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Weed Detection and Control Using Mask-R-CNN

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I. ABSTRACT

RECENT TRANSDISCIPLINARY DEEP LEARNING RESEARCH HAS INCREASED INTEREST IN USING DEEP LEARNING IN THE AGRICULTURAL INDUSTRY. WEED MANAGEMENT AND CONTROL ARE SOME OF THE MOST CRUCIAL TASKS IN AGRICULTURE TO MAINTAIN OPTIMUM CROP PRODUCTIVITY. CORRECTLY IDENTIFYING THE UNDESIRABLE PLANTS MUST COME BEFORE PRESENTING A PRACTICAL MANAGEMENT PLAN IN ORDER TO MANAGE AND CONTROL WEEDS. AGRICULTURE IMAGES ARE COMPLEX AND CONTAIN ELEMENTS LIKE SIMILAR COLOR AND TEXTURE, THEREFORE WE NEED TO APPLY A DEEP NEURAL NETWORK THAT MAKES USE OF PIXEL-WISE GROUPING TO IDENTIFY THE PLANT TYPE. IN THIS THESIS, USING FIELD PICTURES AND AERIAL IMAGES, WE ASSESSED THE PERFORMANCE OF MASK R-CNN, ONE OF THE MOST USED DEEP NEURAL NETWORKS, FOR WEED PLANT RECOGNITION (DETECTION AND CLASSIFICATION). MASK R-CNN WAS CREATED TO ADDRESS ISSUES WITH INSTANCE SEGMENTATION (PIXEL-WISE ANALYSIS). WE EMPLOYED THE CROP/WEED FIELD IMAGE DATASET (CWFID) AND MASK R-CNN TO DISTINGUISH BETWEEN CROP PLANTS AND WEED PLANTS DURING THE FIELD IMAGE ANALYSIS. THE CWFID'S LIMITATIONS, HOWEVER, ARE THAT IT GROUPS ALL WEED PLANTS INTO A SINGLE CLASS AND REQUIRES THAT ALL CROP PLANTS COME FROM A SINGLE ORGANIC CARROT FIELD. TO SOLVE THIS PROBLEM, WE CREATED A SYNTHETIC DATASET OF 80 DIFFERENT SPECIES OF WEED PLANTS AND ASSESSED IT USING MASK R-CNN.

***Index Terms*—**
Mask-R-CNN, Instance Segmentation, Semantic Segmentation, Fully Convolutional Network (FCN).

II. INTRODUCTION

One of the oldest and most important occupations in the world is agriculture. Humanity has used several technologies throughout the ages, including artificial intelligence (AI), to increase agricultural output and efficiency and so lessen adverse environmental effects. Low agricultural yields due to weed infestations are one of the biggest dangers to farmers. The agricultural output is decreased by around 50% by weed plants, which might have negative economic repercussions. Herbicides and AI-powered robots are two of the most popular ways to get rid of weed plants. Although the first alternative is less expensive, there is a concern that these pesticides will infect the agricultural plants and endanger human health. Although the latter alternative is more expensive, it doesn't involve using human labour and has no health hazards. As a result, AI is increasingly being used in agriculture today. Automation is being brought into this industry in order to satisfy this need without depleting the environmental resources that agriculture consumes. A weed is a plant that grows alongside beneficial agriculture goods. Any plant or vegetation that obstructs agricultural or forestry goals, such as raising crops, grazing animals, or establishing forest plantations, may be referred to as a weed. These weeds need to be recognised and categorised because they hinder crop development and diminish agricultural productivity.

A. Motivation

As a subset of machine learning, deep learning simulates how the human brain processes information for object identification, object recognition, and decision-making. A deep neural network subclass known as a convolutional neural network (CNN) is typically used to analyse visual pictures. The connection network between neurons in biological processes that constitute the inspiration for CNNs mirrors the structure of the animal visual cortex. Compared to other image classification methods, CNNs employ a very small number of picture pre-processing steps. Deep learning has been used in the agriculture industry because to its positive outcomes in image identification tasks.

B. Weeds in Agriculture

According to the Weed Science Society of America, a weed is a plant that grows in an unwelcome way in a field and causes ecological imbalances and financial loss. On rare occasions, these weeds may potentially cause health issues in both people and animals. Poison ivy and tree of paradise are two examples of weedy flora. From a taxonomical perspective, the word "weed" has no real meaning. Because a plant may be considered a weed in one situation but not another, it is always a matter of opinion. In certain cases, beneficial weeds are cultivated on purpose in the gardens. Weeds compete with agricultural plants for food, water, sunshine, and soil nutrients, which is detrimental to horticulture.

Some weeds have thorns, burs, and even poisons, which can irritate human skin and cause pain in an animal's digestive tract. They also serve as a host for a number of infections that could reduce agricultural productivity.

To avoid all of the aforementioned problems, it is crucial to eliminate weeds from agricultural areas. Herbicides and fatal wilting are the two procedures that are most frequently used to get rid of weeds. With less human labour, it is significantly more difficult to monitor the agricultural plants in large fields. Also, it takes a specialist to identify the species, and there aren't many technicians who are qualified for the task. As a result, using drones and UAVs to increase crop efficiency became necessary. Drone technology is a remarkable advancement that has applications across many industries. The farmers may use these drones to monitor irrigation mapping and crop spraying. UAVs help to achieve "precise agriculture." Precision farming may be summed up as "growing more with less resources." The high cost of drone use is one of its drawbacks. Yet, as the population grows, the necessity for agricultural will also grow. Future growth in the agriculture sector will raise demand for drones, which will drive down their cost. The success of farmers' crops is impacted by a number of difficulties. Climate change, soil quality, weeds, and insect infestation are a few of the difficulties. UAVs are increasingly being used by farmers to give quicker, more dependable, and more effective outcomes for these problems.

III. RELATED WORK

"Weed Detection Using Image Segmentation and Multiscale Feature Extraction" by Yang et al. (2018) -- This paper proposes a method for weed detection using image segmentation and multiscale feature extraction. The method first performs image segmentation to extract the plant and weed regions and then extracts multiscale features from these regions using a convolutional neural network (CNN).

"Weed detection in soybean fields using deep learning-based image segmentation" by Chakraborty et al. (2020) -- This paper proposes a method for weed detection in soybean fields using deep learning-based image segmentation. The method uses a U-Net architecture to segment the images into plant and weed regions and then applies a post-processing step to remove false positives.

"Robust weed detection in UAV images using Convolutional Neural Networks and Semantic Segmentation" by Zhu et al. (2019) -- This paper proposes a method for robust weed detection in UAV images using Convolutional Neural Networks (CNNs) and semantic segmentation. The method first trains a CNN on a large dataset of annotated images to learn the features that distinguish between plants and weeds. Then, it applies semantic segmentation to segment the images into plant and weed regions.

"Weed Detection and Localization Using Image Segmentation and Random Forest Classification" by Khan et al. (2019) -- This paper proposes a method for weed detection and localization using image segmentation and random forest classification. The method first segments the images into plant and weed regions using a combination of color and texture features. Then, it applies random forest classification to classify each region as a weed or a plant.

IV. DESCRIPTION

A. Mask R-CNN and Move Net

A deep learning model called Mask R-CNN (Region-based Convolutional Neural Networks) is utilised for object recognition and segmentation tasks. It is a development of the well-known Faster R-CNN model, which was created initially for object recognition.

Using a two-stage process, Mask R-CNN finds objects in a picture. In the first step, region suggestions that are likely to include items are generated. In the second stage, the proposals are categorised and their bounding boxes are adjusted. Mask R-CNN can recognise and segment each instance of an object in an image in addition to doing object identification and instance segmentation.

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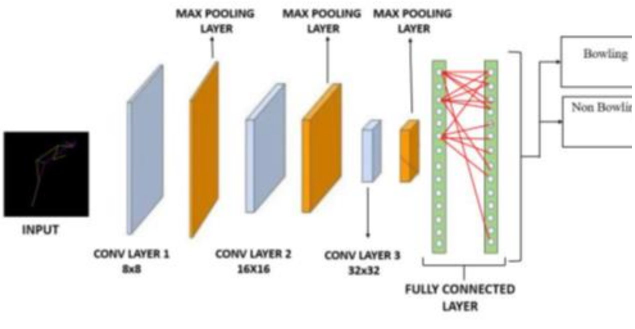

Fig 1. Image Segmentation

'MoveNet' is a super quick and precise model that finds 17 important body parts. Two variations of the model, dubbed Lightning and Thunder, are available on TF Hub. Thunder is designed for applications requiring great precision, whereas Lightning is designed for applications where latency is crucial.

B. Data Generation

Data Training

Functionality for Dataset Training: A training A dataset is a collection of instances used for learning. Data collection is the systematic gathering and measurement of information on the intended variables. Datasets providing activity and other health data are the input.

Data Preprocessing Model

Data pre-processing module is its name.Functionality: The following are included in the pre-processing of genetic data: Data \sTransformation, Aggregation, which gives the genes probabilistic values, and Normalization, which scales the results to a certain range.

Data Synthetization

Module name: Data pre-processingFunctionality: The following are some of the steps involved in genetic data pre-processing: Data \sTransformation, Aggregation, which assigns probabilistic values to the genes, and Normalization, which scales the results to a given range.

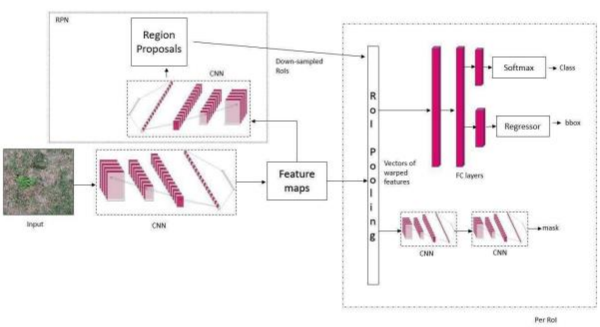

Fig 2. The Network Architecture of Mask-R-CNN

V. METHODOLOGY

Counting items in a picture is often accomplished via instance segmentation. It resembles pixel-level categorization more. For the instance segmentation, we also need to create a segmentation mask around the object and a boundary box surrounding it. R-CNN is used to identify many items in a given picture. It generates an area suggestion using a selective search method and aids in item detection in images. By taking into account how different textures, colours, sizes, and even enclosures change, region suggestions may be developed. We may employ the sliding window approach to address the object localisation issue. This sliding window method finds things in a digital image by using various window widths. Hence, the term "exhaustive search" is frequently used to describe this process. Even for a very tiny image, exhaustive search requires us to look for items in hundreds of windows, which is computationally costly. Segmentation and exhaustive search are both components of the selective search method. By giving unique colours to each new object in the image, R-CNN segmentation is a technique for separating various things in an image.

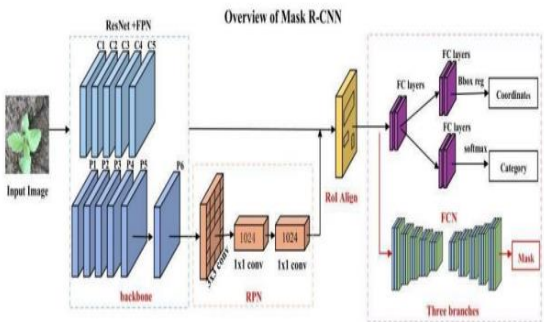

Fig 3. Object Detection using R-CNN

VI. CONCLUSION

Because that weeds are a problem to crops, early weed detection is vital for agricultural output. This research used machine learning and image processing to find weeds in a specific field. The UAV photographs were obtained from a specific farm, and image processing methods were used to pre-process the images. Classifiers were evaluated using Mask-R-characteristics. CNN's According to the experimental findings, Mask-R-CNN outperforms the other classifiers in terms of accuracy and other performance measures. Un-numbered footnote on the first page. We concentrated on identifying weed plants in agricultural settings in this article. Using two classes, we evaluated the effectiveness of the Mask R-CNN for classifying plants. We next enlarged our experiment by producing a fictitious set of data with 80 classes for our field picture research. We concentrated on many techniques to build the dataset for our analysis of aerial images, including localised style transfer and geometrical adjustments. Using this artificial aerial picture dataset, we investigated the performance of Mask

R-CNN and were able to get an AP50 of 91% for the predicted segmentation mask and 95% for the projected bounding box.

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