IDENTIFICATION AND DETECTION OF PESTS IN PLANTS USING DARKNET-53 AND YOLO ALGORITHM

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Abstract - Agriculture is India's primary source of income. However, pests have harmed the primary growth of crops like tomato, rice, maize, and wheat. Crop yield has reduced due to a large number of insects. Food supplies become insufficient. Farmers have difficulty classifying and identifying the insects that devastate growth in the early phases. A computer vision-based approach is utilized in this study to recognize and classify all of the many types of infecting insects that affect plant growth. A convolution neural network was built using the Darknet and Yolo architectures to classify insects in the agriculture sector. The proposed network has a 96 percent accuracy in detecting dangerous bugs.

***Key Words*:** DARKNET, YOLO, Neural Network, Insects, Image Labeller

1. INTRODUCTION

Agriculture faces major threats due to societal development, which has resulted in drastic changes in the environment and climate change. Insect-borne diseases are becoming more common in agriculture. According to the new estimates, there are 1.5 million, 5.5 million, and 7 million species of beetles, insects, and terrestrial arthropods, respectively, on the planet. Pests attack a wide range of agricultural and horticultural crops. Pest infestations can cause complete crop failure. In worst-case scenarios, crop pests such as seed-eaters, herbivores, frugivores, and pathogens (e.g., insects, fungi, bacteria, and viruses) can reduce productivity or cause total crop loss. Pests consume the leaves of crops, reducing the plant's photosynthetic activity. Identification and classification of crop pests are among the most difficult tasks in agriculture. Insects damage crops and have a significant impact on crop yield productivity.

The farmers' traditional method of determining the type of insect attack is based solely on their own experience. However, such a method is slow in identifying the insect attack in the final stages and ineffective. Insect identification can be found early in the development of computer technology, and pesticides can be given to control insect attacks. Darknet 53 and YOLO v2 are deep convolutional neural networks used in this study. Image bounding boxes were created using the image labeller for training to detect the exact location of the insect. Darknet is used to extract features automatically, and the end-to-end structure simplifies exact object detection. Not only does real-time detection save time. It can also help to reduce the massive loss of agricultural products. The YOLO algorithm optimizes feature detection to pinpoint the insect's exact location.

2. RELATED WORK

The software model is developed to suggest remedial pest or disease management measures in crops. Using this software, the user can scan an infected leaf to identify the leaf species, pest, or disease incidence and obtain solutions for its control. The software system is divided into modules: Leaves Processing, Network Training, Leaf Recognition, and Expert advice [1]. The computer-vision-based system is used to recognize and classify insects as harmful and non-harmful to the growth of cotton. Recognition is based upon a neural network approach to classifying insects [2]. A convolution neural network (CNN) can classify habitus images of ground beetles to species level and estimate how to correct classification relates to body size, the number of species inside genera, and species identity [3]. (CNN) with deep architectures being applied as it performs automatic feature extraction and learns complex high-level features in image classification applications. This study helps an efficient deep CNN model classify insect species on three publicly available insect datasets. The data augmentation techniques such as reflection, scaling, rotation, and translation are also applied to prevent the network from overfitting. The effectiveness of hyperparameters was analyzed in this definitive study to improve accuracy [4]. The recognition effect of the models is evaluated by the F1 score and the AP value, and the experiment is compared with Faster-RCNN and SSD models. In the test dataset of images captured under the background of sufficient light without leaf shelter, the F1 score and AP value are 94.13% and 92.53%, and the average IOU value is 89.92%. The F1 score and AP value are 93.24% in all the test sets, and the average IOU value is 86.98%. The object detection speed can reach 246 frames/s on GPU, the extrapolation speed for a single 416 × 416 picture is 16.9 ms, the detection speed on CPU can reach 22 frames/s, the extrapolation speed is 80.9 ms, and the memory occupied by the model is 28 MB[5].

Today, detection tasks become more complex when they come to numerous variations in the human's perceived appearance, formation, attire, reasoning, and the dynamic nature of their behavior. It is also challenging to understand subtle details in their surroundings—for instance, radiance conditions, background clutter, and partial or full occlusion. In this study, we have focused on detecting humans effectively [6]. The traditional technique uses color and texture features for fruit classification. The Traditional fruit classification method depends on a manual operation based on visual ability. The classification is done by a Support Vector Machine (SVM) classifier based on statistical and co-occurrence features derived from the wavelet transform. The classification accuracy for the proposed system is 95.3% [7]—the development of the YOLOV3 model to identify the animal present in the image given by the user. The algorithm used in the YOLOV3 model is DarkNet, which has a pre-trained dataset. The model's overall performance is based on different training images and testing images of the dataset. The image of the animal will be given as input. Then it will display the animal's name as output using the YOLOV3 model. The detection is done by using a pre-trained coco dataset from DarkNet. Train the model using a custom dataset for our no of classes and images in each category to get better accuracy [8].

YOLO (You Only Look Once) with the VGG16 pre-trained convolutional neural network to propose an algorithm improvement for face detection systems. The proposed method considerably increased face detection speed in real-time live video. The work used the Image Processing Toolbox and the Deep Learning Toolbox in MATLAB [9]. The classifying of fruit by using modern techniques in the field of Deep Neural Networking that involves CNN, YOLO, etc. which provides a helping hand to farmers to optimize their farming patterns and boost yields by allowing them to grow taller fruit trees that can be harvested by classifying based on the condition of fruit and saving high labor cost. YOLO holds more advantages in the classification of objects than any other algorithm, and further image classification can be made using increments in dimensions like 3D by keeping much more objective parameters [10].The performance of YOLO-V3 by designing and building a CNN to solve the problem of a large number of YOLO-V3 parameters, using densely connected modules to enhance the interlayer connection of CNNs and further strengthen the connection between dense neural network blocks, and finally improving the YOLO-V3 multiple-scale detection by expanding the three-scale to four-scale detection to increase the accuracy of detecting small objects like drones. The evaluation results of our algorithm obtain 96% average precision and 95.60% accuracy [11]. The YOLO-v3 and Faster R-CNN models are used to solve multi-object detection on our dataset. The performances of the two models are evaluated under different indicators. It is verified that Faster R-CNN has a better detection performance inaccuracy. The detection speed of the YOLO-V3 model is faster and can be used in real-time detection. The average IoU of the Faster R-CNN is 0.882, which has better performance for localization [12].

3. METHODOLOGY

This chapter discusses the various pest images' possible outcomes. The image collection and creation of bounding boxes in the image labeller application were the procedures used in this paper. Darknet 53 and the Yolo algorithm were used to train the images.

3.1. DATASET

The input images were taken from the IP102 Dataset, containing over 3462 images of 8 insects.

3.2. BLOCK DIAGRAM

The proposed algorithm of this research work is depicted in the block diagram above. The input image is the first block. The input images are stored in two separate folders in the imagedatstore: one for trained images and another for testing images. A total of 2110 insect images were used to train the model. Nine hundred images were used to validate the model during the testing process. The Image labeller app, on the other hand, makes it simple to create various shapes to label a region of interest (ROI). Think about the application when choosing a labelling drawing tool to create ROI labels. Manually label an image frame from an image collection after loading unlabeled data. Label image frames automatically using an automation algorithm. A scene's nature is described by its label. The labelled ground truth data should be exported. It is saved in the .mat format.

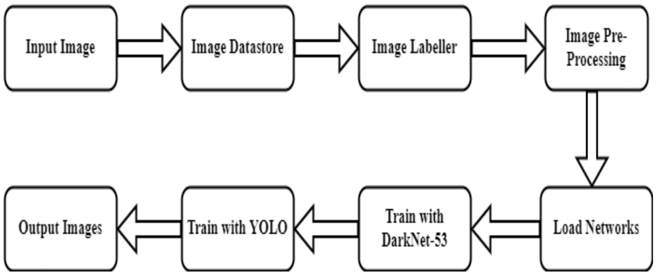

Fig 1: Block Diagram of The Proposed Algorithm

The image pre-processing steps are then performed. Because all of the networks have different input image sizes, the images for the DarkNet should be resized to 224X224. The networks were then loaded and labelled, and resized images were fed into the Darknet-53 and YOLO v2 networks, with the output classified using the YOLO V2 network.

3.3. DARKNET-53

The block diagram above depicts the DarkNet-53 network and the YOLO v2 network. It has 53 layers and is a convolutional neural network. The convolutional layer, batch normalization, and leakyRelu layer make up the convolutional block. Feature Extraction is incomplete without the convolutional layer. The values of all the pixels in a convolution's receptive area are combined. Batch normalization is a technique for training deep neural networks that normalize each mini-contributions batch to a layer. The LeakyRelu layer is a ReLU-based activation function with a moderate rather than flat slope for negative values. The residual block Is a set of layers in which the output of one layer is taken and added to a layer further down in the block. The input images are fed into the first convolutional layer, continuing until the 50th convolutional layer. The YOLO algorithm replaces the 21st leaky Relu layer.

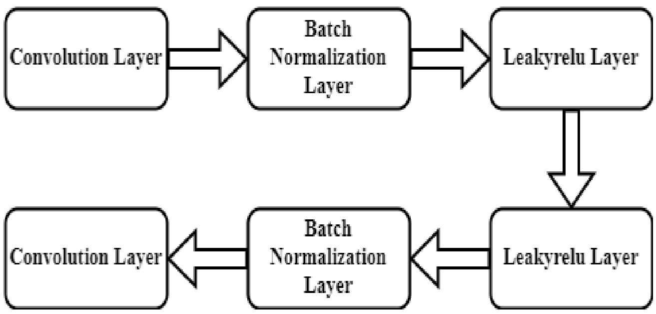

Fig 2: Layers of The Proposed Neural Network

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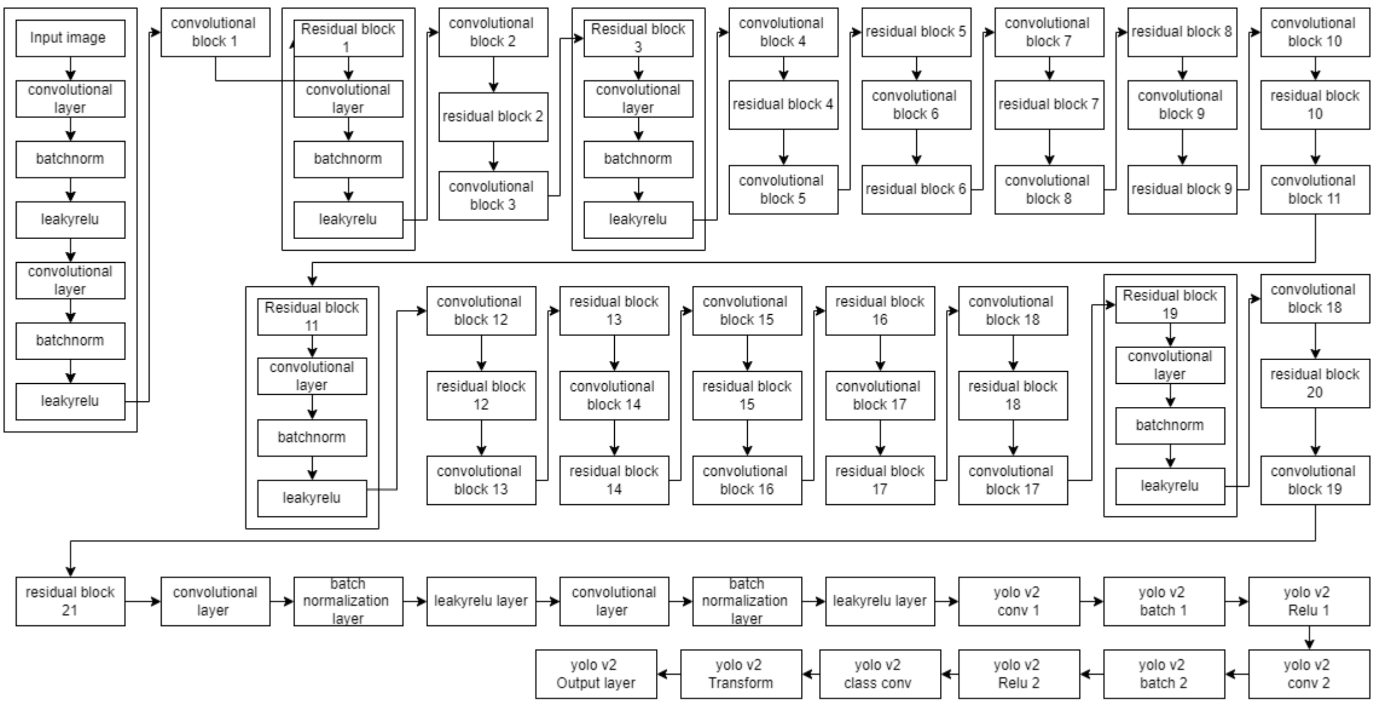

Fig 3: Flow Diagram of The Proposed Neural Network

The You Only Look Once (YOLO) algorithm uses residual blocks, bounding box regression, and intersection over the union are all used in the You Only Look Once (YOLO) algorithm. The image is first divided into grids with specific dimensions. The bounding box is an outline that draws attention to an object in an embodiment. The width, height, class, and bounding box center attributes are the bounding box. It denotes the likelihood of an object appearing within the bounding box. The output box created by intersection over union perfectly encircles the object. The grid cell is in charge of predicting outer boxes, which are defined using a vector of class, probability, and bounded in the box with x-y coordinates as the location. Yolov2 is a real-time object detection model with a single stage. The bounding boxes and more are predicted using a high-resolution classifier and anchor boxes. As a result, the proposed method predicts the insect's exact location in the field.

4. RESULTS AND DISCUSSION

4.1. TRAINING AND TESTING THE NETWORK

Two thousand one hundred sixteen images of harmful insects in eight categories for the network training process were taken. For testing, 450 images were taken in all categories simultaneously. When the training process in the developed network is completed, it has been saved, and the network can now be loaded to classify the insect images.

The training and testing images of the network have predicted the insect, and bounding boxes have been created, as shown in Figures 4 and 5.

The input image is represented by the table above, and after detecting the exact location of the insect, the algorithm automatically draws bounding boxes. The trained model then takes less than one minute to complete.

Table 1: Result of Test Images

S.No.	Input Image	Bounding Boxes	Time Taken for Validation
1			Elapsed time is 0.0996548
2			Elapsed time is 0.0999572
3			Elapsed time is 0.0996547
4			Elapsed time is 0.0996535

4. CONCLUSION AND FUTURE WORK

The proposed neural network's testing accuracy is 95 percent in this research. It took less than one second to find the insects while validating the model. It can correctly detect insects, and only a small amount of pesticide can be applied to the plants, resulting in a nutritious and healthy food item. Furthermore, the farm can be fully automated using the embedded system, and it is connected to IoT for real-time monitoring and data access from anywhere.

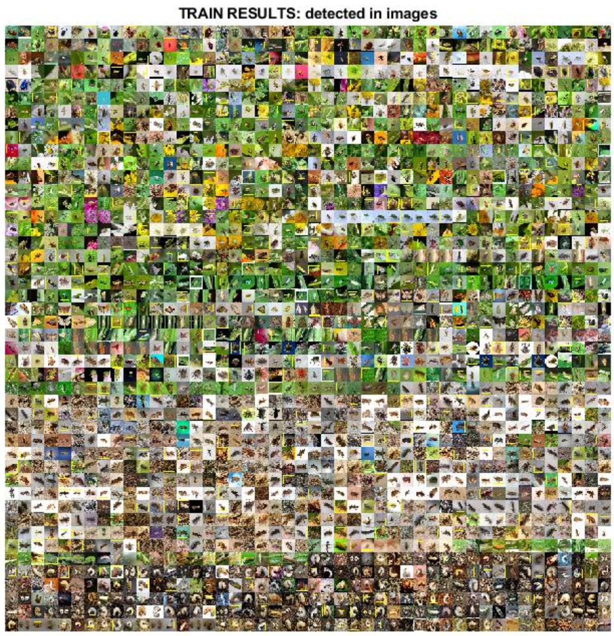

Fig 4: Training Result

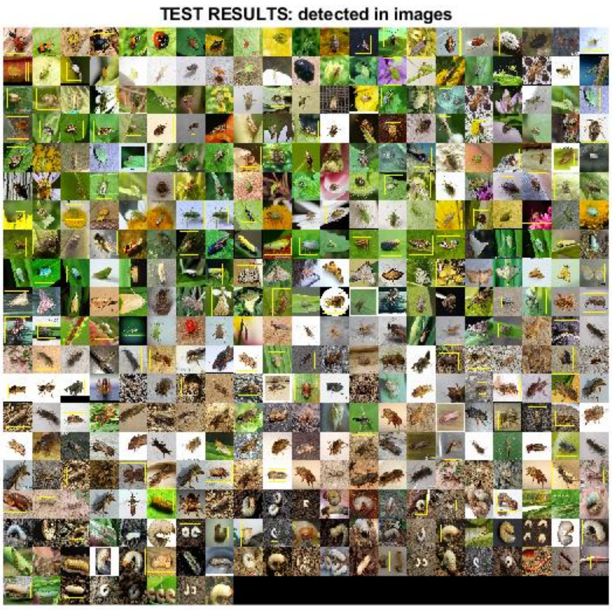

Fig 5: Testing Result

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