USING YOLOV5 TO DETECT PLASTIC GREENHOUSES IN MOROCCO

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ABSTRACT:

Globally, Increasing greenhouse production is causing producing environmental issues. Monitoring the number and determining the locations of greenhouses are essential for the modern agricultural land management. The aim of this study was to detect plastic greenhouses using remote sensing data and the YOLOv5 CNN-based object detection algorithm. In the process, 426 images of plastic greenhouses were manually downloaded from Google and Mohammed 6 satellites and were divided into three datasets, training (63%), validation (15%), and testing (22%). Plastic greenhouse images in the training and validation sets were manually labeled, with the training set being used to train the YOLO-V5 Model. Throughout the training, the validation dataset was used to evaluate how well the network performed. According to the performance results the system reached its highest level of accuracy at epoch 71, with a relatively brief training time of 40 minutes, The model’s average precision was 84.1 percent, Using satellite images. In detecting plastic greenhouses, YOLOv5 can deliver exceptional accuracy and computational performance.

1. INTRODUCTION

Morocco’s agriculture has experienced a rapid rise in greenhouse production in recent years (Ouazzani Chahidi and Mechaqrane, 2022). Basically, plastic greenhouses are made out of a partly transparent plastic cover that allows control over environmental and growing conditions within the greenhouse (Ouazzani Chahidi and Mechaqrane, 2022). However, the expansion and construction of plastic greenhouses has posed many problems for land owners such as the pollution of plastic wastes (Picuno et al., 2011). To track the spatial distribution of plastic greenhouses, an effective detection mechanism must be developed. in order to conserve cultivated lands from plastic pollution and to reasonably develop plastic greenhouses.

Artificial intelligence (AI) first appeared in 1955 (McCarthy et al., 2006). Intelligence is difficult to define by definition, and this term is no exception. It can be described as a process that mimics human abilities and behavior through the application of preprogrammed rules (Nilsson, 1982). Machine learning (ML) is a type of artificial intelligence that by the collected data and using pre-programmed rules, the system can learn and develop on an iterative basis (Michie, 1968). Recently, improvements in machine learning and pattern recognition have enabled to extract information from big data automatically (Ma et al., 2015). A large part of this is due to deep learning (DL) which is a type of ML, It uses multilayer neural networks to characterize the most discriminative and representative characteristics in a hierarchical approach. (LeCun et al., 2015).

One among the most popular network architectures in deep learning methods, convolutional neural networks (CNNs) have gradually replaced conventionally designed feature engineering in image analysis due to their superior performance in resolving high-level features (O’Shea and Nash, 2015), there are two types of based on CNN object detection algorithms. Most of the current high-performance object-detection frameworks are based on R-CNN algorithm series and YOLO algorithm series (Wu et al., 2021).In a variety of disciplines, R-CNN-based object-detection frameworks have demonstrated excellent accuracy. However, the detection time are slow. To address the performance issue, the YOLO algorithm series uses a basic cascade model to treat image recognition as a regression problem.(Wu et al., 2021).

Deep learning is data-driven, the quality and efficiency of object detection algorithms vary greatly depending on the data source. Because of the interference of the atmosphere, backdrop, incidence angle, and lighting is unavoidable, remote sensing images generated from satellite sensors are far more complicated than natural images. Most studies used YOLO-based object detection on a small number of public datasets and a variety of private datasets. Like, Ma et al. used the improved YOLO v3, which provided a precision of 90.89 percent, to detect collapsed buildings in post-earthquake remote sensing images (Ma et al., 2019), Li et al. used faster R-CNN, YOLO v3 and SSD to detect Agricultural greenhouses satellite images, which in YOLO v3 was with the best accuracy and computational efficiency (Li et al., 2020).

The aim of this research was to design a suitable methodology for detecting plastic greenhouses from satellites using YOLOv5, As well as improving accuracy to assist in managing greenhouse growth and to plan agricultural development.

2. AREA OF STUDY

Morocco located in North West of Africa. The Moroccan coast stretches around 3500 kilometers. It has a total area of 710,850 km^2. The capital of Morocco is Rabat, and Casablanca is know as the biggest city. Morocco has a wide range of sceneries. From the highest peaks to the lowest plains, from lush vegetation to total aridity.(Figure 1).

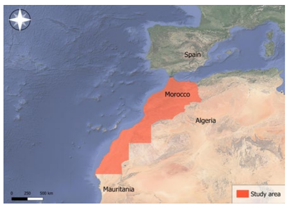

Figure 1: Study area location

Morocco has a Mediterranean climate, which is moderated from the Atlantic Ocean to the west and north. The climate within is

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mostly continental, and large temperature variations. The Atlas region is humid, and snowfall is common. The climate in the South is desert-like.

Morocco’s agriculture generates employment for over 40% of workers in the country. As a result, it is the country’s largest employer. Grains like Barley, wheat, and others can be grown without irrigation in the wet parts of the northwest. Olives, citrus fruits, and wine grapes are farmed on the Atlantic coast’s vast plains, mostly with water provided by artesian wells. Cork, cabinet wood, and construction materials are harvested from forests. A small percentage of the marine population relies on fishing for a living. Larache, Essaouira, Agadir, and El Jadida are one of the most important fishing ports. Climate change is expected to have a negative impact on both agriculture and fisheries.

3. MATERIALS AND METHODS

3.1 Methodology

In order to detect plastic greenhouses the study follows four main steps (Figure 2):
The process started with downloading different Morocco’s plastic greenhouses images from Google and Mohammed 6 satellites. Secondly, the data was prepared by dividing into three parts, training, validation and testing images, labelling the training and validation images. Thirdly, The YOLOv5 model was trained, and after that tested on the testing images. Finally, the results were analysed and presented.

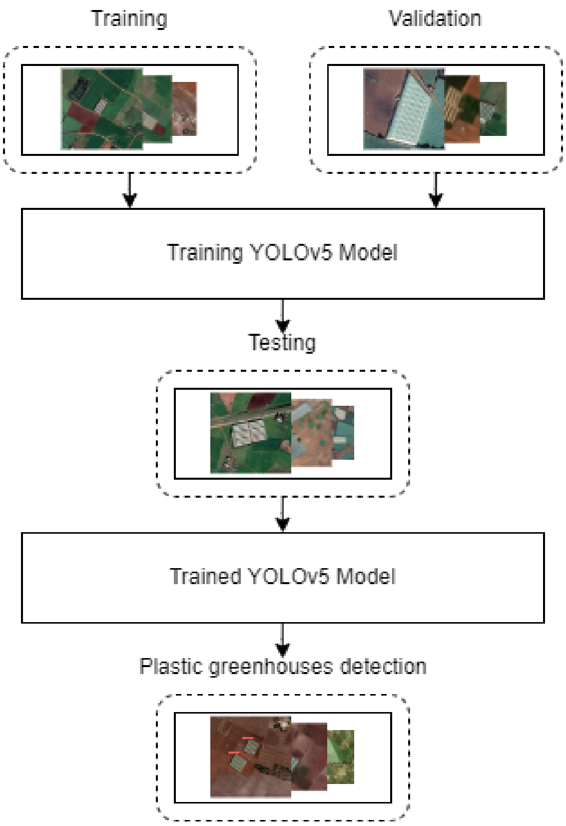

Figure 2: The study’s methodology

3.2 Data Collected

Google Earth and Mohammed 6 images was used to create the input data for the presented detection technique. In QGIS, the images were downloaded using the Python Console and connecting it to google satellite. The pictures where then choosed from different places in Morocco that are known with plastic greenhouses and were donwloaded with a size of 640x640 (Figure 3).

Figure 3: Some of the images used in the study

3.3 Preparation of Data

The set of data was separated into three sets: Training, validation, and test. After that, the training and validation images were labeled in Make Sense website, the labeled image tiles were given to one of three sets at random. the Individual detection model was trained and proposal areas were generated using the training data, while the validation data was used to choose the best hyperparameters. The model’s detection results were tested using testing data. roughly in the ratio of 63%:15%:22%. The dataset details in (Table 1).

Satellite	Image size	Total images	Training images	Validation images	Testing images
Google Earth	640x640	400	252	60	88
Mohammed 6	640x640	26	13	4	9
Total	640x640	426	265	64	97

Table 1: Spatial data used in the study

3.4 YOLOv5

The latest YOLO object detection model is YOLOv5 (Jocher et al., 2020). The YOLOv5 network is divided into three parts: The backbone is used to extract features, the neck is used to fuse features, and the output is used to identify objects. (Jocher et al., 2020) (Figure 4).

The focus module slices and concatenates images in the architecture, with the goal of extracting features more efficiently during down sampling. The Leaky relu activation function, convolution, and normalization are all part of the CBL module. (Mastromichalakis, 2020). There are two types of cross-stage partial

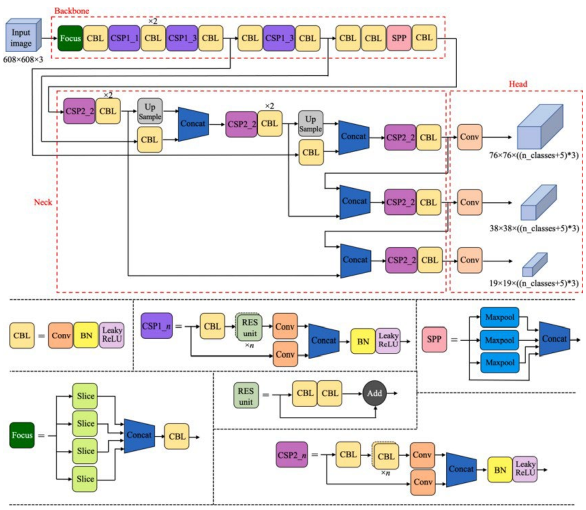

Figure 4: YOLOv5 Architecture

network (CSP) in YOLOv5 used in backbone and neck (Kim et al., 2019). By leveraging cross-layer connections to connect the front and back layers of the network, the CSP network aims to improve inference performance while maintaining precision by lowering model size. The structure of the two types of CSP networks differs only slightly. The backbone CSP network has one or more residual units, whereas the neck CSP network replaces the residual units with CBL modules. Furthermore, the SPP module stands for spatial pyramid pooling, which performs maximum pooling with various kernel sizes and fuses the features by concatenating them. By conducting dimensionality reduction (downsampling) techniques to represent image features at a higher level of abstraction, pooling resembles the human visual system. The input feature map is primarily compressed. On the one hand, it reduces the size of the feature map and reduces the network’s computational complexity. On the other hand, it compresses the features and removes the most important ones. The Concat module is used to perform tensor concatenation.

3.5 Model training

Google Collab was used to execute the model. The model was trained in 40 minutes using the YOLOv5 Github framework. Each detector needs the adjustment of a collection of hyper-parameters prior to training. ImageNet, a natural image dataset for object detection, is used to train the majority of the basic networks. The pre-trained model was introduced to this dataset using the transfer learning technique to establish the weights and bias. For the study, the batch size was set to 16, the training loss converged, and the validation set revealed optimal performance after 71 epochs.

4. RESULTS AND DISCUSSION

4.1 Evaluation Metrics

The performance of the YOLOV5-based method to plastic greenhouses was assessed using two frequently used measures: the F1-measure (F1) and the precision-recall curve (PRC).

4.1.1 PRC Precision-recall curve (PRC) have two elements: recall and precision. When compared to individual accuracy or recall, it is a more conventional and objective evaluation criterion in the realm of object identification. The recall measures the proportion of properly recognized positives and the entire amount of ground truth samples, whereas the precision measures the percentage of accurately recognized positives and the results of detection.

4.1.2 F1 curve The F-measure is a classifier’s weighted harmonic mean of precision and recall, taking =1 (F1 score). It signifies that both measurements are equally important and can be used to determine the highest level of testing confidence.

4.2 Visual Evaluation

The YOLO v5 model is tested using images of plastic greenhouses. The findings of 97 varied images were evaluated, some of the samples are shown in (Figure reffig:testedimg). The majority of the results are correct; the yellow boxes indicate inaccurate detections. The model has been quite successful at visually detecting plastic greenhouses with different geometric designs that are hard to distinguish. The detection accuracy was mostly decent, but it may be better with higher resolution images and more data.

Figure 5: Greenhouse Detection

4.3 Evaluation with Metrics

The model's result on the PRC-measured integrated test set is presented in (Figure 6). A PRC curve near the top suggests superior performance. It was discovered that the network gave satisfactory detection accuracy.

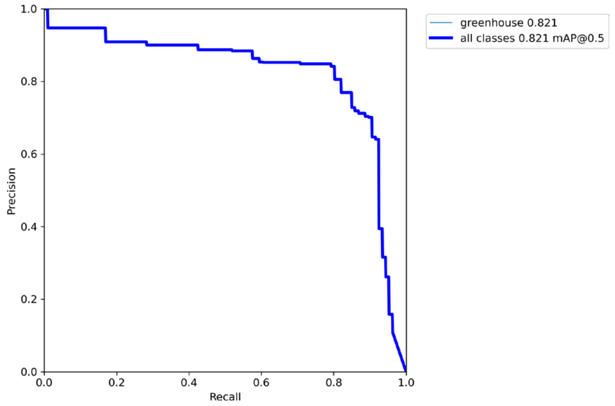

Figure 6: PRC

The F1 curve, on the other hand, demonstrates that the confidence value that optimizes precision and recall is 0.635, as illustrated in (Figure 7).

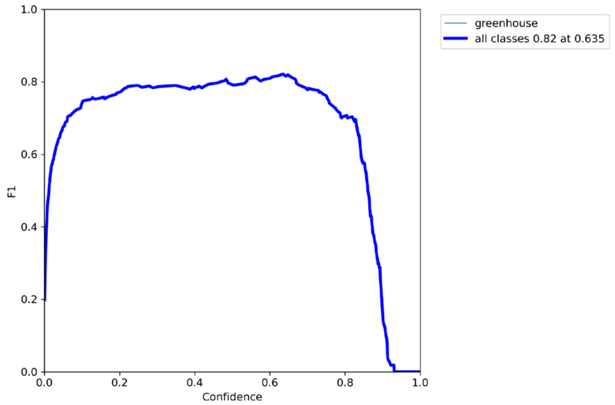

Figure 7: F1 curve

5. CONCLUSION

The goal of this research was to aid in the management of plastic greenhouse growth by detecting greenhouses from satellite photos using the YOLOv5 CNN-based object detection algorithm. The results were reviewed using both integrated test images and metrics to examine the performance. There was no issue with processing time. With the help of Google Collab, the YOLOv5 model is quick. According to the findings, the greater the detection quality, the more and higher the image resolution. In operational monitoring work, YOLOv5 can accomplish rapid and accurate detections utilizing satellite photos, which can be used as a basis for land management and decision-making. Hopefully, as models improve, accuracy improves as well, and research continues to monitor plastic pollution and suggest new ideas that can be developed.

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