

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 3, March 2021



Impact Factor: 7.488

9940 572 462

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e-ISSN: 2320-9801, p-ISSN: 2320-9798 www.ijircce.com | Impact Factor: 7.488 |



Volume 9, Issue 3, March 2021

DOI: 10.15680/IJIRCCE.2021.0903194

Multi Class Pest Detection Using Deep Learning Approach

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Abstract: This paper provides an multi-class pest detection using deep learning approach. Agriculture is aimed towards increasing the food production and food quality while decreasing the plant diseases. Large amount of crops are destroyed every year due to pests . Pest detection and identification is needed to ensure good productivity in agricultural crops. Multi-class pest detection is one of the crucial components in pest management involving localization in addition to classification which is much more difficult than generic object detection because of the apparent differences among pest species. Pest detection consists of three major parts. First, a novel module channel–spatial attention is proposed to be fused into the convolutional neural network back bone for feature extraction and enhancement. The second one is called region proposal network that is adopted for providing region proposals as potential pest positions based on extracted feature maps from images. Position-sensitive score map, the third component, is used to replace fully connected layers for pest classification and bounding box regression. Furthermore, we apply contextual regions of interest as contextual information of pest features to improve detection accuracy.

The project results show that the proposed CNN performs well on multi-class pest detection with mean average precision, which outperforms the state-of-the art methods.

Keywords: Image processing, gray level co-occurance matrix, support vector machine, image filtering, segmentation.

I. INTRODUCTION

The main aim of the project is to detect the pest classification using deep learning. Agriculture not only provides food for the human existence, it is also a big source for the economy of any country. Millions of dollars are being spent to safeguard the crops annually [1]. Insects and pests damage the crops and, thus, are very dangerous for the overall growth of the crop. One method to protect the crop is early pest detection so that the crop can be protected from pest attack. The best way to know about the health of the crop is the timely examination of the crop. If pests are detected, appropriate measures can be taken to protect the crop from a big production loss at the end. Early detection would be helpful for minimizing the usage of the pesticides and would provide guidance for the selection of the pesticides. It has become a wide area for research now a days and a lot of research has been carried out worldwide for automatic detection of pests. Traditional method of examination of the fields is naked eye examination but it is very difficult to have a detailed examination in large fields. To examine the whole field, many human experts are needed which is very expensive and time consuming. Hence, an automatic system is required which can not only examine the crops to detect pest infestation but also can classify the type of pests on crops. Computer vision techniques provide effective ways for analyzing the images of leaves. Support Vector Machine (SVM) is used for classification of images with and without pests based on the image features. This technique is simpler as compared to the other automated techniques and provides better results.

II. LITERATURE SURVEY

This paper presents an automatic approach for early pest detection.[2]Agriculture not only provides food for the human existence, it is also a big source for the economy of any country. Millions of dollars are being spent to safeguard the crops annually Insects and pests damage the crops and, thus, are very dangerous for the overall growth of the crop. One method to protect the crop is early pest detection so that the crop can be protected from pest attack. The best way to know about the health of the crop is the timely examination of the crop. If pests are detected, appropriate measures can be taken to protect the crop from a big production loss at the end. Early detection would be helpful for minimizing

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the usage of the pesticides and would provide guidance for the selection of the pesticides. It has become a wide area for research now a days and a lot of research has been carried out worldwide for automatic detection of pests. Traditional method of examination of the fields is naked eye examination but it is very difficult to have a detailed examination in large fields. Computer vision techniques provide effective ways for analyzing the images of leaves. Support Vector Machine (SVM) is used for classification of images with and without pests based on the image features. This technique is simpler as compared to the other automated techniques and provides better results.[8] We present a pipeline for the visual localization and classification of agricultural pest insects by computing a saliency map and applying deep convolutional neural network (DCNN) learning.

First, we used a global contrast region-based approach to compute a saliency map for localizing pest insect objects. Bounding squares containing targets were then extracted, resized to a fixed size, and used to construct a large standard database called Pest ID. This database was then utilized for self learning of local image features which were, in turn, used for classification by DCNN.DCNN learning optimized the critical parameters, including size, number and convolutional stride of local receptive fields, dropout ratio and the final loss function. To demonstrate the practical utility of using DCNN, we explored different architectures by shrinking depth and width, and found effective sizes that can act as alternatives for practical applications. On the test set of paddy field images, our architectures achieved a mean Accuracy Precision (mAP) of 0.951, a significant improvement over previous methods.

III. THE PROPOSED SYSTEM

An artificial intelligence and image recognition technologies used for pest identification. Real-time agricultural meteorology and pest identification systems on evaluated based on intelligent pest identification. We combined the current mature machine learning technology and deep learning applied it to smart agriculture. We used deep learning vgg19 for image recognition to obtain the Tessaratomapapillosa and some other pest analyzes the environmental information from weather stations through Long Short-Term Memory to predict the occurrence of pests. This project provides the correct pest and the extent of the pests to farmers can accurately use pesticide application at a precise time and place and thus reduce the agricultural workforce required for timely pest control, thus achieving the goal of smart agriculture. The proposed system notifies farmers of the presence of different pests before they start multiplying in large numbers. It improves overall agricultural economic value by providing appropriate pest control methods that decrease crop losses and reduce the environmental damage caused by the excessive usage of pesticides.

IV. WORKING OF PROPOSED SYSTEM

A deep-learning image recognition method for Tessaratomapapillosa was proposed that uses the YOLOv3 model to mark and classify the pests in images and extract the characteristics of the pests. The pest identification accuracy and model training time are used to determine the most suitable model for the application. Also, the data from the environmental sensors was used to analyze locations prone to the presence of pests. The location and distribution of the pests were instantly provided to farmers to provide accurate pesticide application, reduce agricultural pest damage, and increase crop quality and yield. Since Tessaratomapapillosa mostly grows on the backs of leaves and in treetops, it is difficult to collect training samples for the purpose of identifying these pests. Further, the inconsistency of outdoor lighting results in low image recognition accuracy. Therefore, here, an APP installed on a mobile phone was used to collect images of Tessaratomapapillosathat appeared on the back of the leaves in order to locate these pests. We plan to apply the Tessaratomapapillosaidentification model to small drones in the future, hoping to reduce the human effort for collecting pest image samples by the maneuverability of drones. It is hope that this will increase the number of images of Tessaratomapapillosa that appear in treetops and improve identification accuracy. Some difficulties were encountered in the research institute: The first was the need to continuously increase the different angles in the images to solve the issue of insufficient training samples; the second was to stabilize the drone flying between the trees to get good quality images of pests and resolve the disturbances of the leaves caused by the wind from the UAV propeller; the third was speeding up the image recognition process to improve pest positioning efficiency and reduce the time required for farmers to inspect the area for pests. We plan to overcome the problems mentioned above and continue to experiment to find solutions, hoping to achieve immediate recognition of pest by drones as soon as possible and establish intelligent agriculture.

|e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.488 |



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Fig. 1 Proposed Architecture diagram

4.2. Advantages:

- Since we are using high image recognition technique like vgg19 which gives us a good accurate results compare to existing one.
- Here we are not using any hardware device's and sensor's, so it is very much cost efficient. Here we are implementing convolution neural network technique which save the time complexity
- Both Artificial intelligence and Deep learning techniques are implemented in this system, so we can get high efficient outcome.

V. EXPERIMENTAL RESULT

1) Image capturing

The first step of every image processing application is image acquisition or image capturing. The images of leaves are captured by using the camera and it will store it in some formats like .PNG, .JPEG, .JPEG etc.

2) Image pre-processing

Image preprocessing is used to create an enhanced and please full version of the captured image. The image preprocessing steps used in the system are: 1) Conversion of RGB image to gray image 2) Resizing of the image 3) Filtering of the image.

a) Conversion of RGB to Gray Image

In RGB color model, each color appears in its primary spectral components of red, green, and blue. The color of a pixel is made up of three components; red, green, and blue

(RGB). The disadvantages of RGB models are, it requires large space to store and it will take more time to process. So there is a need for converting the RGB model to Gray model.

b) Resizing of the Image

Resizing is an important step in image preprocessing. The acquired image is resized according to the requirement of the system. Resizing of the image: Resizing is nothing but,

changing the dimensions of an image. The captured image is resized using some resizing

methods according to the requirement of the system. There are different methods for the resizing of images. Blinear, Bicubic and Nearest neighborhood interpolation are the common resizing methods. Here in our system, we are using bicubic method.

c) Filtering of the image

Filtering is nothing but, eliminating the unwanted portion of the image. Different types of filters are available. Low pass filters are smoothening filters, it will pass only low frequency signals and eliminate all the high frequency signals. High pass filters are sharpening filters, and it will eliminate all the low frequency signals and pass only high frequency signals. Band pass filters will pass the signals which is having a specific range of frequencies. In our system we are using smoothening filter. The purpose of smoothing is to reduce noise and improve the visual quality of the image. Spatial filters are applied to both static and dynamic images, whereas temporal images are applied only to dynamic images.

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3) Training

A huge number of images are needed in order to generate models for pest detection and identification. The variability between different images is crucial when the objective is to create an accurate model for pest detection and identification in pictures.

TRAINING



4) Testing

The proposed solution is to take pictures every minute on the greenhouse. As a result, there are pictures with distinct angles, directions, illumination, and localization.



VI. CONCLUSION

It is difficult to obtain image data of pests since they prefer hiding behind leaves and in the tops of trees. Therefore, we applied image data augmentation to increase the number of pest training samples and improve the recognition accuracy .we are identifying the pest name by giving the image as input which will recognize it using various techniques like Vgg19 and gives the name of the pest as output along with the pesticide solution.

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