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Research Article

Automated Detection and Localization of Fungal Infections on Cotton Leaves Using YOLO-based Object Detection Model

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Received: 25 May2023; Revised: 15 June 2023; Accepted: 04 August 2023; Published: 16 August 2023

AID: 002-02-000024

Abstract: Cotton is a vital cash crop globally, and its health and productivity are constantly threatened by various diseases. Early detection and accurate diagnosis of these diseases are crucial for effective crop management and minimizing yield losses. In this study, we propose a cotton leaf disease detection system utilizing object detection techniques. Creating an accurate, automated system for spotting and locating illnesses on cotton leaves is the aim of this study. Due to its real-time processing capabilities, we use cutting-edge object detection algorithms, concentrating on the widely used YOLO (You Only Look Once) paradigm. The model is trained using a sizable dataset of cotton leaf photos that have been annotated and creating an xml file and contain samples that have disease infections (fungal). The proposed approach utilizes the ResNet-101 deep convolutional neural network, which has demonstrated strong performance in various computer vision tasks. The model is pretrained on large-scale image datasets to capture high-level features and then fine-tuned on a custom dataset containing annotated cotton leaf images. The dataset used in this research consists of diverse images of cotton plants captured under various environmental conditions. Each image is manually annotated to mark the bounding boxes around individual cotton leaves. These annotations serve as ground truth data for training and evaluating the object detection model. our proposed model achieved an accuracy of 93 percent.

Keywords: Object detection; Cotton Disease Detection; YOLO Model; Cotton Leaf Illness;

1. Introduction

To ensure optimal agricultural output and avoid severe yield losses, crop disease detection is essential. One of the most commercially significant crops in the world, cotton is prone to a number of illnesses that can have a negative influence on both the quality and quantity of the crop. For timely interventions to be put in place and their negative effects on cotton production to be minimized, early diagnosis and correct identification of these illnesses are essential. The "Detection of Disease in Cotton Leaves" project seeks to create an automated system capable of accurately identifying and categorizing illnesses in cotton leaves through visual analysis [2,9,28]. This project aims to create a trustworthy and effective method for farmers and agronomists to detect and control disease outbreaks in cotton crops by utilizing developments in computer vision, machine learning, and image processing techniques. One of the most commercially significant crops in the world, cotton provides the textile sector with essential raw materials. However, cotton plants are vulnerable to a number of illnesses, which causes substantial productivity losses and financial difficulties for producers. Effective therapy and control of many diseases depend on early detection and precise diagnosis. In recent years, automatic and effective disease identification in plants, particularly illnesses of cotton leaves, has been possible thanks to object detection algorithms. The advantages, difficulties, and possible uses in agricultural practices are highlighted in this overview of cotton leaf disease detection utilizing object detection techniques. Fungal, bacterial, and viral pathogens can cause a number of illnesses that can affect cotton plants [22,30]. Verticillium wilt, Fusarium wilt, Bacterial blight, and Cotton leaf curl virus are among the common diseases that affect cotton leaves. These ailments can cause wilting, defoliation, stunted growth, and other symptoms that have a significant impact on cotton yield. To stop the spread of illness and reduce agricultural losses, prompt identification and management are essential.

The training of Cotton Leaf Disease Detection Model (CLDDM) required large amount of cotton leaf images dataset. Need of implementing quality preprocessing techniques (Resizing of images, Augmentation of images and Normalization of images) to improve the quality of images and convert the dataset into a format that understand by the Object Detection Model. Need of constructing an automated Deep Learning (DL) model that accurately detect and classify the Effected and Healthy Cotton Leaf (CL).

The key objectives of this project are, to train a robust disease detection model, a diverse and representative dataset of cotton leaf images infected with various diseases is collected. These images serve as the foundation for developing an accurate and generalizable disease detection system, the collected dataset undergoes preprocessing techniques to enhance image quality, remove noise, and standardize the data. Augmentation techniques also employed to increase the diversity and variability of the dataset, enabling the model to learn effectively from limited data, State-of-the-art deep learning model, convolutional neural networks (Resnet), employed to build a disease detection model. The model trained on the annotated dataset, learning to recognize and differentiate between healthy and effected cotton leaves, the developed model capable of accurately classifying different affecting cotton leaves, including but not limited to bacterial, viral, or fungal infections. This classification capability to enable farmers to identify specific diseases and take appropriate measures for disease management and treatment.

By implementing an automated disease detection system for cotton leaves, this project aims to empower farmers and agronomists with a valuable tool for early detection and management of diseases. Timely and accurate disease identification can lead to targeted interventions, reducing crop losses, optimizing resource allocation, and ultimately contributing to sustainable and resilient cotton farming practices.

2. Related studies

Many research projects are created for the detection of cotton leaves disease some of them are discussed in this section.

2.1. Related System 1

In [2] an object detection system is created in which they explained that Over 6 million farmers in India depend on cotton as one of their main cash crops, and it is vital to the country's agricultural economy. However, a significant drawback is that the cotton crop is extremely vulnerable to pests and diseases, which results in 30–35% of the harvest being contaminated. As a result, early disease diagnosis is essential because delayed disease detection results in crop failure. Utilizing machine learning and computer vision advancements can therefore be very beneficial to the agriculture industry. In order to identify pests and illnesses on cotton leaves, this research focuses on applying the Mask-RCNN object detection technique, which is based on instance segmentation. Regarding cotton in India's agribusiness, it substantially contributes to the subsistence of about 40–50 million people who work in the agricultural sector. India's horticultural sector is very important to its economy. The handling, trading, and farming of cotton are all important aspects of the material industry and the national economy. India possesses the world's largest cotton-growing area, spanning 126 lakh hectares. Since cotton requires a high temperature of roughly 25 to 30 degrees Celsius, tropical and subtropical regions of the world are the greatest sites to grow it [2].

Cotton is a Kharif crop. Considering the fact that Shirpur, a region in Maharashtra, is home to 24 modern industries. 800 transport fewer weavers produce 1.5 lakh meters of cotton textures daily in Shirpur's Material Park. This group receives its cotton from roughly 3 lakh ranchers and has increased productivity by learning about other things like water harvesting and the use of cash crops. In any case, a number of factors, such as excessive precipitation, temperature variations, inadequate infections, bacterial and parasite diseases, bug attacks, and improper manure application, prevent the growth of the cotton crop. Because they might occur frequently, irritant attacks and infections result in enormous financial losses. The hapless use of synthetics and composts to manage these vermin attacks has led to the development of bug sprays. So, it turns out that early sickness detection can prove beneficial for additional therapy. As a result, we suggest in this study a method for detecting cotton leaf disease employing Mask RCNN and ResNet50 as the architecture's backbone.

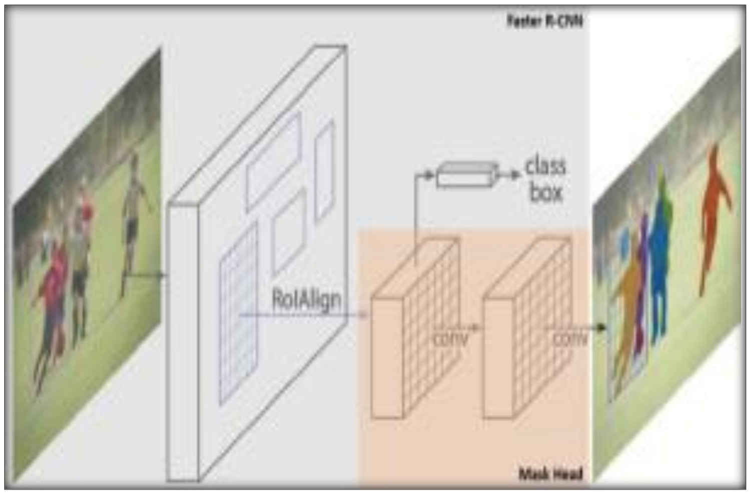

Figure 1: Proposed Architecture of system 1

Contrarily, in a distinct sort of segmentation called Semantic Segmentation, which is used by algorithms like Faster R-CNN, items belonging to the same class cannot be distinguished, making it impossible to forecast where the boundaries would be. Due to this significant drawback of semantic segmentation, Mask RCNN, which is based on instance segmentation, is currently being deployed.

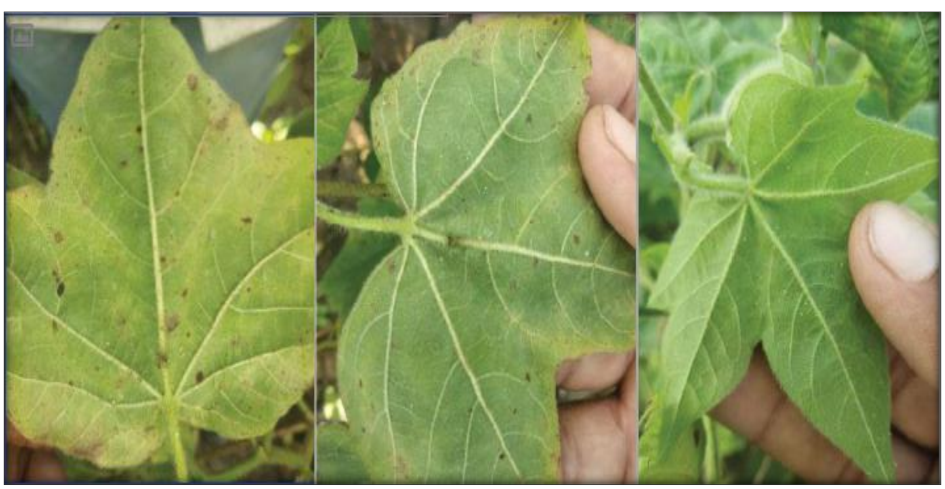

Figure 2: Collected dataset from related system 1

2.2. Related System 2

In related system 2 [3] conduct a study to develop an object detector system for multiclass cotton weed detection. In this work they explain that One of the biggest risks to the production of cotton is weeds. Herbicide resistance in weeds has evolved more quickly as a result of a misuse of pesticides to get rid of weeds, raising worries about the environment, the safety of food, and human health. With the goal of achieving integrated, sustainable weed management, interest in machine vision technologies for artificial or automated weeding is developing. However, the development of trustworthy weed identification and detection technologies continues to be a substantial problem due to the shapeless field environments and important biological heterogeneity of wildflowers. One potential solution to this problem is the development of extensive, labeled pictures of weeds specific to agricultural systems and data-driven artificial intelligence (AI) models for weed detection [21]. Numerous YOLO detectors have garnered significant attention for general object detection and are well-suited for real-time application across various deep learning architectures. In this paper, an additional dataset (CottoWeedDet12) of weed significant to the southern U.S. cotton industry is introduced. It is made up of 9370 bounding box annotations on 5648 photos of 12 distinct weed classes that were taken in cotton fields with natural lighting at different stages of weed growth. A new, extensive A benchmark of 25 state-of-the-art YOLO object detectors of seven versions—YOLO_v3, YOLO_v4, Scaled-YOLO_v4, YOLO_R and YOLO_v5, YOLO_v6, and YOLO_v7—has been built for weed detection on the dataset. YOLOv3-tiny's detection accuracy for mAP@0.5 ranged from 88.14% to 95.22%, whereas Scaled-YOLOv4's accuracy for mAP@ [0.5:0.95] varied from 68.18% to 89.72%. Five replications of Monte-Caro cross validation were used to assess these results. The YOLOv5n and YOLOv5s models in particular have shown a significant deal of promise for cannabis identification in real-time; additionally, data augmentation may increase cannabis detection precision. The weed detection dataset2 and software-programmed algorithms for model benchmarking employed in this study will be useful for future big data and AI-enabled weed detection and control for cotton and possibly other crops.

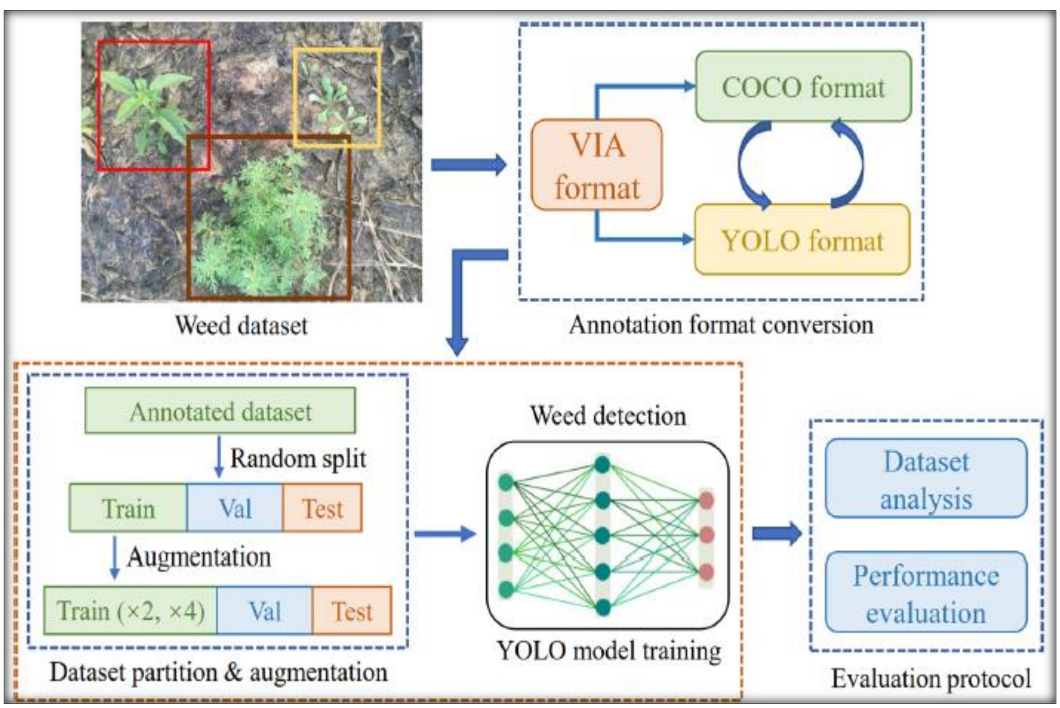

Figure 3: Related System 2

2.3. Other studies

Two important factors that significantly affect the performance of weed recognition are both the amount and quality of the visual data used to train the model and the weed detection techniques. Computer vision algorithms require large-scale labeled picture data to perform successfully. According to study by Sun et al. [4] the performance of advanced deep learning approaches on vision tasks grows logarithmically with the volume of training data. The complete use of deep learning techniques and the creation of reliable machine vision systems in precision agriculture are hindered by the lack of large-scale, high-quality annotated datasets [5]. Good datasets for weed recognition should include appropriate representations of pertinent weed species, environmental factors (such as soil types and light levels), and morphological or physiological changes related to growth stages. In addition to the need for weed detection expertise, creating these datasets is a knowingly costly and time-consuming operation. A number of recent studies, including the Eden Library, Hedge bindweed, CottonWeedID15, Deep Weeds, and Early crop weed dataset, have focused on the creation of image datasets for weed control [6]. To the best of our knowledge, the only available tool for weed identification unique to cotton production systems is CottonWeedID15. However, this dataset is only including image-level annotations, making it unsuitable for applications like weed detection that need bounding box annotations for weed instances in the photographs. While the computations are simple, most of them do not adapt well to changes in imaging settings, particularly when working with images taken under various natural field light situations [7]. CNNs have been applied for weed detection recently, for instance, using data-driven methods based on DL algorithms. Robust against biological variability and imaging circumstances, well-trained deep learning models can reach respectable classification or detection accuracies when fed large-scale datasets [8]. In the interim, a great deal of research has been done on image processing and analysis methods for weed identification [9,15]. For improved weed identification and segmentation from soil backgrounds, a number of color indices that highlight plant greenness have been proposed [10].

Weed identification in plants is a difficult task for ML. On the basis of unmanned helicopters or ground platforms, several automated weed monitor and identification techniques are being developed (Chishun et al., 2019). ML algorithms were paired with handcrafted features that considered a marijuana's, in early weed recognition systems, differences in color, shape, or texture were observed. Support vector machines (SVMs) were employed by the authors to produce local binary features for the classification of agricultural plants. A smaller dataset is frequently required for an SVM's model building. However, it could not be generalizable based on the topic's particulars. DL models are becoming more and more significant in CV because they provide a thorough approach to Identification of weeds for a huge number of datasets that tackles the generalization issues [12]. Sa et al. presented a CNN-based Weednet framework for aerial multispectral photos of sugar beet fields in 2020, and they employed semantic classification for weed detection. Using six experiments, the authors correctly inferred the semantic classes using a cascaded CNN with SegNet applied. The bindweed in the sugar beetroot field dataset was identified by the authors using a YOLO_v3-tiny model. To train the model, they created fake photos and mixed them with actual ones. Using the pooled images, the YOLO_v3 model obtained good detection accuracy. Additionally, weeds can be identified by their trained algorithm in mobile devices and UAVs. The authors of employed an alternative method to recognize weeds in vegetable fields. The authors used the CenterNet model to identify field-grown vegetables before labeling the remaining green spots in the image as weeds [14]. The specific sorts of weeds that exist in fields are ignored by the suggested method, which solely concentrates on crop vegetable identification. In Remote Sens. 2023, 15, 539 4 of 17, the authors presented a thorough examination of the identification of weeds utilizing a 2-stage and a 1-stage detector.

3. Material and Methods

This section describes the project's general research strategy. Indicate the type of approach used, whether experimental, observational, qualitative, quantitative, or a combination of methodologies.

3.1. Architecture of used system

Our used system in dell latitude 6440 and window 10 is installed on it. RAM of 8GB, Hard Disk Drive of 320GB and SSD of 128GB is installed on the used system. Dual core processor is used with two CPU (2.7+2.7). Table 1 list the components of the used system.

Table 1: Used System Specs

Specification	Details
Operating System	Window 10
Used RAM	8GB
Used SSD	128GB
Used HDD	320GB
Software & Tools	Google Colab, MS Word
Language	Python
Model	Dell
Version	Latitude 6440
CPU	2.7+2.7
Generation	4th
Technology	i5
System	Laptop

3.2. Proposed Methodology

Our proposed framework contains two main steps in first step we collect cotton leaf images from different areas of Pakistan such as Multan, Faisalabad etc. The collected images are annotating by using python imglable. The second step of our proposed model is to develop an object detection model to detect cotton disease in the image's dataset.

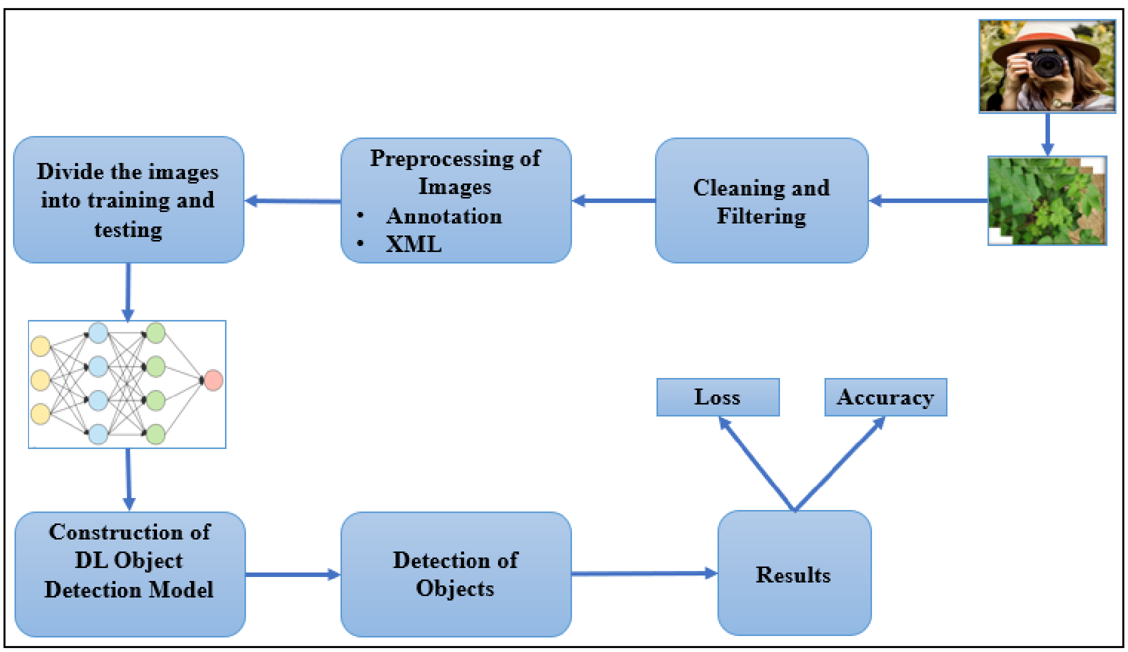

Figure 1: Proposed Framework

Our proposed system firstly focused on collected cotton leaf images dataset and then clean the images by removing blur and unimported images. Secondly preprocessing steps on images are applied to improve the quality of images. thirdly the images are annotating of labeled by using imglable library of python language by creating bonding boxes on the images and create xml file for each image to training the object detection model. Fourthly the annotated images are divided into training and testing images. Finally, an object detection model is developed to detect the disease of the cotton leaf. The steps of proposed methodology are explained below:

3.2.1. Dataset Collection

We collect the dataset from different cities of Pakistan. Four variants from four different areas (ASK1020, MN786, RSK NOOR, and FSD) of cotton leaf images are collected in two classes (Effected and Healthy). There are 501 images are collected. The statics of the images are given in the table 3.2. 130 images are collected from MN786 and 125 images are collected from ASK1020 and 150 images are collected from RSK NOOR and FSD having 96 images.

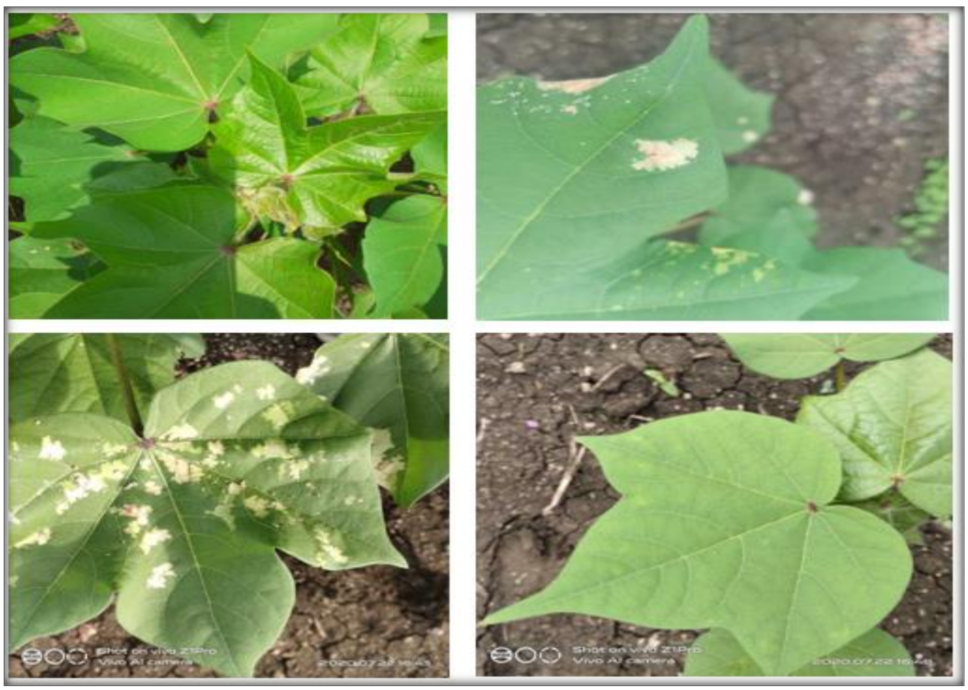

Figure 2: Sample of Collected Images

Table 2: Number of cotton images area wise

Areas	**Counting**
MN786	130
ASK1020	125
RSK NOOR	150
FSD	96

3.2.2. Cleaning and Filtering

All of the 501 selected images are cleaned and filter. The blur and unimportant images are deleted.

3.2.3. Preprocessing

We perform preprocessing steps on the images to improve the quality of images such as Resizing the images by defining the fix (height and width) of the images and normalization of images.

3.2.4. Annotating

Labelimg library is used to annotate the images. Figure 3.3 shows the sample of one image before annotating and figure 6 shows the image after annotating and creating bonding boxes on the image and create xml file for each image.

Figure 3: Image before Annotation

Figure 4: Image after Annotation

3.2.5. Dividing into training and testing

In this step the dataset is divided into training and testing. eighty percent data is used for the training of object detection model and 20 percent for testing.

Table 3: Dataset Division

Data	No of Images	%
Training	800	80
Testing	201	20

3.2.6. Model creation

We used ssd_resnet101_v1_fpn_640x640_coco17_tpu model. The term "ssd_resnet101_v1_fpn_640x640_coco17_tpu" refers to a specific computer vision model that is used for object detection tasks. Let's break down each component:

- SSD: SSD stands for Single Shot MultiBox Detector. It is a popular object detection algorithm that efficiently detects objects within an image. SSD is known for its real-time processing capabilities.
- ResNet101: ResNet101 is a deep neural network architecture that consists of 101 layers. It is widely used in computer vision tasks due to its ability to effectively learn complex features and patterns from images. v1: This indicates the version of the model. Different versions may have variations in architecture, training techniques, or performance improvements.
- FPN: FPN stands for Feature Pyramid Network. It is a feature extraction technique that enhances the ability of a model to detect objects at different scales. FPN utilizes a top-down and bottom-up pathway to extract features from multiple levels of resolution. 640x640: This indicates the input image size that the model expects. In this case, the model is designed to process images with a resolution of 640x640 pixels.
- COCO17: COCO (Common Objects in Context) is a widely used benchmark dataset for object detection, segmentation, and other related tasks. "COCO17" refers to the 2017 version of the COCO dataset, which contains a large number of labeled images with 80 different object categories.
- TPU: TPU stands for Tensor Processing Unit. It is a specialized hardware accelerator developed by Google for machine learning workloads. TPUs are known for their high-speed and efficient processing, particularly for deep learning tasks. Overall, the "ssd_resnet101_v1_fpn_640x640_coco17_tpu" model combines the SSD algorithm with a ResNet101 backbone, FPN feature extraction, and is trained on the COCO17 dataset. It is designed to perform object detection on images with a resolution of 640x640 pixels using TPU hardware for efficient inference.

3.2.7. ResNet101

Residual Network 101, is a deep CNN architecture that has 101 layers. Microsoft Research first presented it in 2015 as a way to overcome the difficulty of training extremely deep neural networks. The idea of residual learning, which enables the network to learn residual mappings rather than the underlying desired mappings directly, is the fundamental innovation of ResNet101. Introduced "shortcut connections" or skip connections that bypass one or more network levels allow for this to be accomplished. By doing this, the residual information—that is, the difference between the desired output and the current input—can be learned by the network more quickly. The skip connections in ResNet101 enable the network to effectively tackle the problem of vanishing gradients, where the gradients diminish as they propagate backward through the network during training. This issue can make it challenging to train deep networks, as the gradients become too small to effectively update the weights of early layers. ResNet101's skip connections mitigate this issue by permitting the gradients to skip over a number of layers, improving the network's capacity to learn and function.

ResNet101 has been widely adopted and has produced cutting-edge outcomes in a number of computer vision tasks, including object identification, image segmentation, and image classification. Its deep architecture and residual learning concept have proven to be effective in capturing complex features and patterns from images, leading to improved accuracy and generalization. It is worth noting that ResNet101 is just one variant of the ResNet family, which includes different versions with varying depths (e.g., ResNet50, ResNet152). Each variant offers a trade-off between model complexity and performance, allowing practitioners as well as researchers should select the best model according to their needs and available computing power.

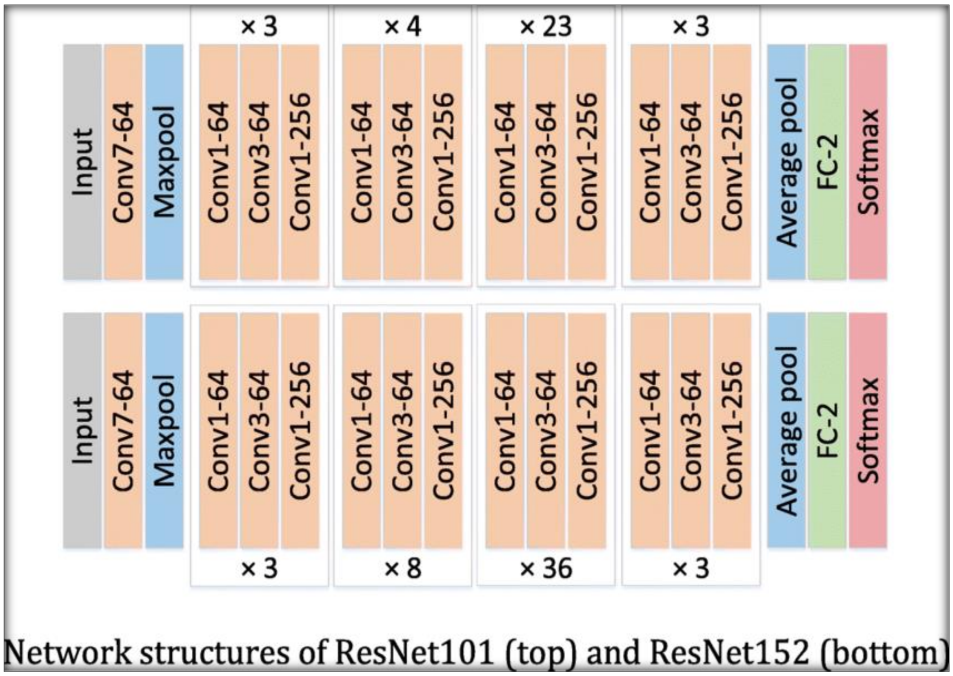

Figure 5: ResNet101 Architecture

4. Experiments and results

In this section of paper, we delve into the exciting realm of experiments and results, where we showcase the empirical evaluation of the proposed model. Here, we present a comprehensive analysis of the performance and efficacy of the system in various scenarios and benchmarks. Through rigorous experimentation, we aim to provide insights into the capabilities, limitations, and potential applications of the model. This chapter's major goal is to evaluate the model's performance and applicability for the tasks at hand. We address crucial issues like: Can the model successfully identify items across a range of images? Which scales, orientations, and occlusions does it handle best? What effect do differ input resolutions have on the speed and accuracy of detection? Through methodical experiments and careful evaluation, these issues and others are investigated. We make use of well-known datasets like COCO17, which offers a wide range of images annotated with object descriptions, to carry out the tests. Advanced methods and architectures, like the SSD (Single Shot MultiBox Detector), ResNet101 backbone, and FPN (Feature Pyramid Network), are used to train the model. To improve the model's capability to recognized things reliably and effectively, these elements are carefully mixed.

4.1. Experimental setup

The experimental setup of our proposed model is given below:

Table 4: Model Architecture

Parameters	Detail
Classes	2
Number of epochs	10
Batch size	16
Loops	2000
Depth	256
Images size	640*640
num_layers_before_predictor:	4
Kernal_Size	3

The above parameters are chosen because result was good on these parameters. We evaluate our proposed model on different parameters other than mentioned above but result was not good.

4.2. Results

We evaluate our model by testing 5 different images and record its results:

4.2.1. Image test 1

We test an image on the trained Object Detection Model (ODM). Table 5 shows the result of first tested image.

Table 5: Results of Test image 1

Number of Turns	Accuracy	Learning Rate (%)	Lose	Average Loss
200	76	7	76	60
400	77	12	34	36
600	75	15	40	35
800	80	15	35	32
1000	85	16	33	28
12001	86	23	32	25
1400	88	26	25	19
1600	92	39	19	15
1800	93	56	11	10
2000	93	60	6	3

Table 5 shows that model gives accuracy of 76, 77, 75, 80, 85, 86, 88, 92, 93 and 93 percent on the turns (200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800 and 2000). Learning rate of 7, 12, 15, 15, 16, 23, 26, 39, 56 and 60 percent is achieved by the model on (200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800 and 2000) turns on image 1. Model on Image 1 gives loss of 76, 34, 40, 35, 33, 32, 25, 19, 11 and 6 on the 200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800 and 2000 turns respectively. Average loss of model on image one is 60, 36, 35, 32, 28, 25, 19, 15, 10, 3 on (200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800 and 2000) turns respectively.

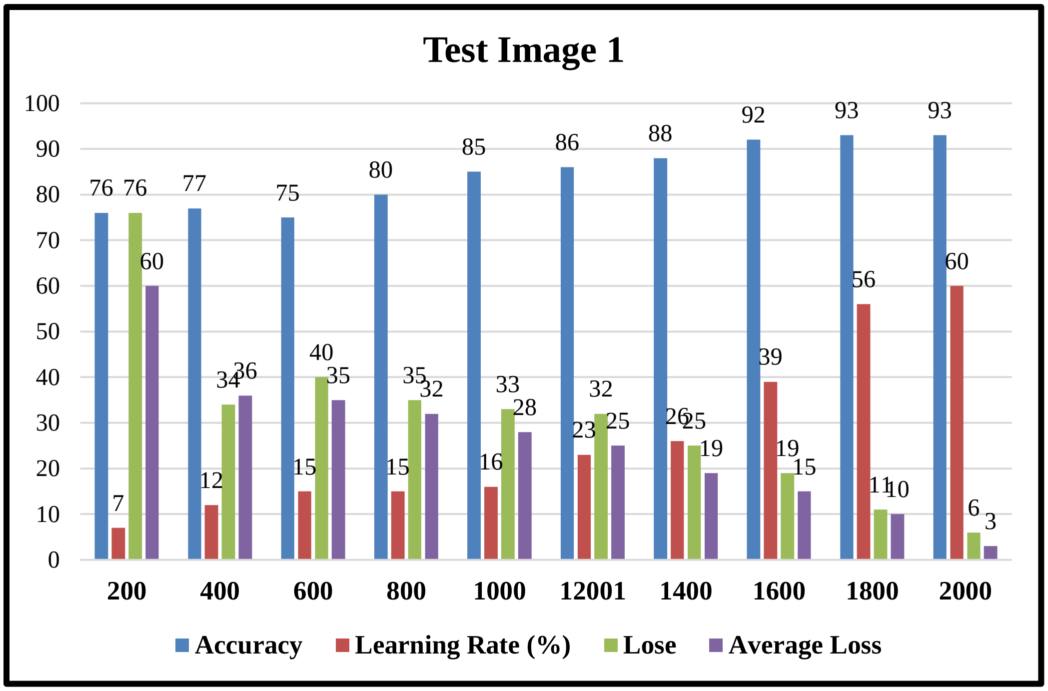

Figure 6: Result of Test Image 1

4.2.2. Images test 2

We test an image on the trained Object Detection Model (ODM). Table 6 shows the result of Second tested image.

Table 6: Results of Test image 2

Number of Turns	Accuracy	Learning Rate (%)	Lose	Average Loss
200	60	9	80	56
400	65	11	76	57
600	67	14	65	51
800	68	14	59	45
1000	70	18	46	42
1200	78	21	41	34
1400	79	23	39	30
1600	84	31	20	24
1800	86	45	15	20
2000	90	55	10	13

Table 6 shows that model gives accuracy of 60,65, 67, 68, 70, 78, 79, 84, 86 and 90 percent on the turns (200, 400, 600, 800, 1000, 1200, 1400, 1600, 18020, 15, 100 and 2000). Learning rate of 9, 11, 14, 14, 18, 21, 23, 31, 45, and 55 percent is achieved by the model on (200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800 and 2000) turns on image 1. Model on Image 1 gives loss of 80, 76, 65, 59, 46, 41, 39,20, 15, and 10 on the 200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800 and 2000 turns respectively.

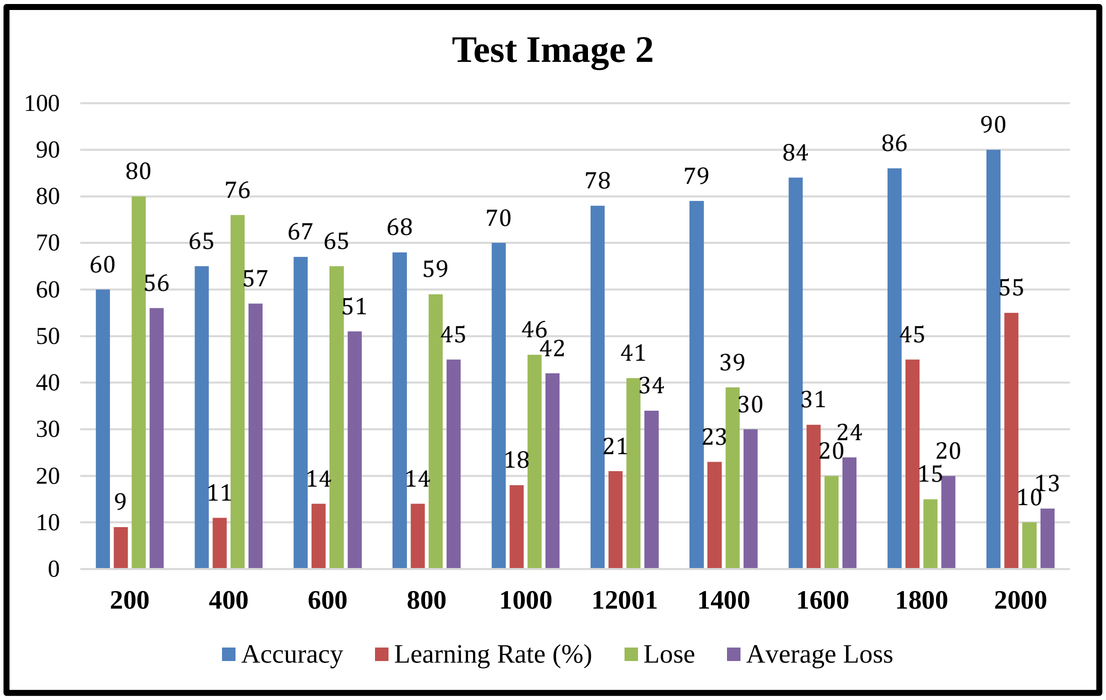

Figure 7: Results of Test Image 2

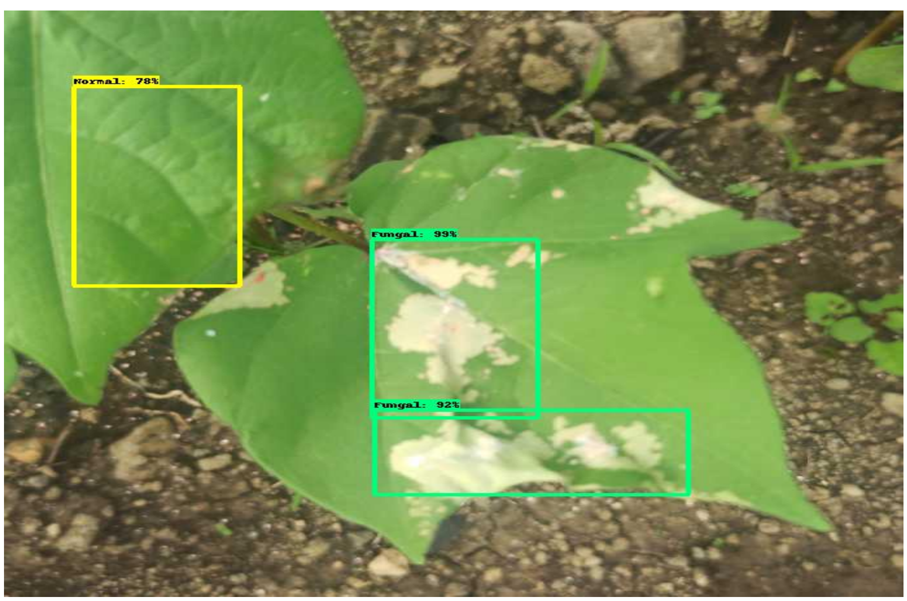

Figure 8: Proposed Model Tested Image Screenshot 1

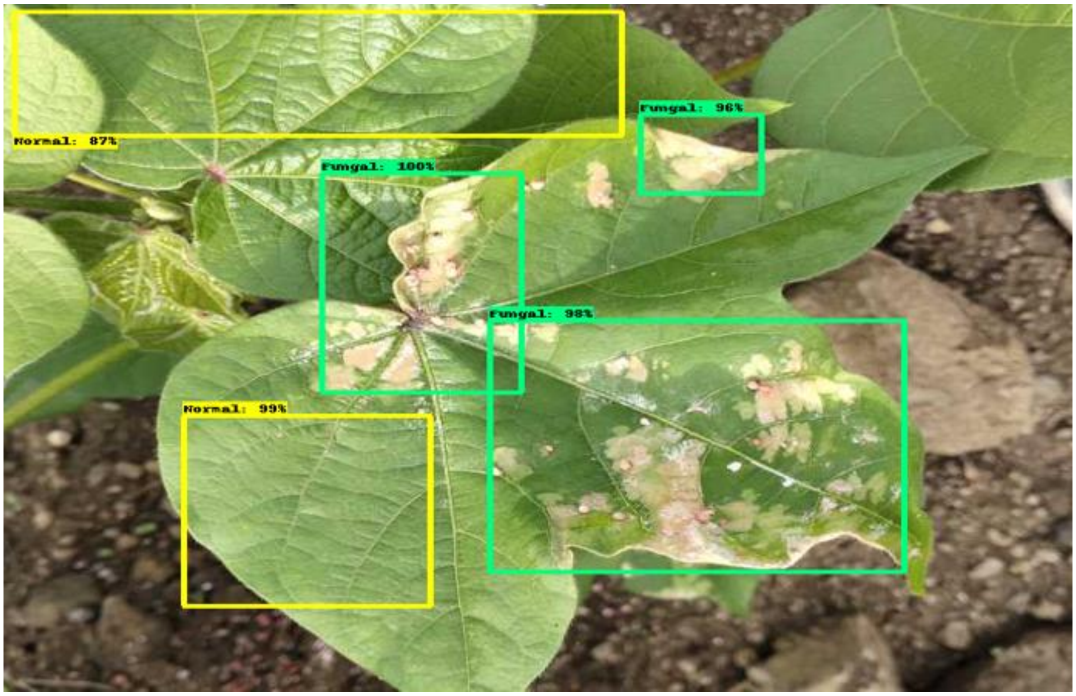

Figure 9: Proposed Model Tested Image Screenshot 2

The results of our proposed model are best as compared to the literatures studies. Proposed experiment results are 10 percent higher than the above-mentioned studies.

5. Conclusion

In this study, we have developed an automated cotton leaf disease detection system using object detection techniques. The proposed approach combines the YOLO paradigm with the ResNet-101 deep convolutional neural network to accurately identify and locate diseases on cotton leaves. The system achieved an impressive accuracy of 93 percent with a low error rate of 6 percent.

We were able to train and fine-tune the model successfully thanks to the use of a sizable and varied dataset and hand annotation of bounding boxes. The ResNet-101 model was able to capture high-level features important for cotton leaf disease diagnosis since it had been pretrained on large picture datasets. The outcomes show the system's potential to help farmers and agricultural specialists identify and diagnose illnesses on cotton leaves early on. The spread of infections can be controlled and yield losses can be kept to a minimum by rapidly detecting unhealthy plants and implementing the necessary remedies.

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