Agricultural Sciences Journal
Available online at http://asj.mnsuam.edu.pk/index.php
ISSN 2707-9716 Print
ISSN 2707-9724 Online
https://doi.org/10.56520/asj.v5i1.253

Research Article

A COMPARATIVE STUDY OF DEEP LEARNING TECHNIQUES FOR BOLL ROT DISEASE DETECTION IN COTTON CROPS

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Abstract

Early detection of plant diseases helps to prevent loss of productivity and overcomes the shortcomings of continuous human monitoring. To solve these problems, many researchers have already completed their work to identify the diseases automatically, rapidly, and with greater accuracy using deep learning methods. This research combines deep learning with agriculture by developing a system for identifying cotton boll rot. We used two states of art pre-trained models SSD with MobileNet-V2 and Faster R-CNN with Inception -V2, which can locate boll rot attacks in cotton crops. It will be determined how much damage our crops have sustained. The trained model achieved 65% and 89% accuracy, respectively. The accuracy results for disease identification demonstrated that the deep network model is prospective and can significantly influence effective disease identification. It may also have the potential for disease detection in real-world agricultural systems of interest, region proposal networks, convolutional neural networks; deep neural networks; bounding boxes; support vector machines.

Keywords: Faster RCNN, Single Short Detector, Bounding box, Region proposal network, Inception -V2
(Received: 9, January 2023, Accepted: 11, April 2023) Cite as: Ali. A., Zia. M. A., Latif. M. A., Zulfqar. S., Asim. M., 2023 A comparative study of deep learning techniques for boll rot disease detection in cotton crops. Agric. Sci. J. 5(1): 58-71.

1. INTRODUCTION

Pakistan is a primarily agricultural country, with approximately 62.82% of the population living in rural areas whose livelihoods are directly or indirectly tied to agriculture, according to the 2021 World Bank report. Experts believe Pakistan is an excellent location for growing all crops, including cotton, ranked as the fifth largest cotton producer globally, after Brazil, India, China, and the United States (FAO, 2021). In 2020, cotton and cotton products contributed approximately 22.69% to the country's GDP. Since cotton is a vital raw material in the textile sector, it is essential to promptly address any issues related to cotton to safeguard the textile industry (Rafiq *et al.*, 2021).

Cotton is a cash crop known as White Gold and is King of Fibber and is susceptible to several diseases, most of which are caused by fungi, bacteria, and viruses. Boll rotting, leading to a loss of 20 to 30% of the cotton yield, is a common issue. Detecting the cotton boll rot disease is crucial to prevent a severe outbreak and minimize crop losses. Therefore, a new method has been proposed for the careful detection of diseases and timely handling to avoid heavy losses in cotton crops (Saleem *et al.*, 2021; Mumtaz *et al.*, 2021).

Detecting and anticipating cotton illnesses early and applying appropriate controls are crucial for producing high-quality cotton. According to estimates from the United Nations Food and Agriculture Organization, the loss rate of cotton due to diseases could be as high as 24%. In Pakistan, boll rotting is a relatively new cotton disease caused by various fungal infections. The disease begins with a small brown or black spot on the boll, eventually spreading and covering the entire boll. In the early stages, the bolls do not open and do not fall off, and in some cases, the pericarp gets infected by the decaying stem, which can lead to internal tissue infection. On infected bolls, various fungi can be observed (Latif *et al.*, 2021).

Despite the prevalence of cotton diseases, most farmers in Pakistan still rely on traditional farming methods, including those for cotton cultivation. This results in higher production costs for conventional cotton farmers and poorer resource utilization (Salman Qadri, 2021). To combat this issue, it is essential to adopt modern farming techniques that improve crop yields and reduce the incidence of cotton diseases .(Imran *et al.*, 2018).

This study aims to develop an efficient object recognition and categorization system for image data using Convolutional Neural Networks (CNNs). First, we review the CNN architecture designed for object recognition and categorization in image data. We also explore several CNN architectures developed over the past decade. To address the issues of detection time and training data availability, we use CNNs to generate region proposals for localizing and segmenting objects.

Next, we provide a detailed overview of two popular CNN architectures for object identification and localization: Faster R-CNN with Inception-V2 and SSD with MobileNet-V2. We discuss their architectural elements and fine-tuning process and compare their advantages and disadvantages regarding detection time, network complexity, and training time. Finally, we choose the most suitable R-CNN framework for real-time object recognition and localization in an image and implement it for the depth estimation task.

2. RELATED WORK

Detecting plant diseases has been an area of research for many years, and in recent times, several studies have aimed to achieve greater accuracy using advanced computing techniques. Here are some notable examples:

Arsenovic *et al.* (2019) proposed a CNN architecture for plant disease classification that achieved an accuracy of 93.67% in a real-world environment.

Lim *et al.* (2019) developed a pollination robot that uses Deep Neural Networks to recognize kiwi fruit flowers. Their method achieved above-average precision, recall, and F1-score, with 91%, 87%, and 88% values.

Wang *et al.* (2019) used deep neural networks and object identification models to identify tomato diseases. They employed Faster R-CNN for disease detection and Mask R-CNN for segmentation.

Guillén-Navarro *et al.* (2020) tested cross-validation from a pessimistic perspective, validation of 24 hours of temperatures to forecast a temperature drop and comparison with ARIMA and the Gaussian process. Their LSTM-based model achieved less than one °C quadratic error and 0.95 R2.

Lin *et al.* (2020) utilized Faster R-CNN and Mask R-CNN to create a knowledge-based system identifying plant pests and diseases. Their models achieved accuracies of 89% and 80%.

Patel and Patel (2020) used NAS-FPN and Faster R-CNN to recognize, localize, and classify flowers. Their transfer learning model achieved mAP scores of 87.6% and an F1 score of 96%.

Sardoğan *et al.* (2020) used Faster R-CNN with Inception-V2 architecture to identify apple leaf disease, achieving an accuracy of 84.5%.

Sethy *et al.* (2020) employed Faster R-CNN to detect false rice smut, generating regional proposal and object detection speed up R-CNN.

Xi *et al.* (2020) used an improved Faster R-CNN model to detect potato buds for automated seed potato harvesting, achieving an AP of 97.71%, 5.98% better than the original 14.38% higher than YOLO-V2.

Yudha Pratama *et al.* (2020) employed Faster R-CNN with an Inception-V2 algorithm to identify diseases in hydroponic plants, achieving 70% accuracy, 97% precision, 68% recall, 80% F1 Score, and a default learning rate setting of 0.0002.

Vasconez *et al.* (2020) evaluated Faster R-CNN with Inception-V2 and SSD with MobileNet for the disease identification of Lemon and apples under diverse field settings. Their models obtained 93% and 90% fruit counting accuracy, respectively.

Villacrés and Cheein (2020) used a deep neural-based portable artificial vision system to improve cherry harvesting estimations. Their system achieved an 85% accuracy rate in detecting cherries and a 25% accuracy rate in estimating production.

Zhang *et al.* (2020) presented an improved Faster R-CNN to identify healthy tomato leaves and various diseases with an accuracy of 2.71% better than Faster R-CNN and faster than the latter.

Azath *et al.* (2021) developed a deep-learning algorithm to identify cotton leaf disease and pests with an accuracy of 96.4%. One of the most promising techniques in this area is deep learning-based image analysis, which has led to the development of several high-performance models for plant disease detection.

Ferrag *et al.*, (2021) proposed a deep learning-based DDoS intrusion detection system that uses convolutional, deep, and recurrent neural networks.

Similarly, (Hassan *et al.*, 2021) established CNN models to detect plant disease from leaves, demonstrating higher accuracy than traditional techniques.

Additionally, Kumar *et al.* (2021) presented machine learning algorithms and image processing methods for identifying cotton leaf disease, with their models achieving an accuracy of 89%.

Other researchers, such as Luaibi *et al.*, (2021) and (Mostafa *et al.*, 2022) have also reported impressive results in using neural networks for plant disease detection. These recent developments in deep learning research demonstrate that machine learning-based methods can be powerful in plant disease detection and analysis.

In addition to these works, there have been many other successful deep-learning applications in various fields. For example, Shah *et al.* (2022) developed a deep learning-based face recognition system that achieved state-of-the-art performance on the Labelled Faces in the Wild (LFW) dataset. Xu *et al.* (2020) proposed a deep learning-based approach for detecting and classifying melanoma skin lesions, which outperformed dermatologists in a study conducted on the ISIC dataset. Khan *et al.* (2021) used deep learning to see fake news and achieved a high accuracy rate of 93% on a dataset of news articles. Ma *et al.* (2021) developed a deep learning model for predicting the toxicity of chemicals, which outperformed traditional QSAR models. Finally, He *et al.* (2021) proposed a deep learning-based approach for detecting and classifying diabetic retinopathy, achieving high accuracy rates on multiple datasets.

These examples illustrate the versatility and power of deep learning in solving a wide range of problems. With further research and development, deep learning will likely continue to play an increasingly important role in many fields, including but not limited to computer vision, natural language processing, and robotics.

The development of advanced deep learning techniques has revolutionized the field of plant disease detection by enabling more accurate and efficient analysis of plant health. These methods involve training deep neural networks using large datasets of plant images, which can recognize patterns and features associated with different types of plant diseases. Unlike traditional computer vision methods, which require specialized knowledge and expertise, deep learning approaches can automate the analysis process and deliver results with a higher success rate. As a result, plant disease identification has become the primary analytical method for assessing the health of plants, helping farmers and researchers to detect and prevent the spread of disease more effectively.

3. MATERIALS AND METHODS

3.1 Implementation Details

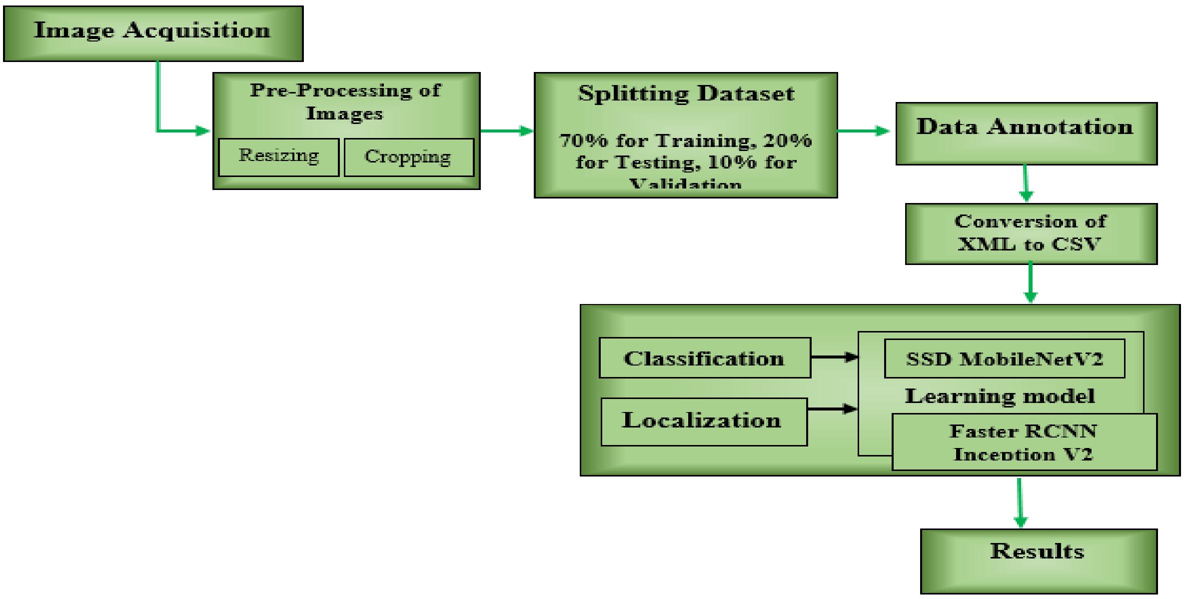
The research team used state-of-the-art hardware and software to conduct their experiments in this study. Specifically, they used 8th Generation Core i7 Quad-Core Processors with 8 GB RAM, 8 GB NVIDIA, and an SSD hard drive with 520 GB of storage capacity to ensure that their system could handle the large amounts of data involved in the research.

The researchers followed a rigorous six-phase process to analyse their dataset, starting with the acquisition of images of both affected and non-affected cotton bolls in the field. Once the images were collected, they were pre-processed and split into training, validation, and testing sets. Experts in the field then labelled the dataset to ensure the images were classified correctly. Finally, the researchers trained their model using two different architectures: SSD MobileNet-V2 and Faster R-CNN Inception-V2.

To improve the performance of their model, the researchers introduced several new hyperparameters, including anchor initialization, the maximum number of bounding boxes, and learning rate decay. Anchors were placed every 16 pixels on the feature map, and each pixel had nine anchors created using three different scales and three height-width ratios. The researchers used RPN to select foreground labels for anchors that overlapped with the ground-truth boxes by more than 0.60 percent and RPN to choose anchors that coincided with every ground-truth box by less than 0.40 percent of the total area.

3.2 Dataset Collection

The researchers used a specific method to collect high-resolution images of cotton bolls directly without relying on web scraping techniques to gather their dataset. They used a Nikon 2000D DSLR camera with a bit depth of 24 and a 29761984-pixel size to capture the images, which were then reduced in resolution to 640640 pixels to make them more manageable for training. The images were taken from various perspectives and focal lengths. Four hundred eighty-seven images were gathered from the University of Agriculture Faisalabad's main campus on September 17 and 20, 2021, between 9:00 a.m. and 1:30 p.m.).



Figur.1: Flow diagram of the proposed methodology

3.3 Data Augmentation

We applied CNN-based data augmentation techniques to address the class imbalance issue in the training set. These techniques aim to increase the model's generalization ability and prevent overfitting. Before augmentation, the training set had a significant class imbalance problem, where the three categories accounted for 70% of the training samples. In contrast, the remaining 30% belonged to the testing and validation sets. We used data augmentation techniques such as flipping, rotating, scaling, and cropping to overcome this issue and generate additional training samples. This resulted in a more balanced distribution of samples across the three categories, with each type having an equal representation in the training set. This approach helped improve the accuracy and generalization ability of the model.

Figure 2: Dataset splitting ratio

3.4 The Proposed Learning Framework

3.4.1 Model 1: Faster R-CNN with Inception-V2

Our study employed LabelImg software to label and annotate the images. The software allowed us to draw bounding boxes around the cotton bolls and assign them to their categories. The images were divided into two folders, one for affected and the other for non-affected cotton bolls. The Faster R-CNN algorithm was used as the primary detection model. The algorithm comprises two stages: the Region Proposal Network (RPN) and the region classifier. The RPN generates rectangular regions that could contain objects, which are then classified by the region classifier. The RPN predicts both the objectness of an image and its bounding box coordinates, taking information from all the anchors to propose a set of bounding boxes. The box proposals are then processed to extract crop feature maps, fed through the remaining feature extractor layers to determine class probability and bounding box coordinates. The RPN system evaluates whether an anchor contains an object or not based on the Intersection-over-Union (IoU) between the object proposals and the ground truth. An all-in-one network that shares full-image convolutional characteristics with the detection network provides almost free region proposals, as per the work of (SARDOĞAN *et al.*, 2020). Our model was trained using CNN-based data augmentation techniques to increase its generalization ability and prevent overfitting. Before augmentation, the training set had a class imbalance problem, with the three categories accounting for 70% of training, 20% of testing, and 10% of validation, respectively (Akbar *et al.*, 2020).

The Inception-V2 model was introduced in 2016 and significantly improved over the previous versions. It used factorization into smaller convolutions and improved architecture, including better use of pooling, smaller filters, and enhanced factorization. This made the Inception-V2 model more computationally efficient and enabled it to achieve higher accuracy than its predecessors. The Inception models have been widely used in various computer vision tasks and have achieved state-of the-art results in many benchmark datasets (Sivakumar *et al.*, 2020).

The Inception architecture has undergone several improvements since its inception, with Inception-V2 being one of them. One of the notable enhancements in Inception-V2 is incorporating a region proposal network (RPN) to improve object detection accuracy. The RPN is responsible for generating region of interest (ROI) proposals from the feature map created by the Inception-V2 backbone network (Mehmood and Zulfqar, 2021).

These ROI proposals are refined through bounding box regression and classified using a separate set of fully connected layers. The refinement process includes adjusting the bounding box coordinates and predicting the objectness probability of each ROI proposal. This process enables

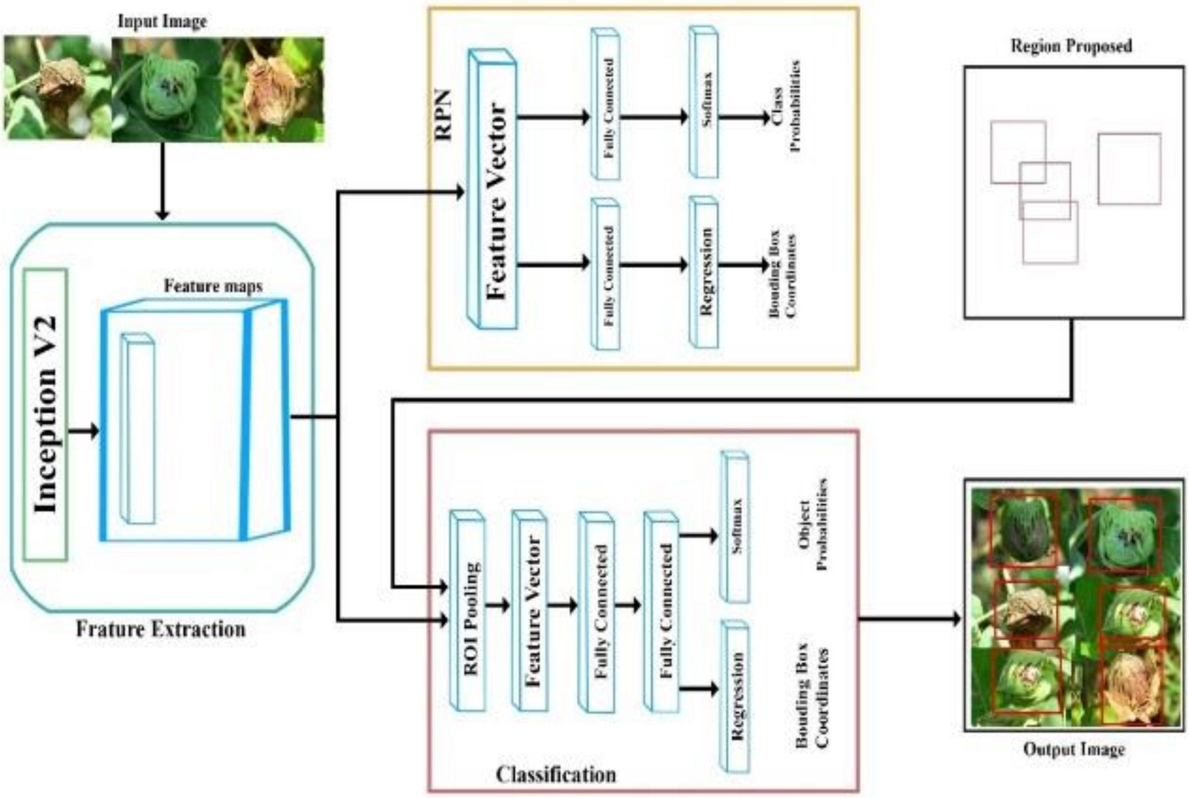


Figure 4: Faster R-CNN with Inception-V2 architecture

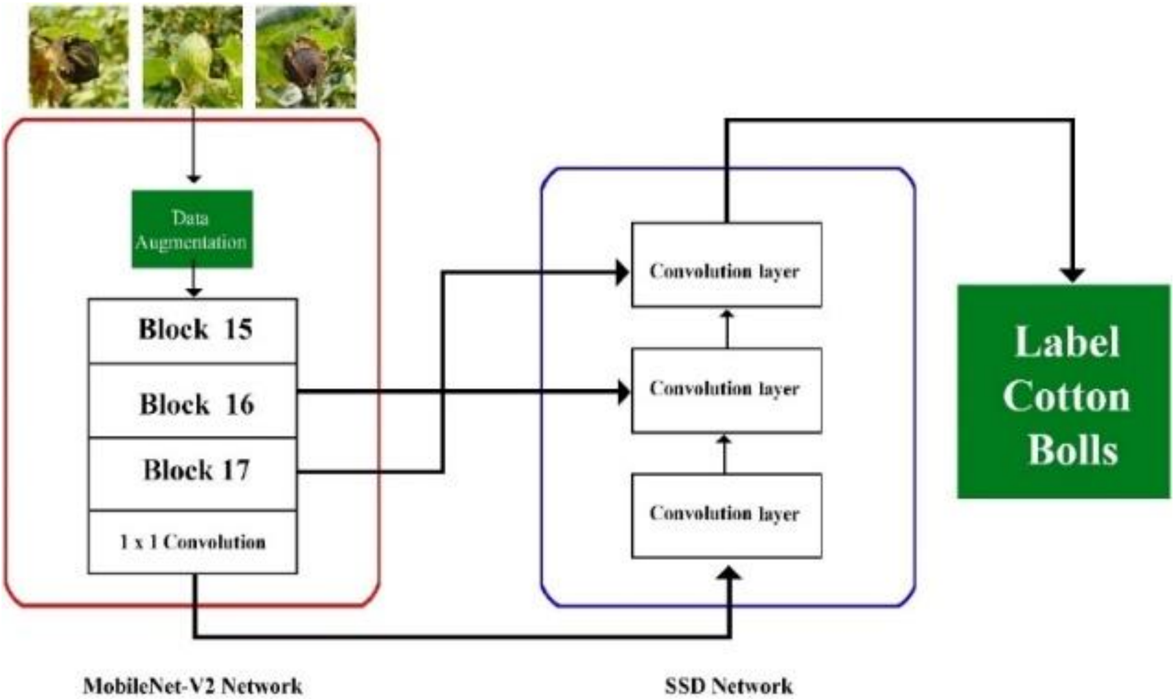


Figure 3: SSD with MobileNet-V2 Framework

the network to localize objects within an image and classify them accordingly accurately.

In addition to the RPN, Inception-V2 employs a suppression algorithm to reduce the number of bounding boxes generated by the network. This algorithm removes highly overlapping bounding boxes, resulting in a more compact set of bounding boxes that accurately represent the objects in the image. Combining the Inception-V2 backbone network, RPN, and suppression algorithm makes it a powerful tool for object detection tasks.

3.4.2 Model 2: SSD with MobileNet-V2

While the Inception-V2 model extracts feature using a feature map and fully connected layers, the Single Shot Detector (SSD) proposed by Liu et al. achieves object detection using a single network pass. By adding convolutional layers to VGG-16's backbone network, SSD can extract features at various scales while reducing input size. Multi-level feature maps enable SSD to identify object aspects across different scales, with low-level maps having a smaller receptive field than high-level maps. To separate feature units on the same layer, SSD employs a box mechanism and various configurations, with maps of different scales using default boxes with different dimensions and aspect ratios (Mahmood *et al.*, 2019).

SSD MobileNet is a lightweight solution to object detection, with each convolutional layer followed by a Batch normalization and ReLU layer. Model developers can adjust the width and resolution multipliers and the number of feature maps to optimize the trade-off between latency and accuracy. Furthermore, Deep-wise Separable Convolution can decompose and calculate standard kernels to reduce computation time. This approach uses a separable convolution that can be split into two halves according to depth, with the outputs being mixed following the depth-wise convolution of the input channels.

Overall, the SSD model is a practical approach to object detection, with the SSD MobileNet, offering a lightweight solution that can be customized to balance accuracy and computation time. The SSD model can accurately identify and classify objects across various scales and contexts by incorporating multi-scale attribute modelling and utilizing different configurations and mechanisms, such as default boxes and separable convolutions.

The MobileNet V2 model for object detection uses a novel approach of utilizing two 1D convolutions with two kernels each instead of a single 2D convolution. Separating downscaling blocks from the remaining blocks with strides of 1 or 2 allows for more efficient feature extraction. Each block consists of three convolution layers: the ReLU6 11 convolution, the deep convolution, and a non-linear 11 convolution. Additionally, MobileNet V2 introduces a bottleneck shortcut link and a linear bottleneck between layers. The bottleneck shortcut link and linear bottleneck enable the transformation of pixel-level concepts into higher-level descriptors by encapsulating intermediate inputs and outputs.

SSD with MobileNet-V2 utilizes MobileNet-V2 as a feature extractor and multi-scale learning layers to extract features. The convolution replaces the combination, requiring fewer parameters to detect an item. Data augmentation is employed to train images in different dimensions, and a convolution filter is used to obtain the output image. Using these techniques, the SSD MobileNet V2 model achieves high accuracy while being computationally efficient, making it a popular choice for object detection tasks in applications with resource constraints.

4. RESULTS

The research utilized an augmented dataset of data collected from the field to evaluate the effectiveness of different pre-trained CNN models for object detection of cotton boll rot disease. The performance of various object detection models was assessed using the dataset, and colourful boxes were used to indicate prediction bounding boxes. In contrast, a red box with squiggly lines inside was used to denote the label for the ground truth. By comparing the results obtained from different pre-trained CNN models, the researchers could determine which model was most effective for identifying the disease. This approach allowed for a comprehensive assessment of the accuracy and efficiency of various object detection models and provided valuable insights for future research in this area. Overall, using augmented datasets and pre-trained CNN models can significantly improve the accuracy and efficiency of object detection for a wide range of applications, including disease identification in crops.

respectively. Table 1 summarizes the accuracy and recall rates of the different detection models evaluated in this study.

- Precision=$\frac{\text{True Positive}}{\text{True Positive+False Positive}}$ (1)

Mean Average Precision=
$$\frac{\text{True Positive+False Negative}}{\text{True Positive+False Positive+True Negative+False Negative}} \quad (2)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive+ False Negative}} \quad (3)$$

Table 1: Results analysis of proposed object detection models

Model	Training duration	Batch Size	No. of training steps	AP	mAP	AR	IoU
Faster RCNN Inception-V2	3 Hours	4	14000	89%	89%	91%	0.50:0.90
SSD MobileNet-V2	8 Hours	4	50000	65%	65%	63%	0.50:0.90

4.1 Quantitative Analysis

The evaluation of object detection models is crucial to determine their effectiveness in real-world applications. In this study, the commonly used performance metrics for object detection, including mean average precision (mAP), average precision (AP), and average recall (AR), were employed. The mAP is calculated based on the Intersection over Union (IOU) of the predicted and ground truth bounding boxes. Precision and recall are other important performance measures. Precision is computed by dividing the number of true positives by the number of predicted positives, and recall is the ratio of true positives to false positives. The precision-recall curve calculates the interpolated precision, and the average accuracy is determined by computing the area under the curve. The inference speed in frames per second was measured to assess the real-time detection capabilities of the models. The recall rate, which indicates the model's ability to recognize positive samples, was also calculated. The proposed models, Faster R-CNN with Inception-V2 and SSD with MobileNet-V2 with 100 proposals, achieved the highest performance with mAP values of 0.89 and 0.65, respectively, and AR values of 0.91 and 0.63,

4.2 Qualitative Analysis

A function called intersection over union can be used to calculate an image's IoU. Intersection over union (IoU) is a commonly used performance metric for evaluating object detection models. It measures the overlap between two bounding boxes, the ground-truth bounding box, and the predicted bounding box. The IoU is calculated by dividing the area of their intersection by the area of their union. This value ranges from 0 to 1, where a higher value indicates a better overlap between the two boxes. In other words, IoU measures how well the predicted box aligns with the ground-truth box. The following two parameters are accepted:

- Ground-truth bounding box
- Bounded box predicted by prediction box.

When two boxes in the intersection and union variables intersect, it computes the intersection and union of those two points on the graph. We employ Intersection over Union for object detection (IOU). The meeting of the two bounding boxes is computed using a Jaccard index-based algorithm, which calculates the union of these two bounding boxes. As a result, a perfect overlap would be 1. The prediction may be either positive or negative when using a threshold value. Let's imagine the IOU threshold is set at 0.5.

- If an IOU is more significant than 0.5, the object detection is classified as True Positive.
- If an IOU is less than 0.5, the detection is incorrect, and the result is classified as a False Positive.

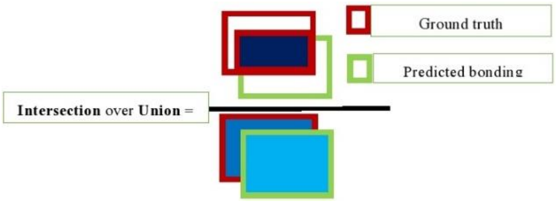


Figure 5: Intersection over Union

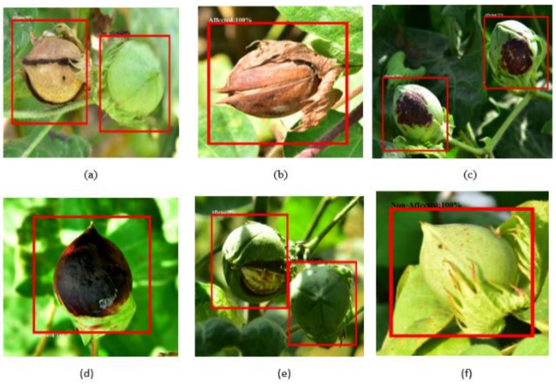


Figure 6: Performance of object detection models for cotton bolls rot dataset for Faster R-CNN with Inception-V2 and SSD with MobileNet-V2

In the above diagram, the trained model detected the cotton bolls and draw a bounding box around the object, it identified the cotton bolls and classify the cotton bolls as affected and non-affected.

4.3 Graphically Analysis

Visualization methods help assess model training success. Visualizing semantic model elements helps engineers understand the model's output. TensorBoard provided visualization and machine learning tools. Localization refers to detection of object and drawing the bounding box around an object in an image. This graph shows the localization loss, at horizontal axis, steps are presented and at vertical axis, loss is presented in points. Classification loss refers to the loss during training the model fails to classify a vehicle. This graph represents the classification loss with respect to steps. In this graph, loss is represented on different steps during training of Model. At horizontal axis, steps are presented and at vertical axis, loss is represented in points. The learning rate shows how quickly the model is adapted to the problem. This graph shows the learning rate of model trained for this research.

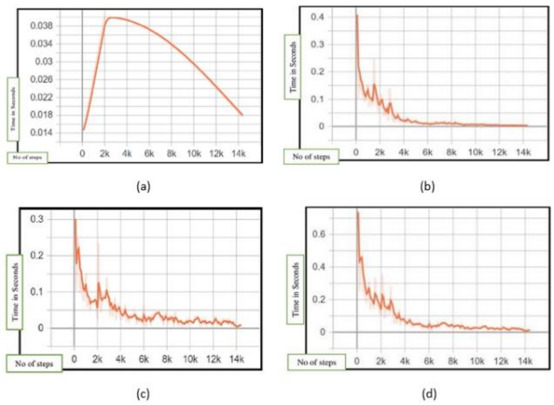


Figure 7: Histograms of the (a) learning rate, (b) localization loss, (c) total loss, (d) classification loss of model Faster R-CNN with Inception-V2.

The number of iterations influences the performance of deep learning models during training. For instance, Faster R-CNN Inception-V2 was trained for 14000 iterations, while SSD MobileNet-V2 was trained for 50000 iterations, as indicated in Figures 7 and 8. The learning rate becomes more stable with an increase in the number of iterations. In this study, we observed that both models learned features effectively, with strong convergence ability, which has the potential to yield desired results. Figures 7 and 8 illustrate the localization, total, and classification loss for Faster R-CNN Inception-V2 and SSD MobileNet-V2, respectively. At the beginning of the training process, the losses were high for both models, but they reduced gradually with each iteration. Faster R-CNN Inception-V2 achieved better detection with lower loss compared to SSD MobileNet-V2.

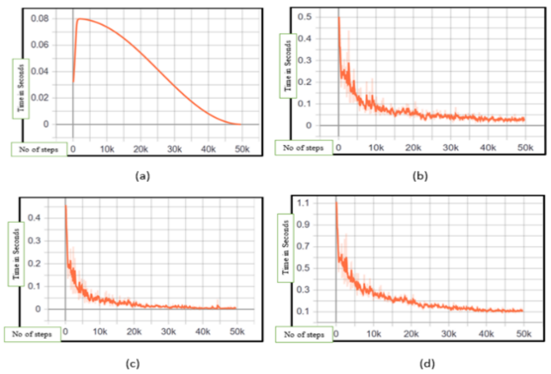


Figure 8: Histograms of the (a) learning rate, (b) localization loss, (c) classification loss, and (d) total loss of model SSD with MobileNet-V2

5. DISCUSSION

In the abovementioned experiment, we contrast the performance of various models and our suggested methods with other traditional target detection models. The effectiveness of each algorithm is determined in the table below: For several algorithms, Table 2 displays the FPS, the number of parameters, and the computational complexity. The model can be used for academic study by students and scientific algorithm research. However, it is still a long way from applications in agriculture. The algorithm still requires work to enhance its real-time performance. Another drawback is that the algorithm is only highly accurate for the species being taught now. They need to be retrained if the plants that need to be anticipated are not mentioned in this study.

On the other hand, the algorithm works better when it is solely used to identify diseases in the same plant. To prevent individual differences from affecting the final detection results and improve the generalizability of the algorithm proposed in this paper, we simultaneously add images of individual differences of the same plant to the data enhancement process. This is done because individual differences can occur in the same plant growing in various environments. The algorithm suggested in this research can identify plant diseases early on and perform prompt corrective action, which lowers production costs. At the commercial level, it is evident that initial capital investment in the chosen method is necessary. Broadly used industrial applications, however, can yield great returns by significantly enhancing process efficiency and cutting costs. This is the algorithm's significance. The object detection technique, Faster RCNN, uses regions to identify the items. The Faster RCNN network adopts a region-based approach that divides the input image into subregions called proposals, then performs object detection on each proposal. However, this strategy poses two challenges. First, to cover all possible objects, the model needs to process multiple proposals per image, which increases the computational cost and slows

Table 2: Results comparison from previous studies in agriculture

Researcher Name	Crop	No. of Images	Image Size	Method	Detection Rate	No. of Iterations
[Gao et al.]	Apple	800	1920*1080	Faster RCNN VGG16	85%	100k
[Patel et al.]	Flower	8000	416*416	Faster RCNN ResNetV2 InceptionV2	86%	80K
[Sardogan et al.]	Apple	700	224*224	Faster RCNN InceptionV2	84%	50k
[Yudha et al.]	Lettuce	873	3264*2448	Faster RCNN InceptionV2	69%	7k
[Vasconeze et al.]	Apple Lemon	1076 943	360*640	Faster RCNN InceptionV2 SSD MobileNet	77% 57%	70k 40k
Proposed Method	Cotton	487	640*640	Faster RCNN InceptionV2 SSD MobileNetV2	89% 65%	14k 50k

down the detection speed. Second, since the proposal generation and object classification tasks are performed sequentially, the accuracy and efficiency of the later tasks can be affected by the quality and quantity of proposals generated in the earlier tasks. In particular, the proposal generation process involves multiple parallel systems, and the preceding system's performance can influence each system's performance. Therefore, optimizing the proposal generation process is critical for achieving fast and accurate object detection with Faster RCNN.

It is important to consider the computational resources required to optimize the deployment of deep learning models. Faster RCNN with Inception V2 is known for its high computational requirements, making it suitable for deployment on GPUs. However, deploying such models at scale can be prohibitively expensive, making it necessary to consider more efficient alternatives. One alternative is SSD with MobileNet V2, designed to be more computationally efficient than Faster RCNN. Despite this, even the 5 x 5 convolutional layer in SSD with MobileNet V2 can be computationally intensive, requiring significant processing power and time.

6. CONCLUSION

Our experiments show that deep learning models performed well in object detection, with our framework able to identify cotton boll rot even with few samples. Of the two models compared, Faster R-CNN Inception-V2 outperformed SSD MobileNet-V2 regarding accuracy and training speed. However, both models require significant computational power and may be expensive to scale. We found that a training set of 489 images yielded promising results, but using a more extensive and diverse dataset may improve detection rates. Additionally, future research should focus on detecting diseases in different plant parts and stages. Our model may have practical applications as part of a decision-support system or mobile app for detecting cotton boll rot diseases. While Faster R-CNN Inception-V2 required 2.8% more computation per frame than SSD MobileNet-V2, both models achieved high levels of accuracy, with the trained model achieving 89% and 65% accuracy, respectively. However, we observed that SSD MobileNet-V2 produced more false negatives, an important consideration in object detection.

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