Efficient model for cotton plant health monitoring via YOLO-based disease prediction

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ABSTRACT

Protecting plants from diseases involves recognizing the symptoms and identifying practical, safe, and reasonable treatment methods. Holistic approaches based on particular times or seasons can reduce plant resistance and minimize tedious work. Technological advancements have led to the development of microscopic examinations and computational methods using machine learning techniques to detect diseases automatically and quickly using leaf images. This study builds the prediction model using EfficientNet and YOLO neural network architectures from computer vision. The development of a model that assists farmers in identifying cotton disease so that they use pesticides that may treat it further utilizes this concept. In the physical world, the input is accepted from many different sources, so observing the model's output is necessary. This work concentrates on model response to the inputs from physical devices, and analysis shows that the monitoring varies the results. A novel convolutional neural network (CNN) based on the EfficientNet architectures and variations of YOLO architectures is used to classify and identify the objects in cotton leaf. The EfficientNetB4 yielded 100% accuracy for healthy leaf and powdery mild leaf classes, and YOLO v4 version with 96%, 98.3%, 99.2%, and 0.70 for precision, recall, mAP@0.5, mAP120.5:095 respectively. These results indicate that consequences vary in real-time per environmental parameters such as light effect and devices, and analysis shows that monitoring affects the results.

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1. INTRODUCTION

The emerging machine learning concept with other domains such as medicine, agriculture, social networks, and e-commerce provided many solutions such as disease prediction [1], identification of plant disease [2]-[5] and many more. Cybernation in agriculture is an emerging domain across the world. Machine learning in agriculture helps farmers to concentrate on intelligent farming, species identification, agrochemical production, selective breeding, soil analysis, disease detection, weed detection, water analysis, grazing control, and many more. Although there is ML hype in agriculture, testing and validating the concept is a different, tedious, and lengthy process with considerable costs. It is necessary to understand farmers' attitudes and perceptions of the technology that will make digital evaluation valuable. The world's largest cotton, around 22%, is produced in India, the second largest consumer. Around 40 million to 50 million people work in cotton processing and trade. Cotton plays an essential part in the industrial economy of India. The world demand and supply situation are represented shown in Figure 1 for the last twenty-five years. According to the survey, approximately 112.94 lakhs demanded during 2023-2024 [6]. In India, cotton is the most widely grown crop. Farmers may make big money from cotton because it is a commercial crop. However, cotton's susceptibility to numerous diseases is one of its fundamental issues.

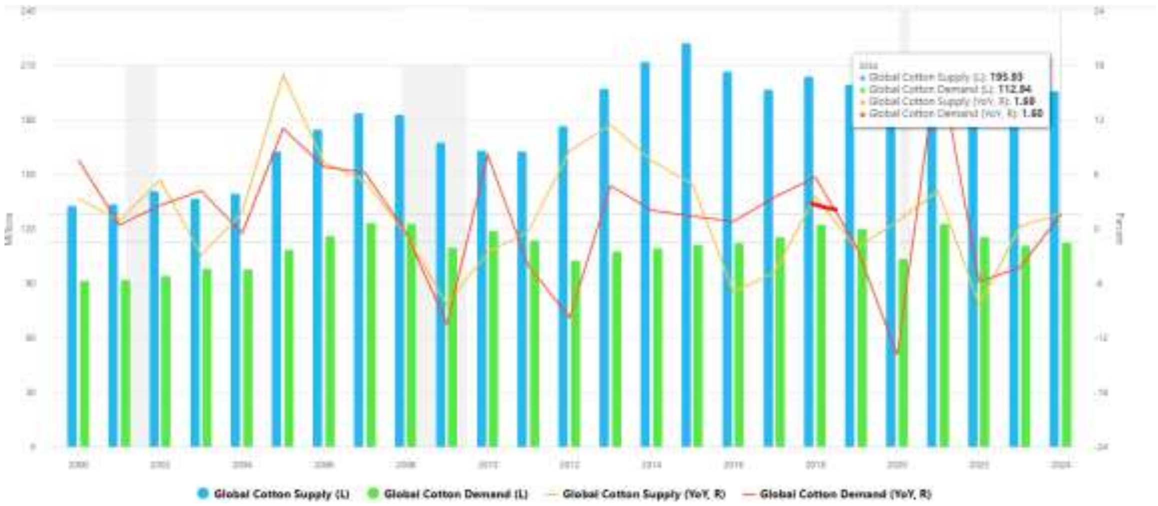

Figure 1. Worlds demand and supply situation in month January, 2024

Agriculture 1.0 uses simple tools, human resources, and animal forces, which limits the crop production process. Agriculture 2.0 concentrates on using chemicals and agricultural machinery and increases productivity. Though machinery is used, farmers have to face many unnatural incidents such as cyclones, draughts, and variability in weather patterns. Agriculture 3.0 uses robots and computer programs to reduce the farmer's efforts and automate the process, and agriculture 4.0 concentrates on smart devices and intelligent systems to increase productivity and reduce steps. The productivity loss can be avoided by discovering infections as soon as possible. Identification of diseases in the plant through image analysis is a regular practice. Agriculture 4.0 helps farmers to respond to changing conditions, capture relevant observations and measurements, manage crop growth in real-time and under changing field conditions, earn up-to-date pricing information, review results, and improve for the next cycle. Many factors affect the crop's growth and quality, such as pollinator decline, plant disease, changes in climate, bacteria, viruses, parasitic plants, and protozoa. In India Farmers in India depend on the agricultural sector for their earnings. Depending on where they are, farmers grow various local periodic crops. Detecting cotton leaf diseases using CNN is a promising application of deep learning in agriculture. CNNs are particularly well-suited for image classification tasks, making them an effective choice for identifying and diagnosing plant diseases based on leaf images [7]-[9].

The increasing prevalence of cotton crop diseases significantly threatens global agriculture and food security. The integration of cutting-edge technologies, such as DNNs, has emerged as a promising avenue for addressing this challenge. By imposing the power of machine learning and computer vision, this work aims to revolutionize the field of cotton disease prediction.

As we embark on this research journey, our primary objective is to contribute a comprehensive and effective solution to the complex issue of timely disease identification in cotton plants. Using advanced DNN architectures, this work concentrates to detect the object and identify the disease to improve the efficiency of disease detection in real time environment, ultimately empowering farmers with actionable insights for crop management. The primary objective of this research is to enhance the efficiency and accuracy of monitoring the health of cotton plants. The work aims to amalgamate an EfficientNet architecture and the YOLO object detection algorithm for predicting disease in cotton plants using the images. The goal is to optimize the results of the deep learning model. Integrating EfficientNet and YOLO improves disease detection capabilities by increasing the true positives. The objective is to use proactive management to absorb real-time monitoring with timely detection of cotton plant disease by providing reliable and efficient monitoring of cotton plant health. The following is the list of contributions to this work:

a) Preparing, acquiring, and preprocessing the cotton dataset to classify it into six significant classes: army warm, aphids, healthy leaf, bacterial blight, powdery mildew, and target spot.
b) This work integrates EfficientNet architecture and the YOLO object detection algorithm. Using EfficientNet and YOLO, the work aims to improve the accuracy of disease prediction with classification and object detection. By leveraging real-time monitoring solutions, the research facilitates prompt detection and response to diseases in cotton plants, enabling timely intervention and mitigation of crop losses.
c) The optimized deep learning techniques proposed in the research contribute to the robustness and scalability of the monitoring system, allowing for effective surveillance of large-scale cotton fields.
d) The research findings have practical applications in agriculture, offering valuable insights and tools for farmers, agronomists, and policymakers to make informed decisions and implement targeted disease management strategies in cotton cultivation.

In this paper’s subsequent sections delve into the state-of-the-art approach to plant disease prediction; the methodology employed and the dataset utilized discussed in section 2, and section 3 explains the experimental design. By combining rigorous scientific inquiry with real-world relevance, our goal is to support a future for cotton cultivation that is both sustainable and resilient.

There are several advanced machine learning algorithms such as convolution neural networks, deep belief networks, recurrent neural networks and deep Boltzmann machines applied to detect leaf disease. Many of the researchers to diagnose the disease have studied algorithms from different domains such as machine learning [10], pattern recognition [11], image processing [12], and computer vision [13]. This study focuses on cotton plant disease detection using CNN while considering the input from the real-time environment.

The neural network is applied to identify tomato frond disease identification with the help hybrid model of the residual network and dense network to improve the model’s accuracy [14]. There are many studies in which samples are taken in a laboratory environment. The model was often developed using samples taken from the lab that failed to generalize on authentic world images [15]. In real-world scenarios, inputs take backgrounds too. Often, inputs are blurred or sometimes overlay with other structures, so extracting the feature another challenge [16].

Often, measurement of the disease level of severity and categorization are much more essential to take corrective action in the field [17]. Lu *et al.* [18] proposed the automatic identification of rice disease in China using CNN with a ten-fold cross validation strategy with 95.48% accuracy. Azath *et al.* [19] proposed a leaf disease prediction model for cotton in Ethiopia using CNN with an accuracy of 96.4%. Cotton ailments are tough to identify through open eyes. The authors focused on four prime feature extraction. The images are captured using smartphones and digital cameras. The authors experimented on color and augmented parameters and observed 99% accuracy at the 100^{th} epoch.

Deep learning has the advantage of the feature knowledge, which extracts the element from higher to lower-level data. It can also solve complex problems, increasing the accuracy level and reducing error. The author discussed various techniques, including data variation, pre-processing, data augmentation, technical details, and performance metrics. This work proves that deep learning provides superior results compared to other methods [20]. Nowadays, deep neural networks are used to segment different objects and feature extraction, drawing conclusions from analysis [21]. Plant disease prediction using deep neural networks has significantly advanced, automating disease detection in agricultural settings. Various studies have explored the effectiveness of different DNN architectures [22]-[30], with recurrent neural networks (RNNs) and, convolutional neural network in accurately identifying and classifying diseases affecting cotton plants.

While these efforts have provided valuable insights, specific gaps and challenges merit attention. First, the inadequate accessibility of large and various labeled data for training robust models continues to be a barrier. Addressing this challenge is crucial for enhancing the generalization capabilities of deep learning models across different regions and disease types. Moreover, the interpretability of DNNs in the context of cotton disease prediction remains an ongoing concern.

The need for more transparency in deep learning models poses concerns regarding their interpretability and hinders farmers' and agricultural stakeholders' adoption of these technologies. The Table 1 discusses the challenges addressed for cotton leaf disease in recent studies. Future research endeavors should bridge this gap by developing transparent and interpretable models that align with end users' needs.

Table 1. Challenges addressed for cotton leaf disease detection in recent studies

Ref #	Method	Dataset	Result accuracy	Contributions	Classes	Location	Challenges
[7]	Convolutional neural network (CNN)	Proprietary dataset, Kaggle 1349 images	99%	Cotton Leaf Curl Disease Detection	Healthy, Fully Susceptible, Partially Susceptible, Fully Resistant, Partially Resistant	Pakistan	Variability in Environmental Factors Model Generalization across diverse environmental conditions
[8]	VGG-16, VGG-19, Inception-V3 and Xception	Dev3v 2310 images [kaggle]	VGG-16-90.22% VGG-19 - 96.74% Inception-V3-97.83% Xception-98.70%	Cotton leaf diseases affecting cotton production	Fresh cotton leaf, Fresh cotton plant, diseased cotton leaf and diseased cotton plant	Bangladesh	Class imbalance, leaf regions or segmentation, requires exploration
[9]	DCPLD-CNN	https://indianaiproduction.com/#google_vignette	98.77%	development of novel CNN-based methods,	Diseased Cotton Leaves, Diseased Cotton Plants, Fresh Cotton Leaves, and Fresh Cotton Plants	India	Enhancing the usability and effectiveness of the developed models
[19]	CNN with RMSprop and Adam optimizer with 50, 100, and 150.	2400 specimens, Melaka-Worker agricultural research center	accuracy of 96.4% 98% of bacterial blight, 94% healthy, 97.6% of leaf minor, and 100% of spider mite]	limited to four different feature descriptors, Effect of color and augmentation presented	Bacterial blight, spider mite and leaf miner	Ethiopia such as Arba Minch, Shele, and Woyto	Images with different shapes, sizes, different backgrounds, light intensity
[25]	CDDLite-YOLO model	1530 images, from Hebei, Hainan Province, China	90.6%	Model Efficiency, To improve the performance of the model addressing new loss function	Verticillium wilt Fusarium wilt Anthracnose	China	Adapting to Field Conditions, Reducing Computational Complexity
[28]	CNN	1200 images	92.5%		Healthy leaves, Fungal (Powdery mildew,leaf spot) Bacterial disease	India	Limited dataset Variability in disease symptoms Similarity between healthy and diseased leaves

To proceed with this study on cotton disease prediction, we seek to contribute to this evolving field by using YOLO and Efficient net models for object recognition and subdivision. By addressing the challenges [13], [16] and leveraging the latest advancements in deep learning, we aim to accept the input in a natural environment. This work aims to progress the correctness of disease forecast and enhance the practicality and usability of the representations in real-world agricultural set-ups. The subsequent sections delve into the methodology, data collection strategies, and experimental design to cotton disease prediction using DNNs.

2. METHOD

The methodology section includes cotton ailment detection and prediction by means of CNNs and provides a detailed study's, procedures, techniques, and tools. Here, a structured high-level representation of the methodology section is denoted in Figure 2. The specific implementation details of the system discussed in further sections. The proposed system is called an Efficient cotton plant health monitoring with Object Detection using YOLO and Classification using an EfficientNet Model. The system includes image acquisition, preprocessing, object detection model, region of interest extraction, classification, filtering, and monitoring. The images are acquired using a camera placed in the field. The raw images are to be processed by the system using preprocessing blocks such as image resizing and augmentation to improve the quality of the input data. The object detection model processes the images to detect cotton plant regions and diseased areas with bounding boxes drawn around the detected regions. Here, the regions of interest from the processed images are extracted based on the coordinates received by the YOLO model. The EfficientNet model processes the extracted regions to classify them into various categories. The post-processing aggregates and analyzes the results to provide the overall assessment of the plant. Finally, the annotated images and reports indicating the health status are ready for farmers to review.

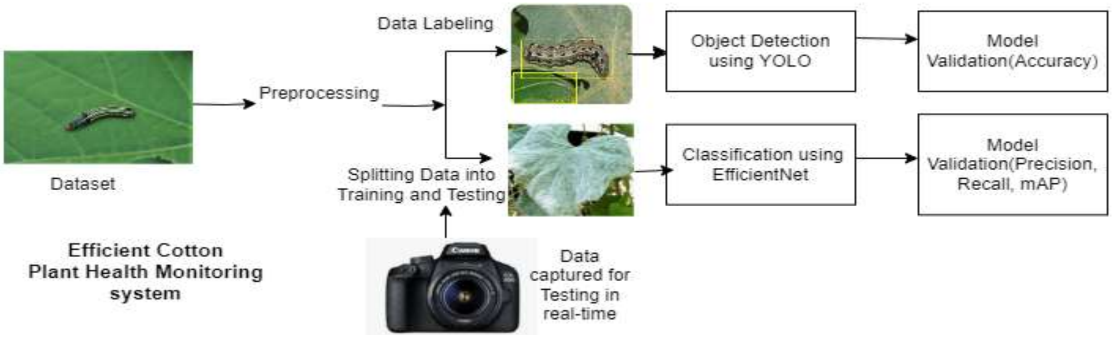

Figure 2. Efficient cotton plant health monitoring system

2.1. Dataset collection

The first step involved the acquisition of a comprehensive and diverse dataset encompassing images of healthy and diseased cotton leaves. This work cotton dataset, sourced from www.kaggle.com/datasets, is a reliable and extensive collection of high-resolution images capturing various stages of cotton plant development and different manifestations of diseases. The dataset contains 1340 color images with six classes as shown in Figure 3: Aphids class shown in Figure 3(a), armyworms in Figure 3(b), bacterial blight in Figure 3(c), healthy leaf in Figure 3(d), powdery mildew in Figure 3(e), and target spot in Figure 3(f). For testing the data from a natural environment, around 200 images are captured using a camera with a resolution of 1080×1920 pixels from Latur district, Maharashtra, India.

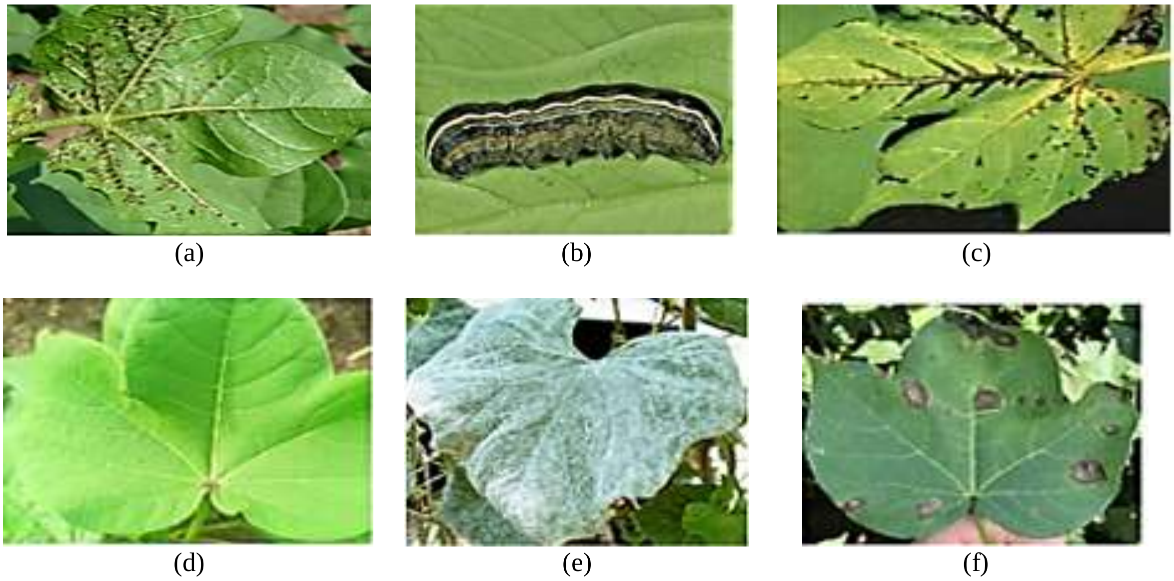

Figure 3. Cotton disease dataset classes: (a) aphids, (b) army worm, (c) bacterial blight, (d) healthy leaf, (e) powdery mildew, and (f) target spot

2.2. Data pre-processing

Prior to training the convolutional neural network models, the dataset underwent rigorous pre-processing to ensure uniformity and enhance model generalization. The samples are transformed into and assigned labels with experts help. This involved resizing images, normalizing pixel values, and addressing any potential imbalances in the distribution of healthy and diseased samples. The images are resized into 224x224 pixels.

2.3. Model architecture

This work adopted a state-of-the-art CNN architecture for the core of cotton plant disease detection and prediction framework. Specifically, this work leveraged Efficient Net versions - EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, and EfficientNetB4 due to their proven efficacy in image classification tasks and YOLO7 model with four variations for object detection. The chosen architecture was fine-tuned to accommodate cotton leaf images specific features and nuances. EfficientNetB0 is a type of CNN that fits to the EfficientNet family. It was introduced by Mingxing Tan and Quoc V. Le [18].

2.3.1. Leaf disease classification

Scaling helps to offer improved accuracy on maximum datasets, but the conventional techniques offer model scaling very randomly, either depth wise or width wise, or consider the images of larger resolution. Traditional methods need manual tuning of parameters, resulting in sometimes no improvement in performance. EfficientNet uses a compound coefficient to scale up models in an effective way. Using the scaling method and AutoMl, this work concentrated on five models with various dimensions.

EffiencientNet B0 follows a compound scaling method, simultaneously scaling the network dimensions (depth(d) width(w) and resolution (r)). It comprises various building blocks, including inverted residual blocks with linear bottleneck and mobile inverted bottleneck blocks. The architecture is scaled by controlling depth, width, and resolution. The number of layers controls the depth of the network. The width is controlled by the width multiplier, which increases or decreases the number of channels in individual layer. The resolution multiplier (r) controls the resolution, affecting the input sample size. The baseline architecture (EfficientNetB0) has seven inverted residual blocks, including the stem block as shown in Table 2.

Table 2. EfficientNet B0 baseline network

Step	Operator lF_p	Resolution $[xW_{Pl}]$	#Channels $[C_{Pl}]$	#Layers $[sL_l]$
s1	Conv 3x3	224x224	32	1
s2	Conv1, L 3x3	112x112	16	1
s3	Conv6, L 3x3	112x112	24	2
S4	Conv6, L 5x5	56x56	40	2
S5	Conv6, L 3x3	28x28	80	3
S6	Conv6, L 5x5	14x14	112	3
S7	Conv6, L 5x5	14x14	192	4
S8	Conv6, L 3x3	7x7	320	1
S9	Conv1x1& Pooling & FC	7x7	1280	1

The stem block consists of a sequence of convolutional layers and pooling operations. The numeral of parameters and floating-point operations (FLOPs) in EfficientNetB0 is significantly smaller than other popular architectures like ResNet and MobileNet while maintaining competitive accuracy. A ConvNet Layer l can be denoted as a function as (1).

$$N = \left(\sum_{l=1}^{s\odot} F_l^{Ll} \right) \left(X\left(H_{l,} W_{l,} C_l\right) \right) \tag{1}$$

Here F_l^{Ll} represents the layer F_l is recurring L_l in steps l,(H_l, W_l, C_l) is the shape of input X of l. Here the channel dimension is extended over layers from input size (224,224,3) to final crop size images (7,7,512). F_l model tries to extend the network length L_l, width w_l and, (H_l, W_l) for every layer. The design space is reduced by scaling all the layers uniformly with constant ratio. The target here is to maximize the accuracy with the available resources which can be formulated as (2):

$$\max_{d,w,r} Accuracy\left(N(d, w, r)\right) \tag{2}$$

subject to:

$$N(d,w,r) = \left(\sum_{l=1}^{s\odot} F_l^{\,d,Ll}\right)\left(X\left(r, H_{pl,} W_{pl,} C_{pl}\right)\right)$$
$$Memory(N) \leq target_{Memory}$$
$$FLOPS(N) \leq target_{\_flops}$$

here, d, w, r are coefficients for scaling network depth, width, resolution. $Fp_l Hp_l, Wp_l, Cp_l$ are predefined parameters from baseline network. B0 to B4, may vary based on the implementation and library used.

2.3.2. Leaf disease detection

The YOLO algorithm is a deep learning-based entity detection system. It divides a sample into a grid and forecasts bounding boxes and class likelihoods for objects within each grid cell. YOLO is designed for detecting diseases in plant leaves; here, it is adapted for structure for such tasks, including cotton leaf disease detection. YOLO takes an image as input, dividing the image into an S X S grid. Each grid cell forecasts B bounding boxes.

Each bounding box is represented by $(x1, y1, w1, h1, c1)$. Here, x1 and y1 are the coordinates of the bounding box's center relative to the grid cell. w, h are the width and the height of the bounding box close to the whole image. c is the confidence score that the box contains an object. Each grid predicts C-class probabilities. The class probabilities are conditioned on the presence of an object in the bounding box. The YOLO is an exclusive-stage identification model premeditated to perceive substances in real-time. The model processes a complete sample in a single forward pass of a CNN, as shown in Figure 4.

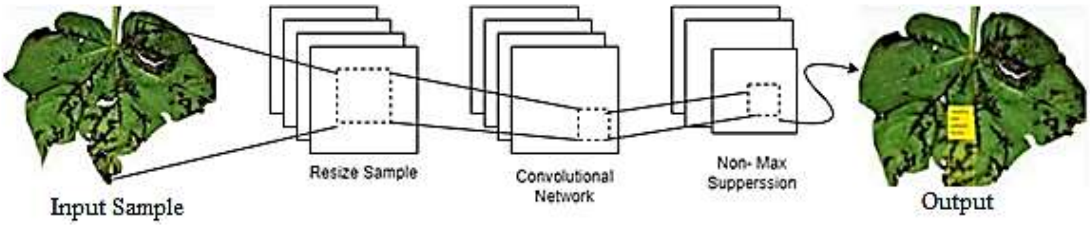

Figure 4. YOLO model for live monitoring substance detection

This work concentrated on real-time object detection using YOLO7. YOLO7 model trains images at multiple scales and combines the predicted results to handle objects of various sizes and shapes. The YOLO loss function is a combination of localization loss, confidence loss, and classification loss as (3):

$$Loss = \lambda coord \sum_{i=0}^{s^2}\sum_{j=0}^{B} 1_{ij}{}^{obj}[(x_i - \hat{x_i})^2 + (y_i - \hat{y_i})^2] + \lambda coord \sum_{i=0}^{s^2}\sum_{j=0}^{B} 1_{ij}{}^{obj}[(\sqrt{w_i} - \sqrt{\hat{w_i}})^2 + \left(\sqrt{h_i} - \sqrt{\hat{h_i}}\right)^2] + \sum_{i=0}^{s^2}\sum_{j=0}^{B} 1_{ij}{}^{obj}[\left(C_i - \hat{C_i}\right)^2 + \lambda noobj \sum_{i=0}^{s^2}\sum_{j=0}^{B} 1_{ij}{}^{obj}[\left(C_i - \hat{C_i}\right)^2 + \sum_{i=0}^{s^2} 1_{ij}{}^{obj} \sum_{ceclasses}[(p_i(c) - \hat{p_i}(c))^2 \quad (3)$$

Here $\lambda coord$ and $\lambda noobj$ are hyperparameters that control the effect of diverse components of the loss. The operator $1_{ij}{}^{obj}$ selects the matched boxes. Here i indicates the cell and j is used for representing box. When jth box from the ith cell is matched to any object then $1_{ij}{}^{obj}$ assigns as 1 otherwise 0. $1_{ij}{}^{obj}$ is the inverted term of $1_{ij}{}^{noobj}$ it assigns 1 value when there are no objects in the cell i.

2.4. Model training

The YOLO model training method involved feeding the preprocessed dataset into the Efficient Net model and optimizing key constraints mentioned in the Table 3. EfficientNet ensures that the model remains efficient, even when scaled to use larger datasets and higher resolutions. By optimizing computational complexity (FLOPS)and the number of parameters, the model can be deployed on embedded GPU chips without significant performance trade-offs. Integrating the YOLO model for object detection and EfficientNet for classification allows for high accuracy in detecting and classifying cotton plant diseases, essential for timely intervention and crop management.

Table 3. EfficientNet network parameter setting for experiment

Model	Image size	Dataset size	\# of Para	Scaling factor	\#FLOPS
EfficientNetB0	224 x 224	250	5.3M	1.0,1.0,1.0	1.8 B
EfficientNetB0	224 x 224	350	6 M	1.0,1.0,1.0	4.2 B
EfficientNetB0	260x260	550	7 M	1.1,1.2.1.1	9.9B
EfficientNetB0	300x300	800	12 M	1.4,1.8,1.2	19 B
EfficientNetB0	384x384	1340	19 M	1.4,1.8,1.2	37 B

2.5. Model evaluation

For the performance of models, a rigorous evaluation was conducted using a separate test dataset. Metrics such as accuracy for Efficient Net and YOLO model’s metrics such as recall, precision, Map@0.5, mAP120.5:095 were computed to understand the model’s effectiveness in disease detection comprehensively.

2.6. Interpretability and visualization

Beyond quantitative metrics, we employed visualization techniques to interpret the decision-making processes of the models. The visualization involves heat maps and attention maps to mark the critical areas of the images that majorly contribute to the model's predictions. For the YOLO model, the results are visualized using the bounding boxes and object detection confidence scores; for the classification model, feature maps are examined to see which features the model focuses on for classification. The visualization helps to verify that the models are making decisions based on relevant characteristics and displaying insights into areas needing further improvement.

2.7. Integration with deployment tools

This work considered integrating trained models with deployment tools suitable for real-world scenarios to ensure practical applicability. This involved exploring options such as containerization and cloud-based deployment to facilitate accessibility and scalability. This involved using the containerization tool Docker to ensure the model can run consistently across various environments, considering all dependencies and configurations. The model is deployed using Google Cloud, allowing real-time monitoring and processing of cotton health data. This configuration ensures that the system is effective in research settings and practical and reliable in the real world.

3. RESULT AND DISCUSSION

This work applied Efficient Net versions to produce the models that give higher accuracy than the existing models, with varying parameters such as FLOPS, image size, dataset size, number of parameters. This scaling is generic and can be applied to other models. The proposed system exceeds in precision using few attributes and reduces training time. The versions of the EfficientNet have details, including the number of parameters, scaling factors (d, w, r), the average time taken, image size, dataset size, and number of FLOPS, as shown in Table 3, resulting in the more robust and efficient model. The number of parameters increases as we move from B0 to B4. The experimentation considered Efficient-NetB0 to EfficientNetB4 and YOLO V1 to V4, considering various parameters. It has been observed that the more complex models are designed to handle larger images and need larger datasets to be used for real-world training. Here, the scaling factors depth(d), width(w), and resolution(r) are used to adjust model architectures. The larger values of parameters observed model complexity. The mean number of hours required for detection is reported for every model. The EfficientNet B0 takes the least time, whereas EfficientNet B4 takes the most significant amount. For real-world applications, this information is essential where prediction results are critical. The computational efficiency of the models is represented using FLOPS, showing higher computational requirements of more complex models. The model selection involves trade-offs between computational requirements, model complexity, and inference time. The upgraded models B3 and B4 offer increased capacity to record complex patterns with higher computational demands. The selection of models depends on practical considerations such as time constraints for predictions, available computing resources, real-time considerations, practical considerations, and application-specific requirements. The EfficientNetB4 is a more complex model that uses superior performance, even at the expense of longer prediction time. The depth indicates the model’s density. It’s significant to note that the actual parameter count may differ based on the implementation and specific configurations applied during training. Additionally, memory and computational requirements increase with larger models, and deploying them may require more powerful hardware. The correlations between the actual cotton leaf classes and the predicted cotton leaf diseases for EfficientNet B0 is shown in Figure 5.

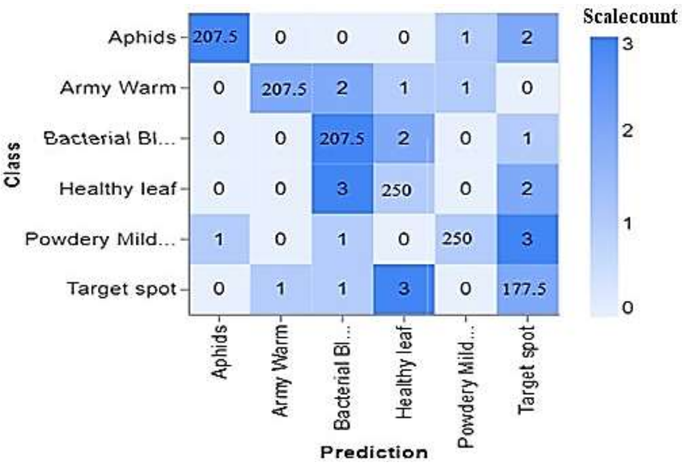

Figure 5. Correlation between the actual samples and the predicted samples

The recommended image size:- 640×640. EfficientNet model performance evaluated using confidence of the model and accuracy of the model for each class as shown in Figures 6 and 7. The confidence of the model changes in real time because of moving objects as shown in Figure 6. As per observation for most of the input is object moving the model incline towards Armyworms. Table 4 offers a concise overview of the model's detection performance across multiple versions, helping to assess its strengths and weaknesses in various aspects of object detection. The metrics include precision, recall, mean average precision at an intersection over union (mAP@0.5), and mean average precision from IOU 0.5 to 0.95 (mAP120.5:095). Each row corresponds to a specific YOLO version, and the values in each column represent the corresponding performance metrics for that version. The model has undergone rigorous training, resulting in low training losses, and its evaluation performance demonstrates high precision, recall, and mAP across various IoU thresholds. The training losses demonstrate the model's proficiency in learning key aspects.

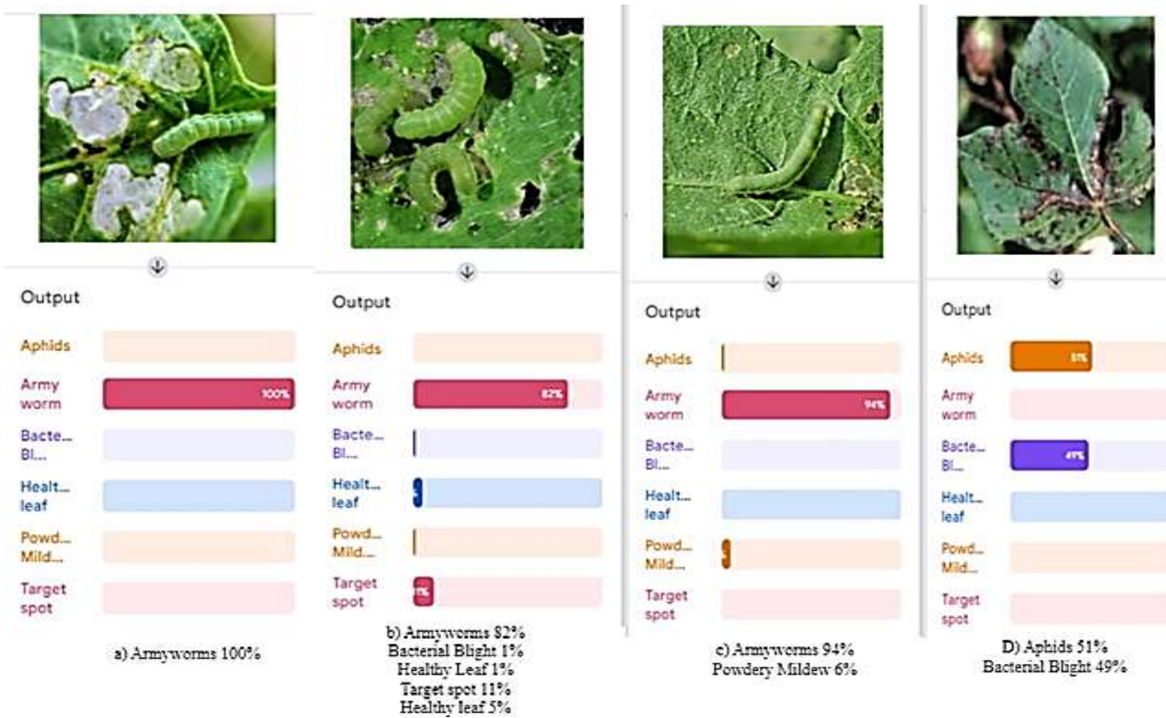

Figure 6. Confidence of the model per each class while observing the samples form real time

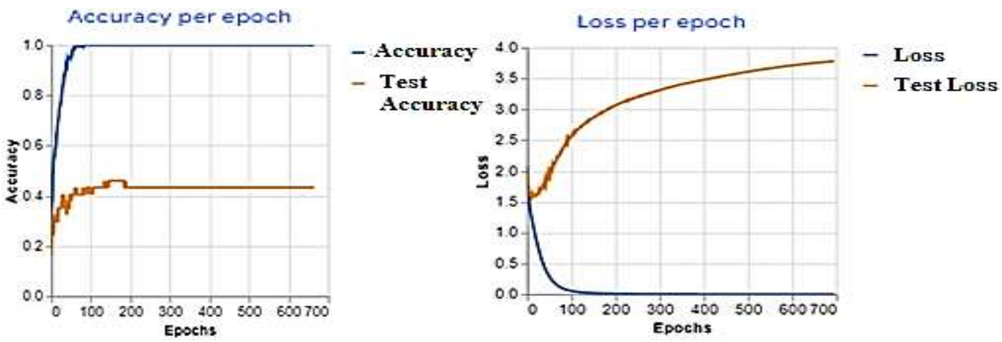

Figure 7. Accuracy per epochs (left) loss per epochs (right)

The low box loss indicates accurate bounding box prediction, while low objectness and classification losses signify the model's ability to distinguish objects and classify them correctly during training. The performance of the trained YOLO model verified using: training losses, box loss, objectness Loss, Classification Loss and evaluation metrics using precision, recall, mAP at IoU 0.5, mAP from IoU 0.5 to 0.95.

Table 4. Comparison of performance analysis of different YOLO model

Model	Precision	Recall	mAP@0. 5	mAP120.5:095
YOLO V1	73%	40%	40%	55 %
YOLO V2	75%	60%	70%	60%
YOLO V3	80%	80%	88%	65%
YOLO V4	96%	98.3%	99.2%	70%

These metrics reflect the robustness and accuracy of our YOLO model as shown in Figure 8. The variation of results as per model is represented from Figure 9 to Figure 12.

- Box loss: the box loss symbolizes the loss in predicting bounding box coordinates. A lower box loss represents that the model is successfully learning to localize constituents.
- Objectness loss*:* phe objectness loss calculates how well the model differentiates between object and background noise. The lower objectness loss represents improved object detection capability. Classification loss*:* The classification loss reflects the accuracy of predicting object classes. The lower classification loss is the better class prediction.
- The evaluation metrics showcase the model's performance on unseen data. High precision indicates a low false positive rate, while high recall reflects a low false negative rate. Additionally, mAP at IoU 0.5 and mAP from IoU 0.5 to 0.95 provide insights into the model's ability to detect objects accurately across different levels of overlap.
- Precision*:* precision measures the percentage of correctly foreseen positive instances to the total foreseen positives. Higher precision value specifies fewer false positives cases.
- Recall*:* recall measures the ratio of correctly predicted positive instances to the total actual positives. Higher recall indicates fewer false negatives.
- mAP at IoU *0.5:* mAP at IoU 0.5 evaluates the model's precision across different classes with a less strict overlap criterion (IoU of 0.5).
- mAP from IoU *0.5 to 0.95:* mean Average Precision from IOU 0.5 to 0.95 considers a range of IOU thresholds. It comprehensively evaluates the model's precision across different IOU levels.

The YOLO model demonstrates robust performance during both training and evaluation phases. The combination of low losses and high evaluation metrics indicates its effectiveness in accurately detecting and classifying objects. As we move forward, we plan to leverage these insights to refine the model further and explore its deployment in real-world scenarios. As per observation YOLO V4 demonstrates the highest precision, recall, mAP@0.5, and mAP120.5:095 among the versions listed. YOLO V1 shows lower performance across all metrics compared to the subsequent versions. YOLO V3 and V2 exhibit improvements in precision, recall, and mAP scores compared to the earlier versions but are outperformed by YOLO V4.

Predicting cotton leaf diseases using deep learning models presents several challenges that researchers and practitioners must address. Here are some common challenges associated with cotton leaf disease prediction: Acquiring a large and diverse labelled dataset for training deep learning models can be challenging. More data may be needed for the model's generalization of unseen examples. Imbalances in the distribution of healthy and diseased samples can affect model performance. Addressing class imbalances is crucial to ensure the model learns to distinguish between healthy and diseased instances effectively.

Figure 8. Object detection using YOLO Model

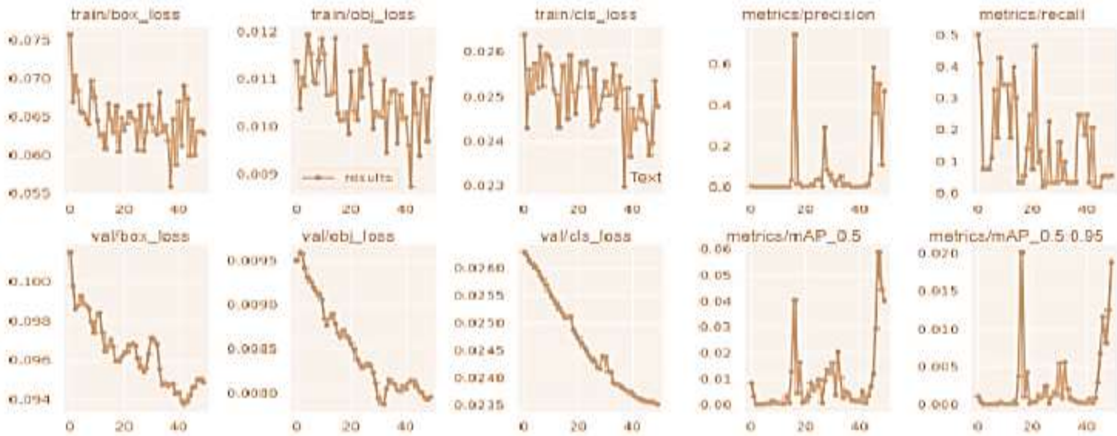

Figure 9. Training graph YOLO -V1

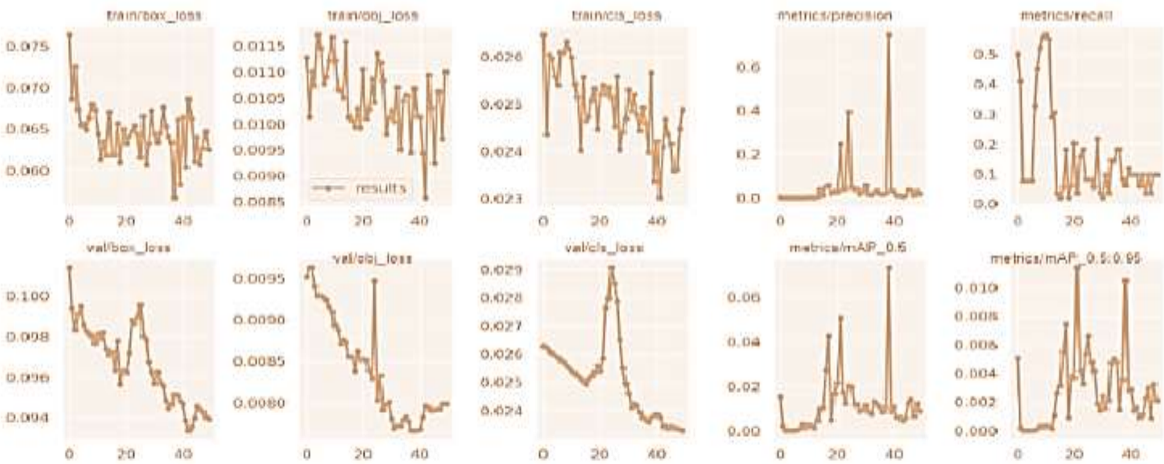

Figure 10. Training graph YOLO -V2

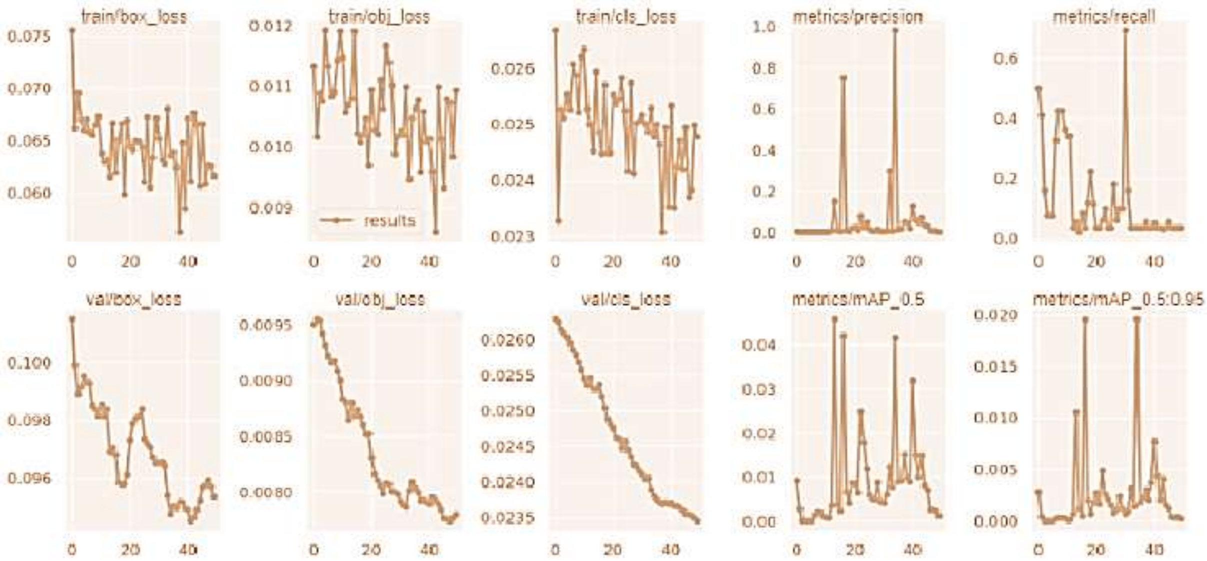

Figure 11. Training graph YOLO -V3

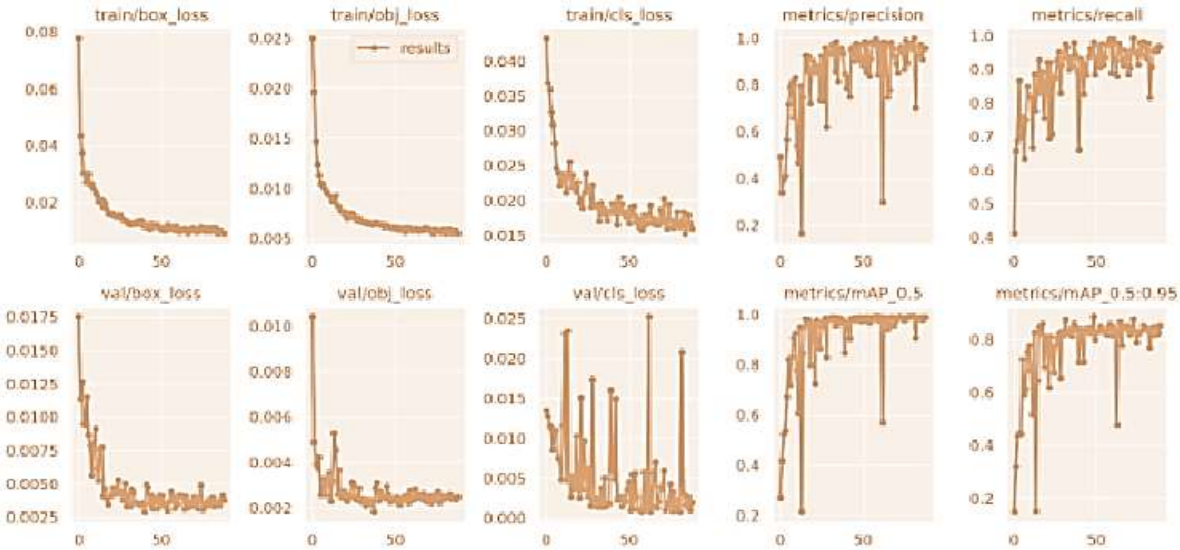

Figure 12. Training graph YOLO -V4

Cotton plants and leaves can exhibit significant color, size, shape, and orientation variability. Models must be robust enough to handle these variations to perform well in real-world scenarios. There are many challenges needs to be concentered as follows: cotton plants can be afflicted concurrently with many diseases simultaneously. Developing a model that identifies multiple diseases in single sample considers more complexity to the inference task. Cotton diseases many appear differently in different geographic regions. Models trained on data from one region may not generalize to the other regions. There might be possibility the appearance of symptoms may change. The deep learning model makes the prediction challenging because of the black-box. To train CNN it requires significant number of resources. With limited resources its very challenging to acquire data, model integration with existing system and deploying the model for real world. Other challenges such as addressing issues like varying lighting conditions and camera angles also privacy and data ownership, is an important consideration.

4. CONCLUSION AND FUTURE WORK

The efficient cotton plant health monitoring system uses YOLO and an EfficientNet for object detection and classification, demonstrating its effectiveness in precisely predicting and monitoring diseases that affect cotton plants. The system monitors the health of cotton plants in real-time. Prompt detection of diseases allows for reducing the risk of extensive crop damage. The proposed model shows the robustness across diverse environmental conditions and variations in plant appearance. The system is adaptable to different environmental conditions, such as weather and variation in lighting, enhancing the plant growth stages in various agricultural settings. The proposed system, driven by YOLO-based disease prediction, shows promise for integration and scalability with current agrarian technologies. The system allows scalability in terms of systems deployment with varying agricultural landscapes and field sizes while enhancing the overall effectiveness of farm management. This work addresses the challenges, such as an images with different shapes, sizes, and backgrounds. The system improved in real-time capabilities, robustness, precision, and scalability, and it can be utilized as a valuable tool for modern agriculture. Future enhancement is considered as an exploration of additional data sources and the use of emerging technologies. In conclusion, the proposed cotton disease prediction system presents an efficient and more reliable solution for monitoring the health of cotton plants. As with technological advancement, ongoing improvement will be pivotal in sustainable and optimized crop management practices.

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