Weed Detection using CNN and YOLO frame work

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ABSTRACT

Agriculture plays a most important role in our Indian economy and therefore lowering the cost of production and improving the quality of agricultural products is highly demanded. A weed is a plant which grows in wrong place at the wrong time and doing more harm than good. Weed competes with the crops for water, light, nutrients and space, and therefore it reduces crop yields. This paper proposes a new method in a contrary way, which combines deep learning and image processing technology to prevent these weeds. Machine learning technologies, are becoming crucial in agriculture to increase productivity, where advanced automation and control have been required. Based on large training datasets and pre-trained models, (Deep Learning) DL-based Convolutional Neural Networks (CNN) methods have proven to be more accurate than previous traditional techniques. Recently, Deep Learning (DL) has gained much attention due to its advantages in object detection, classification, and feature extraction. The system implementation of image processing technique for weed detection, a trained image is taken as a sample in order to demonstrate the difference between weed and the crop. Yolo frame work is used for annotate boundary boxes to the image with datasets. The effectiveness of the (You Only Live Once) YOLO-WEED system for real-time Unmanned Aerial Vehicle (UAV) weed detection, given its high speed and high accuracy in detection. After certain steps, we get desired output, where the weeds are separated from the crop that has been taken in the sample image.

Key words: you only look once (YOLO), deep learning (DL), real time weed detection, convolutional neural network (CNN), unmanned aerial vehicle (UAV).

1. INTRODUCTION

One of the biggest issues that farmer facing when raising crops is invasive weeds. Weeds destroy crop growth by stealing water, nutrients, and sunlight. Herbicides are used by farmers to eradicate weeds, or they can be pulled out by hand. herbicides have a lengthy half-life in the environment, which increases the risk of soil and water contamination., negatively affecting non-target creatures and having an impact on people's health. Manual weeding requires a lot of labour, is ineffective, and raises production costs. The ability to anticipate yield as early as possible is still another major issue. When attempting to anticipate yield, there are numerous factors to take into account, such as the weather, temperature, pests, and many more. Given the limited amount of land available, knowing crop output allows us to comprehend food security and forecast whether there will be enough food in the future.

One of the most important problems farmers today confront across the globe is weed suppression. The ground-based camera's images are constrained in terms of coverage and are fixed at the same height for both taller and shorter weed species. Plant holes and noisy backgrounds cause segmentation issues. Automatic feature extraction is advantageous in (Deep Learning) DL-based models llike Convolutional Neural Networks(CNN), which is why people frequently use them for classification. Otherwise, it is challenging to define the feature extraction manually. Recent uses of Convolutional Neural Networks(CNN) include: classifying weeds using Unmanned Aerial Vehicle(UAV) vision utilising a single shot detector and quicker Convolutional Neural Networks (CNN), which reached 84% and 85% accuracy, respectively. As the models require considerable training, restricting them to a real-time solution, they can be employed in near-real-time. [8] employed Residual Networks of 50 layers deep (ResNet-50) Xception and Visual Geometry Group 16 layers (VGG16) pre-trained Convolutional Neural Networks (CNN) models for weed detection in maize, sunflower, and potato crops. For weed density mapping and calculation using Unmanned Aerial Vehicle (UAV) pictures, [9] modified U-shaped encoder-decoder network (U-Net). [10] achieved an accuracy of 93.50% while mapping weeds using photos from a Phantom 4 Unmanned Aerial Vehicle (UAV) and Convolutional Neural Networks (CNN). The suggested model has limitations due to the vast amount of labelling data required for training [10], hence unsupervised learning was used, which increased the subjectivity of interpretation. Another drawback of [10] work was that crops and weeds were found in separate fields, hence this strategy was not tested on weeds that were connected to crops. a network with complete convolutions [11].

2. LITERATURE SURVEY

Detection of weeds Agriculture has always been vital to human existence. Agriculture has begun to mechanize and digitize throughout the past century, and more specifically over the last 15 years. As a result of this development and automation, labor flow has become virtually entirely standardized. There is no longer a need for standardization in agriculture because to the introduction of robotics and artificial intelligence; instead, robots collaborate with people to carry out routine chores like weed detection, watering, and seeding (Marinoudi, et al., 2019). To forecast weed from crop, the data will be employed in a Convolutional Neural Networks (CNN) and deep learning base model. (2015) incorporate such methods into a robot that sprays herbicides, taking pictures with a Raspberry Pi camera, extracting the colors of the pixels, and processing the pictures in a variety of ways to determine if they are weeds or not. After randomly arranging plants and weeds, the robot was tested, and weeds were almost entirely detected and sprayed, taking the processing stage about 3 seconds. Results were more than successful. Liang et al. (2019) use image processing in drones rather than robots to monitor crop growth in addition to weed detection. Drones that combine image processing and Convolutional Neural Networks (CNN) achieve varying degrees of accuracy, ranging from 98.8% with Convolutional Neural Networks (CNN) to 85% with Histograms of Oriented Gradients (HOG) All of the aforementioned procedures can be carried out using either static images or real-time recordings. Researchers Marzouki Mustafa et al. (2007) studied the application of real-time video processing. Various image processing techniques and a newly designed algorithm that reacts appropriately to real-time situations are used to record and process the crop offline. In the end, they exceeded 80% accuracy. Wafy, et al. (2013) used Scale-Invariant Feature Transform (SIFT), an algorithm that extracts the interest points from an image, to discriminate the weeds seeds; by utilizing this technique, they had a minimum accuracy of 89.2%. More recent studies have also been done on this topic.

3. IMPLEMENTATION STUDY

3.1 Existing System

The classification of weed gained attention with the advancements of Machine Learning (ML) and Deep Learning (DL) techniques, such as MLbased Support Vector Machine (SVM), Random Forest (RF), ANN (Artificial Neural Network), Machine Learning (ML) has been utilized for weed detection, such as: [2] compared (Machine Learning) ML-based feature classification of an area infested due to weed and concluded that the Relief method outperformed other methods based on f-score values. Other models applied by [2] were Support Vector Machine (SVM), Decision Tree Learning (DT), and Random Forest (RF) to map the parthenium weed. Reference [2] achieved an accuracy ranging between 70.3% to 82.3% for the weed classification;

Disadvantages Of Existing System:

- Accuracy is less
- Detection is not accurate
- Large Dataset cannot be trained

3.2 Proposed System

In this project We proposed a convolution neural network as artificial intelligence to train all plant diseases images and then upon uploading new images Convolutional Neural Networks (CNN) will predict weed available in uploaded images. For storing Convolutional Neural Networks (CNN) train model and images AI author predicting weed from crop so we build it as python. Using Convolutional Neural Networks (CNN) model will get trained and user can upload images and then application will apply Convolutional Neural Networks (CNN) model on uploaded images to predict weed from crop here we used the yolo frame work to annotate the image and apply the boundary boxes our approach gives 97 % accurate results in detection of weed from the crop

Advantages Of Proposed System:

Accurately accuracy is better and detection is better than the machine learning algorithms and get solutions with a mobile app by photographing.

4. METHODOLOGY

Dataset

The dataset used in the current investigation was taken from Kaggle This dataset contains 1300 images of sesame crops and different types of weeds with each image labels. Each image is a 512 X 512 color image. Labels for images are in You Only Live Once (YOLO) format.

The dataset was split for the ratio of 70:10:20, i.e., 10500 images for training, 1500 images for validation, and 3000 images for the final testing. Convolutional Neural Networks (CNN) with 18 layers was developed in the current study for classification. Python 3.7 anKeras 2.3.0 Application Programming Interface (API) with TensorFlow 2.0 backend was used in this research. Firstly, we have done the data pre-processing. We have used four hidden convolutional layers. The rectifier linear activation unit (ReLU) was also used in each convolution layer. The batch normalization layer and dropout were used following each convolution layer. The batch normalization standardized the inputs with mean value and standard deviation as 0 and 1 respectively to each mini-batch layer. The work of the batch normalization layer is to stabilize the training process and decrease the number of training epochs needed to train the deep Convolutional Neural Networks (CNN) networks. The dropout layer is added between two convolution layers, and outputs of the last layer are fed to the subsequent layer to prevent overfitting. It works by "dropping out" or probabilistically removing inputs to a layer, which may be input variables from a previous layer. A value of 0.5 was chosen with two dropout layers. Two max-pooling layers were used between the second to the third convolution and the third to the fourth. A flattening layer was added as the 10th layer; it was required to utilize the fully connected layers after convolutional/max-pool layers. The flattening layer combines all the observed local features of the CSSE, 2022, vol.42, no.2 841 previous convolutional layers. After flattening the layer, the Learning Vector Quantization (LVQ) layer was used to classify the images. In our proposed method, weighting parameters are selected by using the Learning Vector Quantization (LVQ) algorithm for classification. The first fully-connected dense layers and second fully connected Learning Vector Quantization (LVQ) layer were added. Learning Vector Quantization (LVQ) layer, was used as the output layer to make the predictions to specify the output's transform and structure. The Kohonen layer consists of 40 neurons, i.e., ten neurons for each class. The number of epochs for Learning Vector Quantization (LVQ) was 30 after trying the combination of 10, 20, 30, and 40. The learning rate of 0.01 was used, and the input vector was initiated with the random value. From Fig.3. we can see that it has focused on the creation of an image-processing algorithm to detect the existence of tiny weeds in a specific site of lettuce crop. From Fig.4. By using edge detection process, we can separate weeds from cotton crop. From Fig.5. Automatic weed detection using deep learning techniques are emerging using Convolutional Neural Networks (CNN) approach where we can see the weed in boundary boxes detected.

Methods

The implementation process of the proposed model Texas extreme Gradient Boosting (TX-XGBoost) is shown in Fig. 1. Firstly, we performed the data augmentation and background segmentation on the weed dataset. Secondly, we replaced the full connection layer and SoftMax module of Xception with the newly designed global average pooling layer and extreme Gradient Boosting (XGBoost) classifier to construct a new network model. Thirdly, the weights and parameters of the Xception convolutional layer that has been trained on the ImageNet data set are transmitted and loaded into the convolutional layer of the new model. At last, weed images can be trained through the new model, and the trained new model can detect and recognize weed images [12].

and recognize weed images [13].

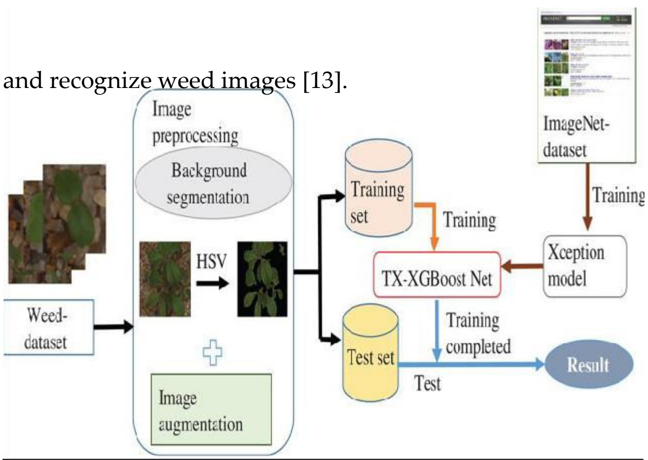

Fig 1: System Architecure

Algorithm

Generalized Framework

The generalized framework of training and testing the Deep Learning (DL) models is presented in Fig. 2. Which consists of dataset images having their corresponding Extensible Markup Language (XML) files. The Extensible Markup Language (XML) data were converted into Comma-Separated Values (CSV) format. Then, Tenser Flow (TF) records from the Comma-Separated Values (CSV) files were generated, as TensorFlow accepts the Tenser Flow (TF) format of the data to feed into the network while training the DL architectures. The Deep Learning (DL) detectors were constructed by taking training images with bounding box coordinates and then evaluated their performance on the testing dataset [13].

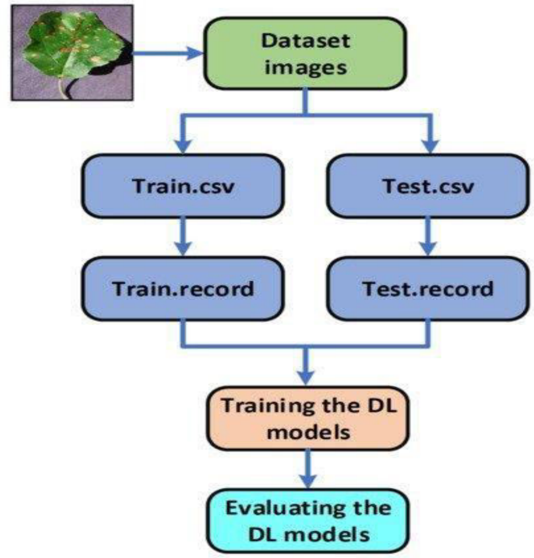

Fig 2: Generalize framework to train and test the deep learning.

5. RESULTS AND EVOLUTION METRICS

Fig 3: sample images from which we can see that it has detected the weed and crop

Fig 4: where we can see in the boundary boxes weed from the crop

Fig 5: where we can see the weed in boundary boxes detected using CNN approach

6. CONCLUSION

In this study, we created a system for identifying invasive weeds in lettuce plants using pictures and videos. Modern objection detection models can detect weeds with high accuracy and high recall, according to tests conducted on a variety of models. We were able to identify some of the major flaws, such our inability to find tiny weeds. These findings allow us to draw the conclusion that real-time object detection algorithms are just as accurate at weed detection as their non-real-time counterparts. Next, we discovered that deep learning base models can forecast yield prediction more accurately. The model was able to predict yield of data with low variance and very early in their growing stage. However, the prediction from imagery struggled to predict high yield plants. In such case, these models have the potential of replacing classical methods.

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