International Journal of Advance Research in Science and Engineering
Volume No. 11, Issue No. 06, June 2022
www.ijarse.com
IJARSE
ISSN 2319 - 8354

IDENTIFICATION OF WEEDS IN SESAME CROP FIELD USING IMAGE PROCESSING

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ABSTRACT

AI, especially machine learning, is a fast-growing field of research today. One of the many applications is object recognition using computer vision. The combination of these two techniques leads to the purpose of this paper. In this paper, we developed a system to identify a variety of crops and weeds as an alternative to the system found on the Farm Bot robot. This is done by accessing images via the Farm Bot API and applying transfer learning to an RCNN that uses computer vision and AI for image processing to perform plant identification offline. Accurate weed detection is a prerequisite for accurate weed prevention and control in the field. Machine vision provides an effective means of accurately detecting weeds. To accurately detect various weeds in sesame fields, in this document, You Only Look Once v4 (YOLO v4) is converted into a lightweight weed detection model called YOLO v4weeds for weeds in sesame seedlings. From a technical point of view, this study offers an alternative to traditional weed detectors in agriculture and opens the door to more intelligent and advanced systems.

Keywords: *YOLO-V4, RCNN, Farm Bot, CSP Darknet-53.*

1. INTRODUCTION

One of the newest and most studied technologies today is deep learning. Deep learning is a technology used to create intelligent systems that closely resemble the human brain. It has a huge impact on all types of fields such as video, audio and image processing. Wason, 2018 [1]; Sharma, 2019 [2]. On the other hand, agriculture is the oldest and most important human activity for survival. Population growth in recent years has led to increased demand for agricultural products.

You Only Look Once is a classic object detection algorithm. It is famous for its fast detection speed and high detection accuracy. The new version of YOLO, YOLOv4, combines various optimization strategies and improves small object detection to provide the right tool for accurate weed detection. However, CSPDarknet53, the backbone of YOLOv4, requires a large amount of storage space due to its high complexity and heavy computational load for image processing. Therefore, YOLOv4 is not suitable for real-time discovery of embedded devices.

To solve the above problem, this paper improves YOLOv4 for weed detection. The backbone network of YOLOv4 was replaced with a lightweight neural network. The improvement can effectively reduce the memory required for image processing and improve the small weed detection efficiency and accuracy in complex environment, making the model more suitable for deployment in embedded devices.

Another challenge to beneficial agriculture is the differentiation and segmentation of weeds that are harmful and beneficial to the crop. There are a few weeds that are helpful for the growth of the crop and participate in a symbiotic relationship that is beneficial for both, but in other cases and more often than not, the weeds present are damaging to the crop and consume all the nutrition's that are intended for the crop, they have to be removed.

2. LITERATURE REVIEW

The field this paper is based on has been researched many times before; in order to get an overview of the previously done work, this chapter analyses some of those documents for the paper.

Agriculture has always been an essential activity for survival. Over the last century, and more specific, over the last 15 years, agriculture has started to mechanise and digitise; due to this evolution and automation, labour flow was almost totally standardised. Nowadays, after introducing robotics and AI into agriculture there is no need of standardization, robots are working collaboratively with humans and learning from them how to realize the basic agriculture tasks such as weed detection, watering or seeding (Marinoudi, et al., 2019) [3].

Weed detection is one of those basic agriculture tasks that are being automatized and digitised, in this case, because of toxicity related to herbicides; so, reducing human intervention will make possible a decrease in the use of herbicides, increasing health care. To achieve this, robots able to detect plants and classify them into crop or weed are now introduced into agriculture (Dankhara, et al., 2019) [4]. This implementation has been done in multiples studies such as Dankhara, et al., 2019, where Internet of Things IoT is applied into an intelligent robot to differentiate crop and weed remotely. This paper shows an accuracy of 90%-96% depending on if it is used a Convolutional Neural Network CNN, a datasheet is being created or it is being used the training set.

Daman, et al., (2015) and Liang, et al., (2019) both introduce the use of automation into agriculture to identify weeds, and to do so, they make use of image processing techniques. [5] Daman, et al., (2015) implement those techniques into an herbicide sprayer robot, capturing images from a Raspberry Pi camera and extracting pixels' colours to process them with diverse techniques in order to know whether it is a weed or not. Results were more than successful, after placing plants and weeds randomly, the robot was tested and weeds were almost totally identified and sprayed, taking the processing stage approximately 3 seconds. [6] Liang, et al., (2019) implement image processing in drones instead of robots, that way, they not only detect weeds, but also monitor the growth of crops. By combining image processing and CNN in drones, they get different accuracies depending on the processing, which is from 98.8% with CNN to 85% using Histograms of Oriented Gradients (HOG).

Marzuki Mustafa, et al. (2007), have done research about the implementation of a real-time video processing. The crop is recorded and processed, offline, using various image processing techniques and a new developed algorithm that respond correctly to real time conditions. Finally, they achieved an accuracy over the 80% [7].

International Journal of Advance Research in Science and Engineering
Volume No. 11, Issue No. 06, June 2022
www.ijarse.com
IJARSE
ISSN 2319 - 8354

Not only the weed as a plant can be differentiated, more advanced studies such as Wafy, et al., (2013), differentiate the weeds seeds using Scale-Invariant Feature Transform (SIFT), an algorithm that extracts the interest points from an image; by using this technique, the minimum accuracy they have is 89.2% [8].

3. EXISTING SYSTEM

This model's aim is to determine whether the image given is that of a crop or that of a weed. The algorithm does this with the help of a Recognition based convolution neural network, and it is trained by a custom data set that we ourselves have prepared.

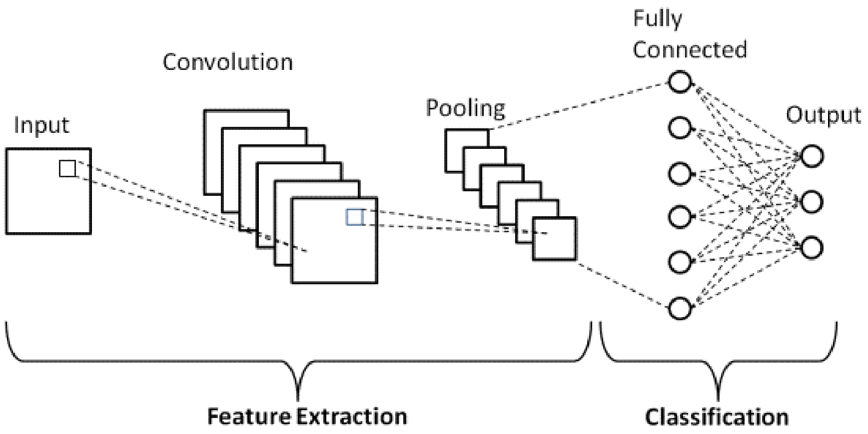

FIG-1: CNN ARCHITECTURE

A custom image library of about 1300 images was collected in order to provide material to train the model.1000 of these were used to train the algorithm and 300 were used to test it. Then we used the RCNN model to train the model which involved 2 sub phases.

The VGG16 model was trained with the region proposals from the previously trained sections.

The system was successfully projecting an accuracy of 95.8%. An automated system designed to help identify plant diseases by the plant's appearance and visual symptoms could be of great help to amateurs in the gardening process and also trained professionals as a verification system in disease diagnostics. Advances in computer vision present an opportunity to expand and enhance the practice of precise plant protection and extend the market of computer vision applications in the field of precision agriculture.

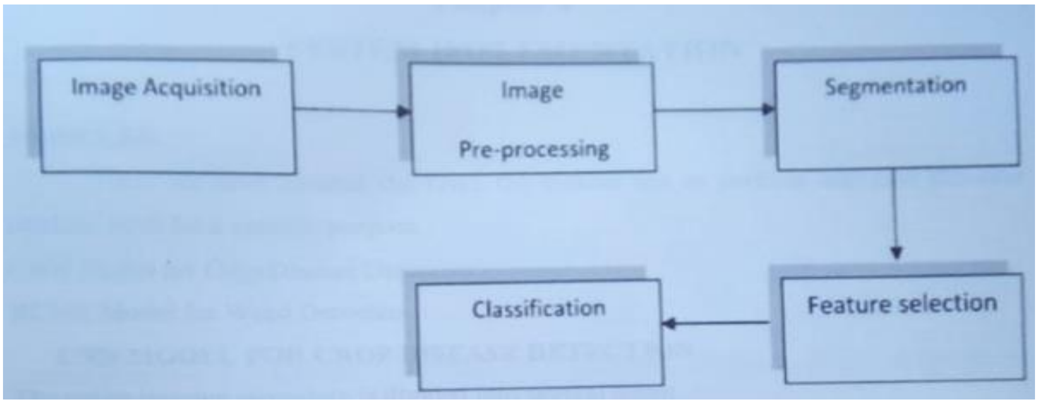

FIG-2: DATA FLOW DIAGRAM

4. PROPOSED SYSTEM

The System we propose will be developed with the help of **YOLO (You Only Look Once),** which is an object detection system targeted for real-time processing. YOLO is known for its fast detection speed and high detection accuracy. Unlike faster RCNN, YOLO is trained to do classification and boundary box regression at the same time. The input given is the part of the plant to detect if it is a weed or not.

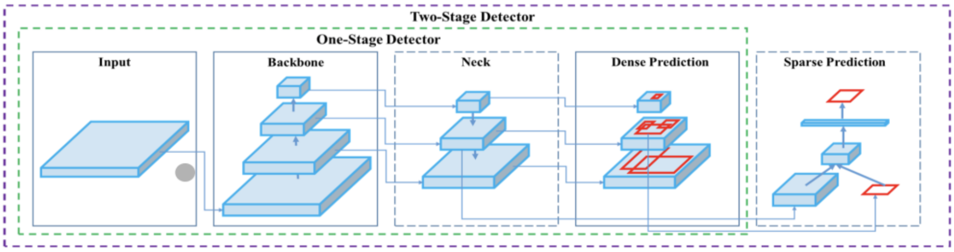

FIG-3: ARCHITECTURE

System Design

System Design is the process of defining the architecture, modules, interfaces, and data of a system to meet specific requirements.

System Elements

• Architecture

A conceptual model that defines the structure, behaviour, and other representations of a system. You can use flowcharts to represent and describe your architecture.

• Module

A component in a system that performs one specific task. A combination of modules makes up a system.

• Component

Provides a specific function or group of related functions. It is made up of modules.

• Interface

This is a common boundary through which system components exchange information and interact.

• Data

Information and data flow control.

YOLOV4

YOLOv4 is a SOTA (state-of-the-art) real-time Object Detection model. It was published in April 2020 by Alexey Bochkovsky; it is the 4th installment to YOLO. It achieved SOTA performance on the COCO dataset which consists of 80 different object classes.

YOLO is a one-stage detector.

Backbone Network:

The authors initially considered CSPResNext50, CSPDarknet53 and EfficientNet-B3 as the backbone networks. Finally, after a lot of testing and experimental results they chose CSPDarknet53 CNN. ("YOLOv4: Optimal Speed and Accuracy of Object Detection").

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IJARSE
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CSPDarkNet53 is based on the DenseNet design. It concatenates the previous inputs with the current input before proceeding into the dense layers - this is referred to as the Dense connectivity pattern.

CSPDarkNet53 consists of two blocks:

- Convolutional Base Layer
- Cross Stage Partial (CSP) Block

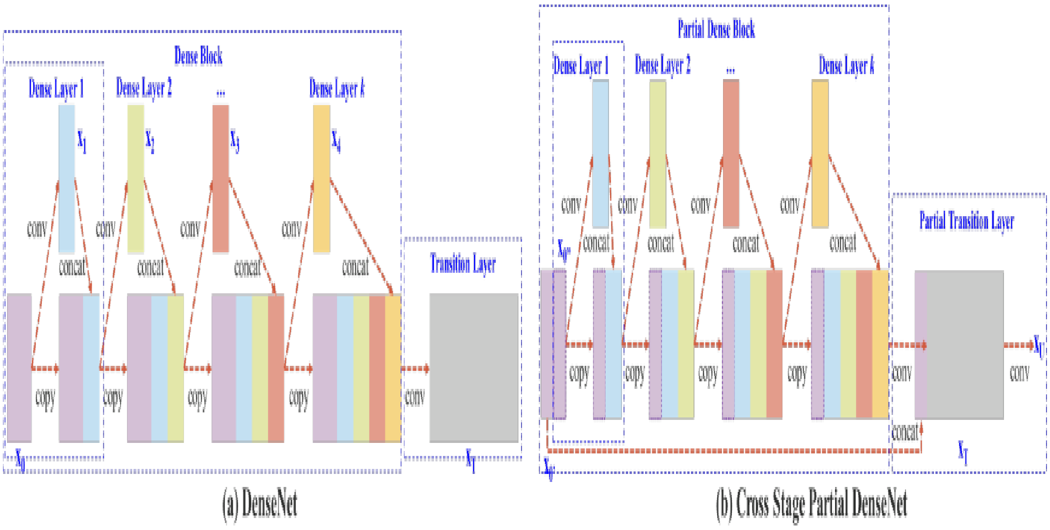

FIG-4: Containing DenseNet & CSP.

Table 1: Darknet-53

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

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CSPDarknet53 is a convolutional neural network and backbone for object detection that uses DarkNet-53. It employs a CSPNet strategy to partition the feature map of the base layer into two parts and then merges them through a cross-stage hierarchy. The use of a split and merge strategy allows for more gradient flow through the network.

This **CNN** is used as the backbone for YOLOv4.

The output will be shown as

FIG-5: THE OUPUT IMAGE

5. METHODS OR TECHNIQUES USED

As the aim of this paper is implementing a weed detection system, it will be reached by creating a program able to identify crops and weeds using image processing techniques.

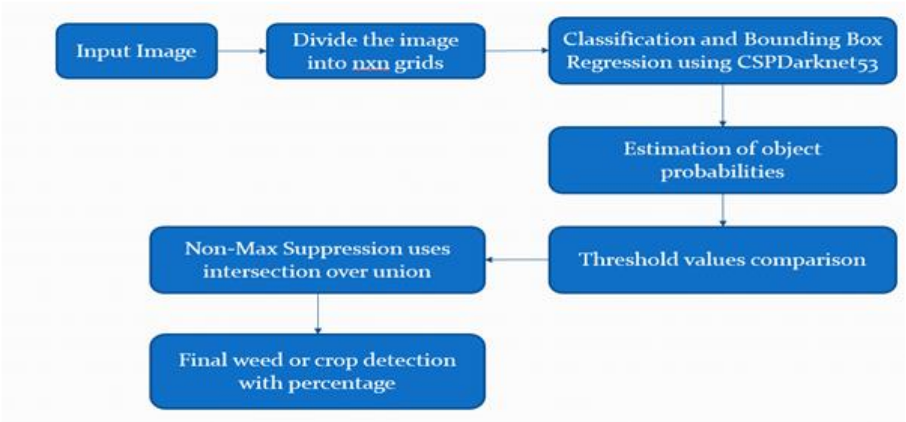

FIG-6: FLOWCHART

This paper work describes the methodology for weed detection process in sesame crops. It follows seven steps. The task flow is shown in Figure 1. The tasks and process represent the steps of the algorithm. Our algorithm includes the following steps

This paper's aim is reached by using DL to develop a program capable of identifying crops and weeds, therefore the strategy followed will be the one denominated as 'Design and Creation' Oates, 2006. This strategy aims to contribute to knowledge by developing new IT products, such as models, methodologies, concepts or systems

FIG-7: DESIGN AND CREATION PROCESS

CONVOLUTION NEURAL NETWORK

A Convolution Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field.

There are two types of results to the operation one in which the convolved feature is reduced in dimensionality as compared to the input, and the other in which the dimensionality is either increased or remains the same.

Adding a Fully-Connected layer is a (usually) cheap way of learning non-linear combinations of the high-level features as represented by the output of the convolutional layer. The Fully-Connected layer is learning a possibly non-linear function in that space.

6.RESULTS

In weed detection, the system automatically detects weed when the user inputs only an image, determines whether the image is a weed or crop, and outputs it as text. This avoids inefficient manual work and increases

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ISSN 2319 - 8354

efficiency and productivity. The Input can also be video and the output will be a video containing the detection of the weed & crop.

FIG-8: INPUT IMAGE OF THE MODEL

FIG-9: OUTPUT IMAGE OF THE MODEL

[('weed', '65.83', (179.45, 213.83, 99.66, 375.27)), ('weed', '70.74', (262.40, 539.62, 60.80, 79.91)), ('crop', '90.0', (436.24, 329.93, 233.53, 547.08))]

FIG-10: TEXT FILE OF THE OUTPUT IMAGE

7. CONCLUSION

In conclusion, the undertaking developed in this thesis has successfully performed the fundamental goal set. The main intention of this thesis turned into the implementation of a machine able to discover plants and weeds the usage of ANNs with snap shots captured via the Farm Bot that allows you to later be compared with Farm Bot built-in weed detector. The accuracy obtained isn't of a one hundred%, however the community differentiates nicely sufficient the extraordinary kind of flowers it's been educated on. consequently, the primary purpose of the thesis is taken into consideration as finished.

Comparative experiments show that our version accomplished higher normal performance than YOLOv4, YOLOv4-tiny, YOLOv3, and YOLOv3-tiny, as evidenced by means of its mmAP of 88.46%, common detection time of 12.65 ms, and weight of 159.0 MB. this means the proposed version can correctly detect the sesame seedlings and various weeds within the complex scene of sesame subject, and be without difficulty implemented to embedded gadget. however, the detection impact of our version on a few pix is confined with the aid of the fact that: there are especially few objectives of some weed kinds within the images of our dataset, that is, the schooling samples are unbalanced, with an inter-magnificence distinction of image capabilities; as an end result, the capabilities of some goals aren't sufficiently extracted all through model training. This hassle will be solved in future research.

8. FUTURE SCOPE

Here, a few viable future tasks primarily based in this thesis are proposed. Deeper research on the topic of this thesis can be achieved by way of thinking about the creation of the neural network from scratch, instead of the usage of transfer learning on an existing network. via creating the community architecture there may be more manipulate over its studying technique. any other viable subject matter to research primarily based in this thesis is the implementation of a weed detector contemplating a larger wide variety of crop and weed kinds, no longer most effective spinach, cleavers and dandelions. eventually, the implementation of an automated FarmBot weed removal based totally on DL detection could be an interesting topic to don't forget, for the reason that the cutting-edge weed elimination machine of FarmBot can't discover weeds placed near a crop.

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