other deep learning models GoogleNet and AlexNet. GoogleNet model achieves 49% accuracy in NBAIR dataset and AlexNet model achieves 47% accuracy. From that we can tell that our proposed model gives better accuracy than the other deep learning models. Finally a solution is given to the farmers regarding the pesticides.

5. Flow Chart

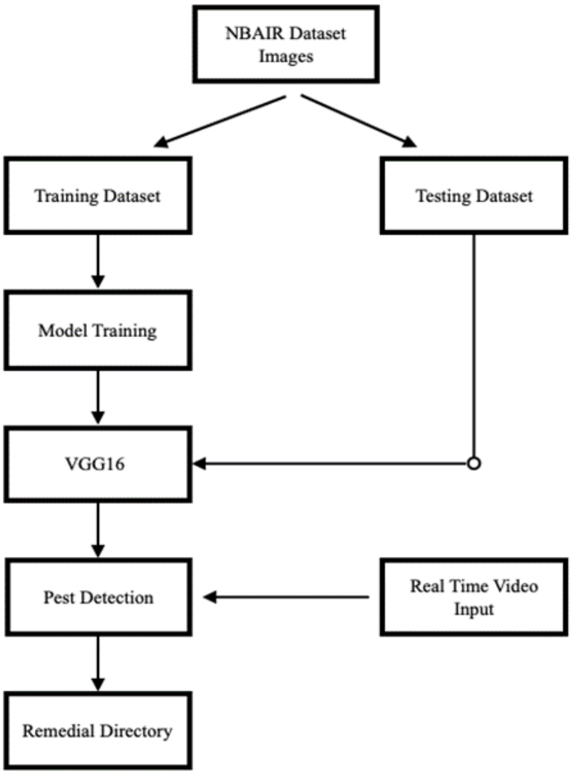

Figure 1. Flow Chart

6. Result

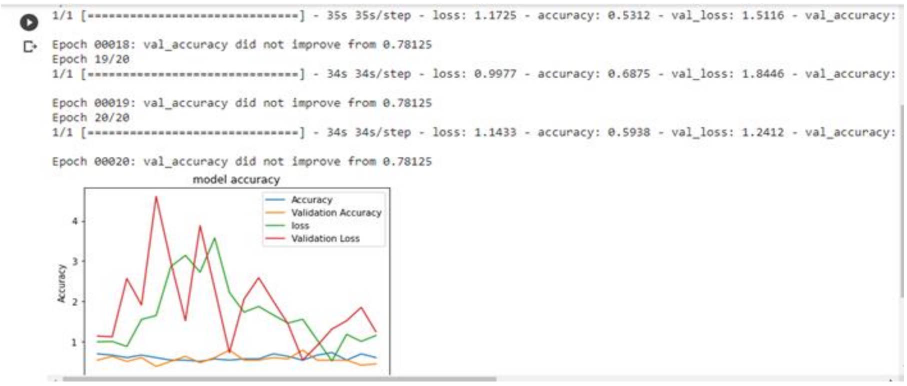

Figure 2. VGG16 Training

Figure 3. Pest Detection in Image Input

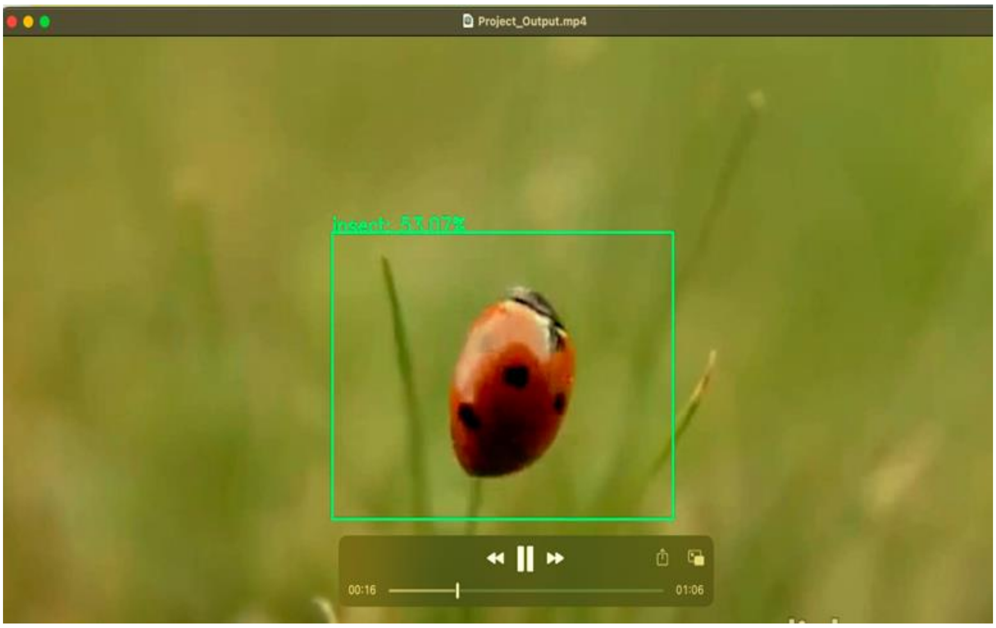

Figure 4. Pest Detection in Video Input

```
  warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/10
29/29 [==============================] - 146s 5s/step - loss: 44.4684 - accuracy: 0.3610
Epoch 2/10
29/29 [==============================] - 142s 5s/step - loss: 1.3928 - accuracy: 0.4956
Epoch 3/10
29/29 [==============================] - 141s 5s/step - loss: 1.2135 - accuracy: 0.5007
Epoch 4/10
29/29 [==============================] - 140s 5s/step - loss: 1.1926 - accuracy: 0.5263
Epoch 5/10
29/29 [==============================] - 140s 5s/step - loss: 1.1857 - accuracy: 0.5167
Epoch 6/10
29/29 [==============================] - 151s 5s/step - loss: 1.1956 - accuracy: 0.4930
Epoch 7/10
29/29 [==============================] - 142s 5s/step - loss: 1.1415 - accuracy: 0.5189
Epoch 8/10
29/29 [==============================] - 141s 5s/step - loss: 1.2075 - accuracy: 0.5046
Epoch 9/10
29/29 [==============================] - 141s 5s/step - loss: 1.1273 - accuracy: 0.5359
Epoch 10/10
29/29 [==============================] - 141s 5s/step - loss: 1.2159 - accuracy: 0.4592
Found 906 images belonging to 6 classes.
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1877: UserWarning: `Model.evaluate_gener
  warnings.warn('`Model.evaluate_generator` is deprecated and '
Loss = 1.1716492176055908
Test Accuracy = 0.4757174253463745
```

Figure 5. AlexNet

```
10/10 [==============================] - 40s 4s/step - loss: 1.5290 - main_loss: 0.9282 - aux1_loss: 1.0178 - aux2_loss:
Epoch 3/3
10/10 [==============================] - 40s 4s/step - loss: 1.6655 - main_loss: 1.0322 - aux1_loss: 1.0348 - aux2_loss:
```

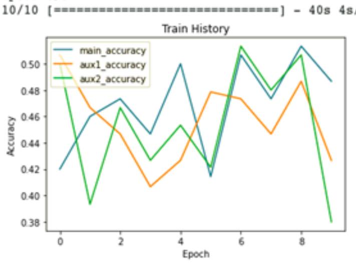

Figure 6. GoogleNet

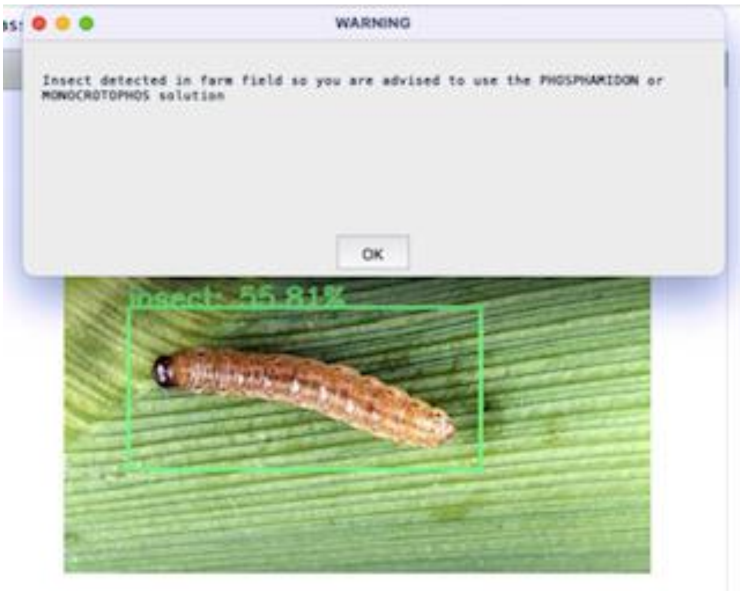

Figure 7. Remedial Directory

7. Conclusion

The deep learning technique were used to identify the pest in rice crop field. Our work mainly concentrates on all types of pest in rice crop. Our proposed system is very much useful for the farmers to identify the pest in earlier stage. Our proposed work gives better accuracy of 78% and also our system will provide a remedial measure to the farmers.

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