

COTTON LEAF DISEASE DETECTION

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ABSTRACT Cotton leaf diseases are responsible for major economic losses in agriculture, and hence early and precise detection is of utmost importance to ensure proper management of the disease. Conventional manual inspection is time-consuming, subjective, and error-prone, resulting in tardy interventions. Current automated solutions are often not sufficiently accurate, generalizable, or interpretable, and hence their practical application is curbed. To overcome these difficulties, this research proposes a sophisticated deep learning-based system for detection of cotton leaf diseases that incorporates EfficientNet for classification, U-Net for segmentation, YOLOv8 for real-time object detection, and the Segment Anything Model (SAM) for accurate segmentation. Explainability is improved through the use of Local Interpretable Model-Agnostic Explanations (LIME) for delivering transparency in model decision-making. The classification model obtained good accuracy, with the training, validation, and testing accuracies being 98.69%, 96.53%, and 98.06%, respectively. U-Net showed strong segmentation performance, recording 97.61% accuracy in training, 96.99% in validation and 97.49% in testing. YOLOv8 achieved a mean average precision (mAP0.5) of 0.820, a precision of 0.938, and a recall of 0.812, which ensured good disease detection with very few false positives. The system measures disease severity by quantifying infection percentages through calculations, facilitating data-driven decision-making among farmers and agricultural experts. Through high detection accuracy, accurate segmentation, and interpretability, the framework provides an efficient and scalable solution for the early diagnosis of cotton leaf disease, enhancing disease control and sustainable crop management.

INDEX TERMS Accuracy, Agricultural Productivity, Agriculture, AI, Aphids, Army Worm, Attention Mechanisms, Automated Detection, Bacterial Blight, Blockchain, Classification, Computational Resources, Convolutional Neural Networks (CNNs), Cotton, Cotton Leaf Curl Virus (CLCuV), Crop Management, Crop Yield, Data Augmentation, Deep Learning, Disease Detection, Disease Management, Disease Severity, Disease Segmentation, Drones, Early Detection, EfficientNet, Ensemble Learning, Explainable AI (XAI), False Positives, Farmers, Feature Extraction, Federated Learning, Fine-Tuning, Fungal Infection, Ground Truth, HSV Thresholding, Hybrid Models, Image Processing, Infection Percentage, Interpretability, IoT, LIME (Local Interpretable Model-Agnostic Explanations), Machine Learning, Mask Creation, Mean Average Precision (mAP), Model Explainability, Object Detection, Overfitting, Precision Agriculture, Powdery Mildew, Real-Time Detection, Recall, Remote Sensing, RoboFlow, SAM (Segment Anything Model), Segmentation, Smart Agriculture, Sustainable Farming, Target Spot, Transfer Learning, U-Net, YOLOv8

I. INTRODUCTION

Cotton is an important cash crop globally, and it is a key player in the textile sector and the economies of most nations. Cotton leaf diseases like Aphids, Bacterial Blight, Army Worm, Target Spot, Powdery Mildew and cotton leaf curl virus (CLCuV) are significant threats to crop yield and quality. Plant diseases account for global crop production losses of up to 40% per year, as reported by the Food and Agriculture Organization (FAO). In India alone, cotton leaf diseases can lead to yield losses of 30-35%, severely impacting farmers' livelihoods and the agricultural economy (FAO, 2021). Early and precise disease detection is critical for effective management, but conventional manual

inspection techniques remain time-consuming, labour-intensive, and susceptible to human error.

Recent studies have demonstrated the effectiveness of deep learning in plant disease classification, underscoring the potential of automated detection systems in agriculture. Brahimi et al. pointed out how deep learning models drastically enhance the accuracy of classification. Additionally, recent architectures like ConvNeXt and attention mechanisms improved the accuracy of cotton disease identification (2). Moreover, studies by Noon et al. utilized the enhanced YOLOX (3) model to manage the severity levels of multiple concurrent cotton plant diseases and showcased deep learning potential for real-time disease evaluation.

Current disease detection techniques are based on color thresholding and manually crafted features, which are very sensitive to variations in lighting, leaf texture, and disease development. Even machine learning algorithms demand a lot of feature engineering, restricting their practicality in real-world agricultural environments. Moreover, the absence of explainability in most AI models creates doubts regarding their reliability and acceptance. In response, researchers have investigated blockchain-based disease detection (4) and hybrid methods that integrate numerous different deep learning approaches (5).

Deep learning has transformed intelligent farming by providing automated, high-precision disease classification with very little human input. Advanced architectures such as EfficientNet for classification, U-Net for segmentation, and YOLO for real-time object detection have performed better. Additionally, explainable AI techniques such as LIME (Local Interpretable Model-Agnostic Explanations) have been utilized to improve trust in AI-based disease diagnosis by demystifying model decision-making (1).

Recent works have also well supported the efficacy of such approaches. Islam et al. used fine-tuned deep learning architectures for predicting cotton diseases in smart web-based applications, proposed predictive models for CLCuD under different ecologic conditions using machine learning. Shahid et al. also proposed an ensemble deep learning model for the classification of a cotton crop and highlighted the potential of AI in precision agriculture.

Our study integrates advanced deep learning techniques to develop a robust and efficient approach for cotton leaf disease detection. By leveraging EfficientNet for classification, U-Net for segmentation, YOLOv8 for real-time detection, SAM for precise segmentation, and LIME for model interpretability, we aim to create an automated, scalable, and reliable system for early disease identification. This framework enables farmers to take timely corrective measures, enhancing cotton yield and safeguarding agricultural productivity.

II. LITERATURE REVIEW

Cotton is an important cash crop globally, and it is a key player in the textile sector and the economies of most nations. Cotton leaf diseases like Aphids, Bacterial Blight, Army Worm, Target Spot, Powdery Mildew and cotton leaf curl virus (CLCuV) are significant threats to crop yield and quality. Plant diseases account for global crop production losses of up to 40% per year, as reported by the Food and Agriculture Organization (FAO). In India alone, cotton leaf diseases can lead to yield losses of 30-35%, severely impacting farmers' livelihoods and the agricultural economy (FAO, 2021). Early and precise disease detection is critical for effective management, but conventional manual

Cotton Disease Detection Using ConvNeXt and Attention Mechanisms (1) introduced a novel method employing the ConvNeXt model with a Multi-Scale Pyramid Attention (MSPA) module. The research utilized two datasets,

CottonDataset1 and CottonDataset2, recorded using a quadruped robot, providing accurate and real-time disease detection. The model proposed performed remarkably well with an accuracy of 97.2% to 100% and low inference time, thus being remarkably efficient for field deployment in real-world agricultural applications. The study solved major challenges like complex background noise and limited annotated data, demonstrating the capability of attention-based deep learning models to heavily enhance robustness and reliability of crop disease detection. Severity Level Management of Simultaneous Co-Occurring Cotton Plant Diseases via Improved YOLOX Model (2) addressed the challenging problem of simultaneous symptoms in cotton plant diseases. With an improved YOLOX model augmented by a modified Spatial Pyramid Pooling (SPP) module and α -IoU loss function, the study proposed a strong detection framework to distinguish multiple co-occurring diseases. Utilizing a self-harvested dataset of 1,112 images, the model attained a mean Average Precision (mAP) of 73.13%, which proves its ability to deal with variations in disease severities. This research is highly applicable in agricultural fields where plants tend to be infected by various diseases at once, prompting a precise diagnosis to be important for effective disease control. Incremental Cotton Diseases Detection Based on Aerial Remote Sensing Image and Blockchain Sharding (3) suggested a new integration of lightweight YOLOv5n with ShuffleNetV2, SE attention, and blockchain sharding for improved disease detection while maintaining data security. The research employed a dataset of 3,000 images collected via UAVs in Xinjiang which addressed nine types of cotton disease. Utilizing federated learning, the work achieved an accuracy of 94.31%, successfully addressing catastrophic forgetting in machine learning models. Besides, the application of blockchain sharding ensured data privacy, and thus this approach was highly suitable for large-scale agricultural monitoring and real-time disease tracking without the risk of centralized data breaches. Hybrid Approach of Cotton Disease Detection for Improved Crop Health and Yield (4) explored an ensemble learning approach by combining Decision Tree and Random Forest models for cotton disease diagnosis. Using the Kaggle Cotton Disease Dataset, the hybrid model outperformed single-classifier models such as SVM and Decision Tree with a 94.5% accuracy rate. The study demonstrated the power of ensemble learning in agricultural applications where multiple weak classifiers are combined to improve disease prediction reliability. The proposed method presented an effective and scalable solution that can be used in smart farm systems for crop health monitoring and yield maximization. Hybrid Ensemble Learning with CNN and RNN for Multimodal Cotton Plant Disease Detection (5) introduced a new multimodal approach through the combination of convolutional neural networks (CNN) for image processing with recurrent neural networks (RNN), specifically LSTMs, for environmental data processing. The research utilized the Kaggle Cotton Disease

Dataset with additional real-time environmental data to achieve more accurate diagnoses. The hybrid model had 93.01% accuracy, which proves the improvement of disease prediction accuracy due to the incorporation of environmental parameters. The study emphasized the need for integrating disparate data modalities for creating more effective disease detection mechanisms in precision agriculture.

Deep Learning Model for Cotton Disease Prediction Based on Fine-Tuning with Smart Web App in Agriculture (6) developed a fine-tuned transfer learning approach through models such as VGG-16, VGG-19, Inception-V3, and Xception. The study used a dataset of 2,310 images from the Kaggle Cotton Disease Dataset and determined that Xception performed best at an incredible rate of 98.70%. In addition, the model was integrated into an intelligent web-based system, which permitted real-time detection and analysis of diseases. The system provided a scalable, user-friendly solution for cotton disease diagnosis for farmers and agricultural experts.

Cotton Leaf Curl Disease (CLCuD) Prediction Modeling in Upland Cotton Under Different Ecological Conditions Using Machine Learning Tools (7) was concerned with the prediction of Cotton Leaf Curl Disease spread under different ecological conditions. The research made use of machine learning methods, such as Artificial Neural Networks (ANN), Bootstrap Forest, Boosted Tree, and Multiple Linear Regression, with 8,000 plants from four cultivars in Northwestern India analyzed. Bootstrap Forest showed the best performance amongst the models that were executed, with an R^2 of 0.81. The study highlighted the significance of using ecological variability in the construction of predictive models in agriculture disease management. An Ensemble Deep Learning Models Approach Utilizing Image Analysis for Cotton Crop Classification in Smart Agriculture Enabled through Artificial Intelligence (8) suggested an ensemble learning methodology combining Alex Net, Google Net, InceptionV3, and VGG-19 with Continuous Wavelet Transform (CWT) and Fast Fourier Transform (FFT) techniques. The research work was conducted over a handcrafted dataset of Pakistani cotton fields and achieved 98.4% accuracy using the images based on CWT. Taking advantage of several deep learning architectures and deep image processing techniques, this solution has immensely improved classification accuracy in smart agricultural applications. A Comprehensive Cotton Leaf Disease Dataset for Enhanced Detection and Classification (9) focused on creating a high-quality labeled dataset for machine learning model training employed for cotton disease detection. The dataset had well-annotated images of different cotton leaf diseases so that researchers and developers could leverage it to improve their deep learning solutions in precision agriculture. The research sought to fill the gap in available datasets to enable stronger and more generalizable machine learning models for disease identification. Dominance of Cotton Leaf Curl Multan Virus-Rajasthan Strain with the Third Epidemic of Cotton Leaf Curl Disease in Pakistan (10)

performed a phylogenetic analysis based on AlphaFold protein structure modelling of Cotton Leaf Curl Disease outbreaks occurring in Sindh and Punjab, Pakistan. The research found dominance of the Rajasthan strain during the third epidemic, which helped them understand the disease-spreading genetic drivers. This study helped advance knowledge of virus mutations and their relevance to cotton crop management.

Cotton Leaf Curl Disease's Susceptibility Scale Level Detection Using Deep Learning (11) outlined a deep learning model that involved the use of data normalization and augmentation strategies in enhancing accuracy. The research established a self-compilation dataset comprising 1,349 images with a 99% accuracy score. The dataset was handled very well by the model, giving proof of how preprocessing strategies enhance disease classifying work. Interpretable ResNet50 Copula Entropy-based Learning Model for Cotton Plant Disease Prediction (12) proposed an explainable deep learning model by fusing ResNet50 with Copula Entropy-boosted Grey Wolf Optimization. The proposed model was learned using 2,400 images from the Kaggle Cotton Disease Dataset with an accuracy of 99%. Deep learning explainability was highlighted as a priority to ensure that the decisions made by the model would be interpretable and trustworthy to be applied to real-world situations in agriculture. An Ensemble Transfer Learning-Based Deep Convolution Neural Network for Detection and Classification of Diseased Cotton Plants and Leaves (13) utilized a combination of InceptionV3, InceptionResNetV2, Mobile Net, VGG16, and Xception to improve classification accuracy. The model attained 99.48% accuracy on binary-class datasets to overcome the problems of overfitting and scant data availability. This work illustrated the efficacy of ensemble learning in enhancing disease detection performance. Boosting Cotton Whitefly (*Bemisia tabaci*) Detection and Counting with a Low-Cost Deep Learning Solution on the Raspberry Pi (14) designed an optimized YOLO v8s model using Swin-Transformer and SAHI slicing methods for real-time pest monitoring. The model was trained on 1,200 whitefly images on cotton leaves and achieved an accuracy of 0.87 and a recall of 0.89. This method offered a low-cost, real-time pest detection solution through edge computing. Few-Shot Cotton Leaf Spots Disease Classification Using Metric Learning (15) proposed a few-shot learning model that used CNN and SVM to overcome the problem of limited training sets. The research used only 150 samples for training and obtained an accuracy rate of 95.13%, proving the applicability of metric learning in agricultural uses.

Classification of Diseased Cotton Leaves and Plants Using Enhanced Deep Convolutional Neural Network (16) proposed an optimized Deep Convolutional Neural Network (DCNN) motivated by Alex Net. With training data comprising 2,293 images of the Kaggle Cotton Disease Dataset, the model produced a test accuracy of 97.98% at a lesser computational time. An Effective Deep Learning with a Big Data-Based

Cotton Plant Monitoring System (17) investigated the pre-trained CNN model utilization, i.e., ResNet18, Google Net, InceptionV3, and MobileNetV3. MobileNetV3 had 93.9% accuracy when trained with 1,200 real-time field images taken from Indian cotton fields, recommending early disease diagnosis in large-scale agriculture monitoring. Cotton Crop Classification Using Satellite Images with Score Level Fusion Based Hybrid Model (18) utilized hybrid models for satellite image-based cotton crop classification. Through score-level fusion to improve classification accuracy, this method facilitated large-scale agricultural monitoring through remote sensing technology. Improved Conditional Self-Attention Generative Adversarial Network for Cotton Plant Disease Detection in IoT-Based Crop Management (19) proposed a self-attention GAN to enhance disease detection in IoT-based crop management systems. Although the dataset information was not specified, the model aimed at facilitating smart farming applications using deep learning. Smart Cotton Verticillium Wilt Identification Based on Spectral and Image Feature Fusion (20) integrated hyperspectral imaging with Efficient Net and SVM for the identification of cotton Verticillium Wilt. The 997-cotton leaf sample dataset led to a stunning 98.99% accuracy, enabling precision agriculture non-destructive disease testing.

This research emphasizes remarkable progress in cotton disease diagnosis using deep learning, attention mechanisms, blockchain, and ensemble models. The research presents real-world problems like small data sets, symptoms overlapping, real-time observation, and ecological heterogeneity and provides real-world solutions for precision agriculture.

III. PROPOSED SYSTEM

In this paper, we present a stable and scalable Cotton Leaf Disease Detection System that integrates deep learning-based image segmentation, classification, and explainability techniques. Our system has two independent processing pipelines with support for different computational resource levels while ensuring high accuracy in disease detection

A. Pipeline 1: EfficientNetV2 + U-Net + LIME (Lightweight Approach)

This pipeline is computationally efficient but highly accurate and consists of three main stages: classification, segmentation, and disease severity estimation with a further layer of explainability through the application of XAI methods. EfficientNetV2B0 is used in the first stage for classifying cotton leaf images into multiple disease categories. The model is fine-tuned to produce greater accuracy, giving a classification tag to every input image, e.g., "healthy" or "infected."

In the second phase, segmentation is done via a combination of HSV thresholding and a U-Net model. As a first step, HSV thresholding is utilized to produce training binary masks; pixels belonging to healthy color ranges (e.g., green and orange) are marked as healthy, and all the rest are labeled as

infected. These thresholded masks are used as ground truth for training the U-Net, which then learns to produce more accurate segmentation masks. On inference, the U-Net accepts input images and produces high-precision segmentation maps. The third phase involves disease severity estimation. The created segmentation masks, which are normally in grayscale format, are inspected by quantifying black (infected) and white (healthy) pixels to determine the percentage of infection within the leaf image. Last but not least, to further boost interpretability, Local Interpretable Model-Agnostic Explanations (LIME) is applied. LIME identifies the most important areas of the image that contributed to the classification outcome, providing insight into the model's reasoning and further improving transparency

B. Pipeline 2: YOLOv8 + Segment Anything Model (SAM) (High-Performance, Advanced Detection & Segmentation)

This pipeline takes advantage of the strength of YOLOv8, a highly developed object detection model, combined with the Segment Anything Model (SAM) in order to provide very accurate disease detection and segmentation. Precision and dependability-focused, it relies on sophisticated compute capabilities to optimize performance in crop disease surveillance.

In the initial phase, detection of objects is carried out through YOLOv8, and it has been trained on a pre-annotated RoboFlow dataset, which is properly formatted for YOLO. This model detects diseased areas in real-time efficiently, annotating them through bounding boxes to indicate the affected regions over the input images.

The second step is segmentation with SAM. The bounding boxes produced by YOLOv8 are used as input prompts for the Segment Anything Model, which in turn generates very accurate segmentation masks. These masks outperform conventional methods such as U-Net by a large margin in terms of precision, and hence SAM is a perfect fit for fine-grained segmentation tasks.

In the last phase, estimation of disease severity is done by segmenting the masks. By using thresholding, the system measures the degree of infection by calculating the ratio between black (infected) and white (healthy) pixels. This reading gives a clear percentage of the infected region, and thus disease effect can be estimated accurately. In total, this combined YOLOv8 and SAM pipeline provides an advanced solution to precision agriculture with state-of-the-art detection, segmentation, and severity estimation for efficient plant disease control.

IV. METHODOLOGY

This section provides a detailed description of the pipelines utilized in detecting, segmenting, and analyzing cotton leaf diseases in the proposed system. It provides the methodologies employed in Pipeline 1 (EfficientNetV2 + U-Net + LIME) and Pipeline 2 (YOLOv8 + SAM) to ensure high accuracy, effective disease segmentation, and precise infection severity estimation.

A. Pipeline 1: EfficientNetV2 + U-Net + LIME

This pipeline is a robust and effective system to diagnose cotton leaf diseases using a combination of modern deep learning algorithms and image processing techniques. It starts with acquiring input images and preprocessing, in which the system takes an input image of a cotton leaf, perhaps showing signs of discoloration, wilting, or leaf spots. The image gets resized and normalized to ensure consistent input dimension.

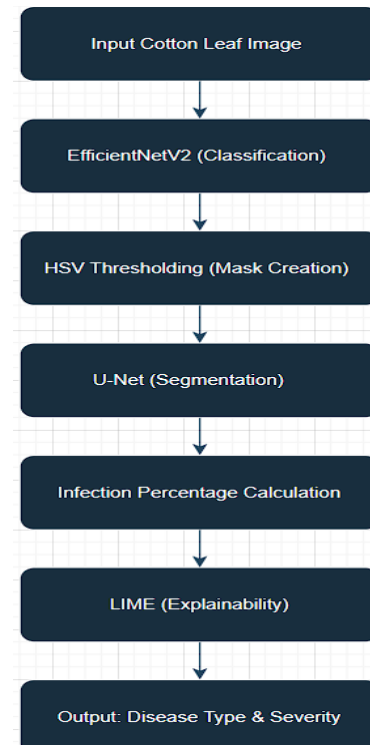


Fig 1: Block Diagram of Pipeline 1

Classification then comes next employing EfficientNetV2, one of the greatly optimized convolutional neural network designs famous for high accuracy and high efficiency. EfficientNetV2 builds on what the previous generation has to offer, including minimal convolutional kernel sizes to eliminate heavy computation load, MBConv layers to maximize gradient flow as well as the extraction of features, and progressive learning to customize training for differing image resolutions. The preprocessed cotton leaf photograph undergoes many layers of EfficientNetV2 within this pipeline. The key elements are a stem convolution layer to take low-level features, depthwise separable convolutions to extract efficient features, Squeeze-and-Excitation (SE) blocks to perform channel-wise attention, combined MBConv layers for enhanced performance, and lastly, a global average pooling layer followed by a fully connected layer producing the predicted class label—e.g., Healthy, Bacterial Blight, or Leaf Curl Virus.

After classification, HSV-based mask generation is done in the pipeline using color thresholding within the HSV color space to identify infected areas as a function of color anomalies such as yellowing, browning, or dark spots. This produces a binary mask representing likely infected areas.

To further sharpen this preliminary segmentation, the system then uses U-Net, a powerful deep learning architecture specifically tailored for biomedical image segmentation. U-Net enhances the HSV-based mask with its fully convolutional structure, learning from labeled training data to better separate infected areas without compromising the structural integrity of

the leaf. The result is a high-precision segmentation mask that highlights the diseased areas.

In the estimation of infection severity phase, the ultimate segmentation mask is examined by determining the proportion of infected (black) pixels to overall pixels in the image. The infection percentage is calculated using the following formula:

$$\text{Infection percentage} = (\text{Infected pixels} / \text{Total pixels}) \times 100$$

This provides a quantitative measure of disease severity, which is vital for making sound agricultural decisions.

Local Interpretable Model-Agnostic Explanations (LIME) is used to enhance the transparency of the system. LIME determines and displays the parts of the images with the highest impact on the classification decision, providing a heatmap which shows these essential areas and enabling researchers to better comprehend the reasoning of the model.

The output of the pipeline is an informative report with predicted disease type (e.g., Leaf Curl Virus), estimated level of severity (e.g., 40% infection), and a heatmap-based visualization of important areas that drove the classification.

Benefits of this pipeline are its high classification accuracy because of EfficientNetV2, accurate segmentation of diseases using U-Net, increased transparency through LIME-based explainability, and trustworthy estimation of infection severity, which all contribute to it being an efficient tool for early disease identification and intervention in crop management.

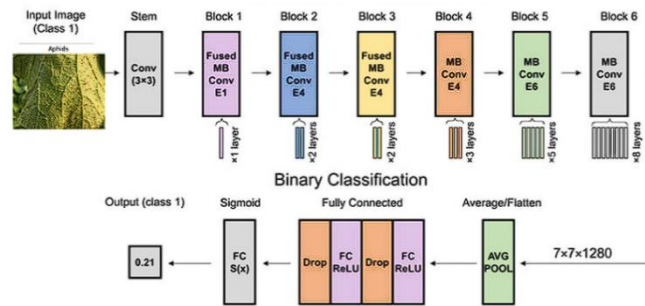


Fig 2: EfficientNetV2 Architecture Diagram

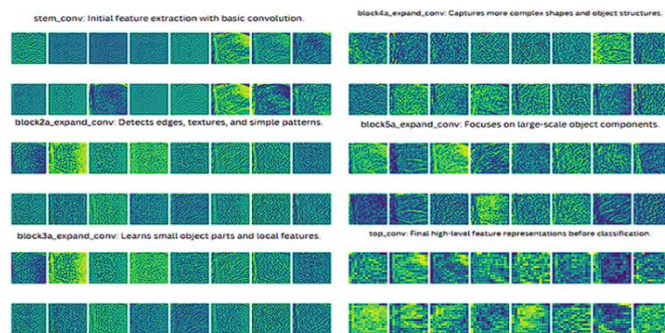


Fig 3: EfficientNetV2 in our pipeline

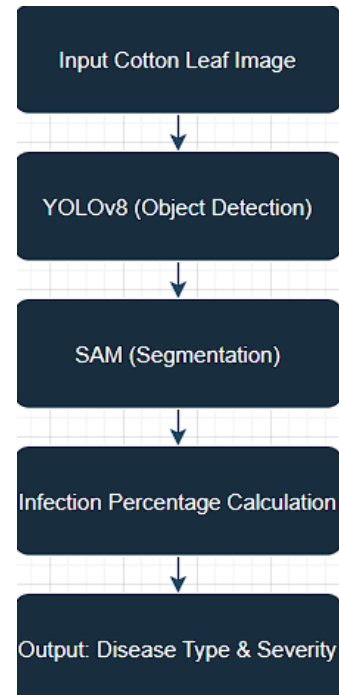


Fig 4: Block Diagram of Pipeline-2

B. Pipeline 2: YOLOv8 + Segment Anything Model (SAM)

This second pipeline offers a strong, real-time framework for disease detection, segmentation, and analysis in cotton leaves with high emphasis on speed and accuracy. It starts with input image acquisition and preprocessing, where cotton leaf images are gathered from different sources like real-time farm monitoring cameras, smartphones, drones, and pre-labeled datasets like PlantVillage and RoboFlow. These images are then preprocessed to enhance feature extraction and compatibility with the object detection model.

The heart of the detection stage is YOLOv8, a cutting-edge real-time object detection model. YOLOv8 is responsible for detecting whether a cotton leaf is healthy or not. It applies convolutional neural networks (CNNs) to extract deep features from the image, predicts the bounding boxes around the detected leaves, and classifies them into categories like Healthy, Bacterial Blight, Leaf Curl Virus, or Fungal Infection. Of particular interest is that YOLOv8 includes sophisticated improvements such as attention mechanisms to improve focus on infected regions, and an anchor-free detection structure, which enhances bounding box accuracy and the adaptability of the model to leaf shape and texture variations.

After detection, segmentation is managed by the Segment Anything Model (SAM). SAM takes the bounding box from YOLOv8 and carries out zero-shot segmentation, i.e., no task-specific retraining is needed. It produces high-resolution segmentation masks that accurately mark the infected areas without including healthy tissue. One of SAM's biggest

strengths lies in its capacity to generalize to different types of diseases without requiring a large labelled training dataset or fine-tuning. It even surpasses classic segmentation models such as U-Net in sharpness and accuracy.

In the **infection severity estimation** stage, the segmentation mask is analysed using the formula: **Infection Percentage = (Infected Pixels / Total Pixels) × 100**. This computation provides a precise quantification of how much of the leaf is affected, enabling targeted disease assessment.

The **final output** includes the disease classification (as determined by YOLOv8) and the calculated infection severity percentage. This information is valuable for multiple agricultural applications such as early disease intervention for farmers, disease tracking and research for agricultural scientists, and the automation of pesticide spraying systems based on infection levels.

Advantages of Pipeline 2 include real-time detection capabilities with YOLOv8, high-accuracy segmentation using SAM without the need for retraining, and precise quantification of disease severity for proactive crop management.

Conclusion: Both Pipeline 1 (EfficientNetV2 + U-Net + LIME) and Pipeline 2 (YOLOv8 + SAM) offer powerful approaches to cotton leaf disease analysis. Pipeline 1 excels in classification accuracy and interpretability due to LIME, while Pipeline 2 is better suited for real-time applications and segmentation precision without the overhead of additional model training. The selection between the two should be guided by specific use-case priorities, such as computational resources, latency constraints, and the need for model explainability.

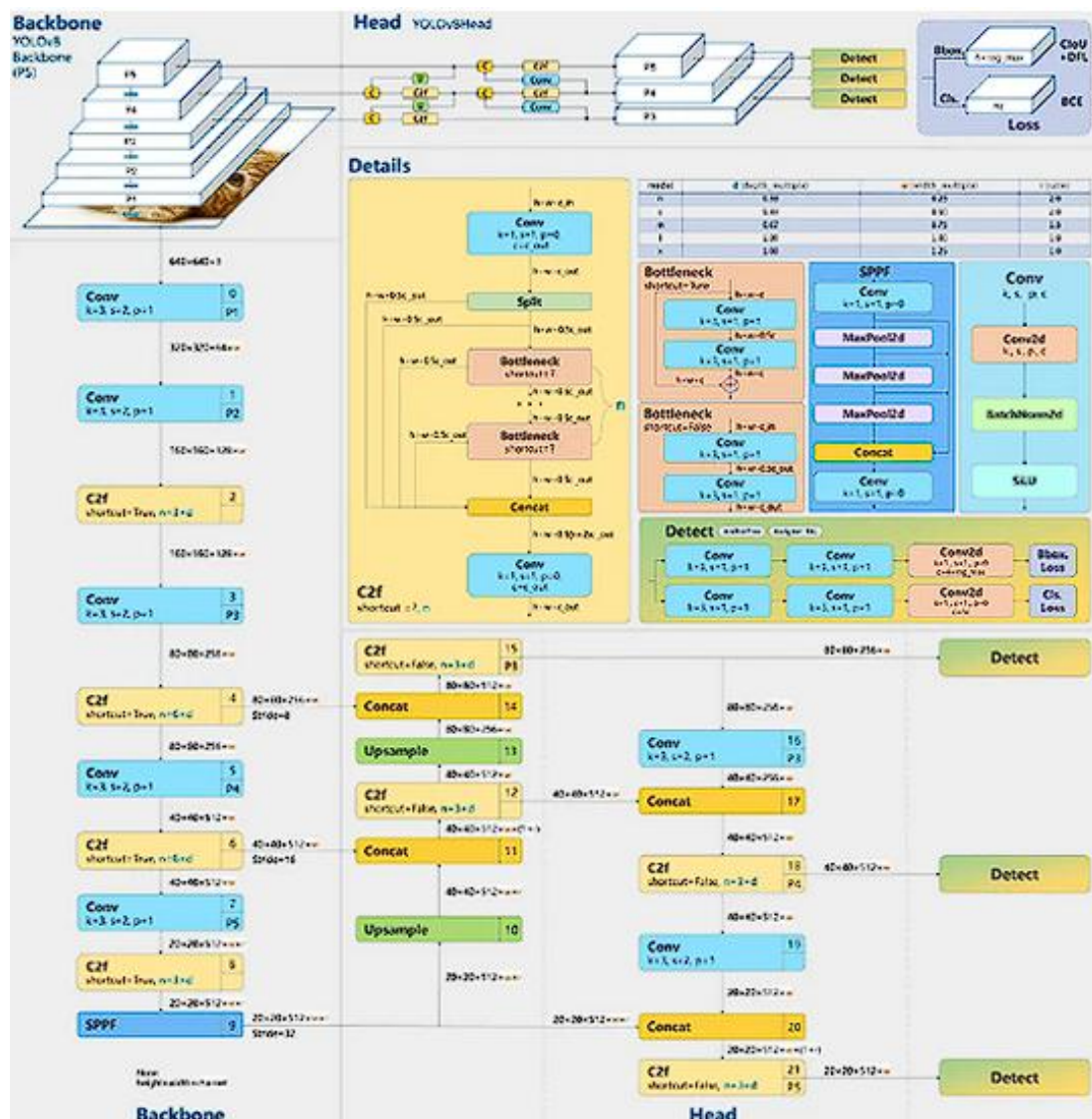


Fig 5: YOLOv8 Architecture Diagram

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

1. HARDWARE AND SOFTWARE REQUIREMENTS:

To deploy and test the suggested cotton leaf disease detection system, a clear-cut blend of hardware and software resources was used. The hardware configuration consisted of an NVIDIA RTX 3050 GPU with 4GB VRAM, which facilitated effective parallel processing for deep learning operations like image classification and segmentation. The system was driven by an AMD RYZEN 4800H CPU, supported by 8GB of DDR5 RAM for managing data-intensive operations and multitasking. A 512GB SSD was utilized to provide rapid data access and efficient model training, and a high-resolution camera was utilized to capture high-quality and diverse images of cotton leaves under different field conditions, building a strong dataset.

At the software level, Python 3.9 was the main programming language because it has robust support for machine learning and image processing. Deep learning models were implemented using TensorFlow versions 2.10 and 2.18, as well as the Ultralytics version of YOLOv8 for real-time object detection. Image preprocessing and augmentation were handled through OpenCV and PIL libraries. Jupyter Notebook and Google Colab served as interactive environments for model training and development, with the latter adding GPU acceleration. Streamlit was employed as a final step to deploy the system using a simple web-based interface where users could easily interact with the model and visualize output.

2. TOOLS USED FOR DEVELOPMENT:

The construction of the cotton leaf disease detection system depended on a varied array of tools across deep learning, explainability, and visualization to provide robustness and interpretability across the pipeline. For the deep learning models at the core, EfficientNet in both its base and fine-tuned variants was used for high-accuracy classification tasks. U-Net was utilized for standard segmentation because it is good at maintaining image structure, while real-time object detection was done with YOLOv8. The Segment Anything Model (SAM) was also incorporated for sophisticated, zero-shot segmentation, providing accurate outlining of infected tissues without the need for retraining.

To improve model interpretability, LIME (Local Interpretable Model-Agnostic Explanations) was added as an explainability method. It gave insight into the most powerful areas contributing to the model's classification outcome, thus enhancing interpretability and trust.

For visualizing and monitoring performance, tools like Matplotlib and Seaborn were utilized to create plots for result interpretation and data exploration. TensorBoard was used as

the primary platform for tracking model performance, visualizing training metrics, and optimizing network architectures during the development cycle.

3. THRESHOLDS SPECIFIC TO WORK:

a) mAP (Mean Average Precision) Evaluation:

The object detection module in the pipeline for cotton leaf disease detection is assessed using standard evaluation metrics like mAP50-95 and mAP50, which are commonly used in computer vision. They are used to measure how well the model can detect and localize diseased regions on cotton leaves.

mAP50-95 calculates the Mean Average Precision over a variety of Intersection over Union (IoU) thresholds from 0.50 up to 0.95 in increments of 0.05. This more fully and tightly evaluates the detection performance of the model under lenient and stringent bounding box alignment conditions. It is especially appropriate for evaluating the overall reliability and robustness of the model because it takes into account different extents of overlap between predicted and actual object locations.

mAP50, however, measures precision at a specific IoU threshold of 0.50. Here, a bounding box is said to be correct if it shares at least 50% overlap with the ground truth. This measure is more of a real-world benchmark where perfect precision is not as important and a moderate overlap is adequate for actionable detection. Combined, these measures give a well-rounded view of the model's performance, with insights into precision and recall at various levels of detection strictness. The application of these standards of measurement, particularly with YOLOv8, ensures that the system is not only accurate but also trustworthy across various agricultural settings.

b) HSV Thresholding for Infection Detection:

HSV thresholding is critical in the segmentation and early detection of infected areas on cotton leaves by separating distinctive color patterns linked to infection. In this approach, the image is transformed from the RGB color space to the HSV (Hue, Saturation, Value) color space, which is better suited for highlighting subtle variations in leaf coloration that can be indicative of disease. Thresholding is performed using specified lower and upper limits for each HSV component to separate the infected areas. For the Hue (H) value, between 10 and 30 is chosen to act on yellowish and pale orange hues, which are typically seen in diseased leaf tissue displaying discoloration or initial indication of rot. Saturation (S) is set between **50 and 255**, ensuring that only

areas with noticeable color intensity are detected, effectively ignoring dull, grayscale, or shadowed regions that could lead to false positives. Lastly, the **Value (V)** component, also set from **50 to 255**, captures both brightly lit and slightly darker infected patches, providing robustness under different lighting conditions.

By applying these HSV thresholds, the system efficiently isolates symptomatic regions, enhancing the performance of subsequent feature extraction steps. This preprocessing technique supports more accurate segmentation and improves the overall reliability of the object detection and classification models in identifying disease presence.

4. DATASET USED AND DESCRIPTION

The training and testing of the two suggested cotton leaf disease detection pipelines were conducted on two different datasets, each chosen and organized to suit the aim of the corresponding approach.

Pipeline 1: EfficientNetV2 + U-Net + LIME:

This pipeline utilized the Cotton Plant Disease dataset found on Kaggle. It consists of 3,601 images, divided into six classes: Aphids, Army worm, Bacterial Blight, Healthy, Powdery Mildew, and Target Spot. The dataset was divided into three sets to provide balanced training and testing: 2,520 images for training, 720 images for test, and 361 images for validation. This dataset was especially well-suited for segmentation and classification tasks because of its labeled disease classes and visual diversity in symptom presentation.

Pipeline 2: YOLOv8 + SAM:

For this real-time object detection and sophisticated segmentation pipeline, the Roboflow cotton_disease-2 dataset was used. This dataset contains 3,940 images labeled for object detection tasks and covers six disease classes: blight, curl, grey mildew, healthy, leaf spot, and wilt. A greater amount of the dataset was reserved for training, and 3,708 images were utilized for model training while 232 images were reserved for validation. The annotations gave bounding boxes and segmentation masks, and therefore this dataset was well-suited for YOLOv8 and SAM integration, which depend on accurate object localization and good-quality mask generation.

In combination, these datasets facilitated the training of the pipelines with varied disease presentation and testing on real-world situations, promoting generalization and insensitivity to image quality variations as well as variability in plant health.

5. INITIALIZATION AND HYPERPARAMETERS

Table 1: Hyperparameters for Model Training EfficientNetV2B0

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	16
Epochs	50(initial),32(EarlyStopped)
Loss Function	Categorical Cross entropy
Activation Function	SoftMax

Table 2: Hyperparameters for Model Training UNET

Parameter	Value
Optimizer	Adam
Learning Rate	Default (0.001 for Adam)
Batch Size	16
Epochs	50 (with Early Stopping if no improvement for 5 epochs)
Loss Function	Dice Loss (custom function)
Activation Function	ReLU (Hidden Layers), Sigmoid (Output Layer)

Table 3: Hyperparameters for Model Training YOLOv8

Parameter	Value
Optimizer	Adam
Learning Rate	Not explicitly defined, defaults to 0.001 in Adam optimizer
Batch Size	16
Epochs	20
Loss Function	Combination of Box Loss, Classification Loss, and DFL Loss
Activation Function	SiLU (Swish) for hidden layers, Sigmoid for final bounding box predictions

B. Findings and Comparison with Contemporary Works

Our two-pipeline method for cotton leaf disease detection significantly improves accuracy compared to traditional deep learning models. Below are key findings:

1. COMPARISON WITH TRADITIONAL CNNs:

Conventional CNN models, such as VGG16 and ResNet50, failed to deliver satisfactory segmentation accuracy. However, our approach, which utilizes U-Net for segmentation and EfficientNet for classification, achieved higher accuracy with enhanced feature extraction.

2. COMPARISON WITH PREVIOUS STUDIES:

Many studies have relied solely on classification models, whereas our work integrates segmentation (U-Net & SAM) and object detection (YOLO) to enhance robustness. Additionally, the use of LIME for explainability improves model interpretability, addressing a key limitation in prior works.

3. PERFORMANCE METRICS:

Table 4: Model Accuracy for Base EfficientNet

Model	Training Accuracy	Validation Accuracy	Testing Accuracy
Base EfficientNet	97.78%	96.11%	96.40%

Table 5: Model Accuracy for Base Finetuned EfficientNet

Layers Unfrozen	Training Accuracy	Validation Accuracy	Testing Accuracy
20	98.29%	96.38%	98.06%
30	98.29%	96.67%	98.06%
40	98.65%	96.39%	97.78%

Table 6: Evaluation Metrics and Interpretation UNET

Metric	Value	Interpretation
Validation Loss	0.0169	Very low, indicating the model fits the data well.
Validation Accuracy	97.37%	High accuracy, meaning the model correctly classifies most pixels.
Dice Coefficient	0.9834	The segmentation is highly accurate, with a strong overlap between predictions and ground truth.
Hausdorff Distance	3.4641	Small distance, indicating that predicted boundaries are close to actual boundaries.
Precision	0.9749	High precision means fewer false positives (incorrectly labeled infected regions).
Recall	0.9920	Very high recall, meaning the model detects nearly all infected regions correctly.
IoU (Jaccard Index)	0.9237	High IoU indicates strong agreement between predicted and actual segmentations.

Table 7: Comparison of YOLO models

Metric	YOLOv11n	YOLOv8	Best Model
Precision	0.901	0.938	YOLOv8
Recall	0.6834	0.812	YOLOv8
mAP50	0.815	0.881	YOLOv8
F1 Score	0.77	0.82	YOLOv8

C. Comparison of Approaches Used

Table 8: Comparison of Approaches: EfficientNet + U-Net vs YOLO + SAM

Approach	EfficientNet + U-Net	YOLO + SAM
Strengths	High accuracy in classification and segmentation Works well with moderate GPU resources U-Net provides fine-grained segmentation	Fast and precise object detection SAM provides accurate, generalizable segmentation Better for real-time applications
Weakness	Computationally expensive for training Slower inference speed compared to YOLO	Requires high GPU power for fast inference Can struggle with very small or overlapping leaf infections
Best Use Case	Suitable for offline analysis and high-accuracy segmentation tasks	Ideal for real-time detection in the field and high-resolution segmentation

D. Performance Visualization

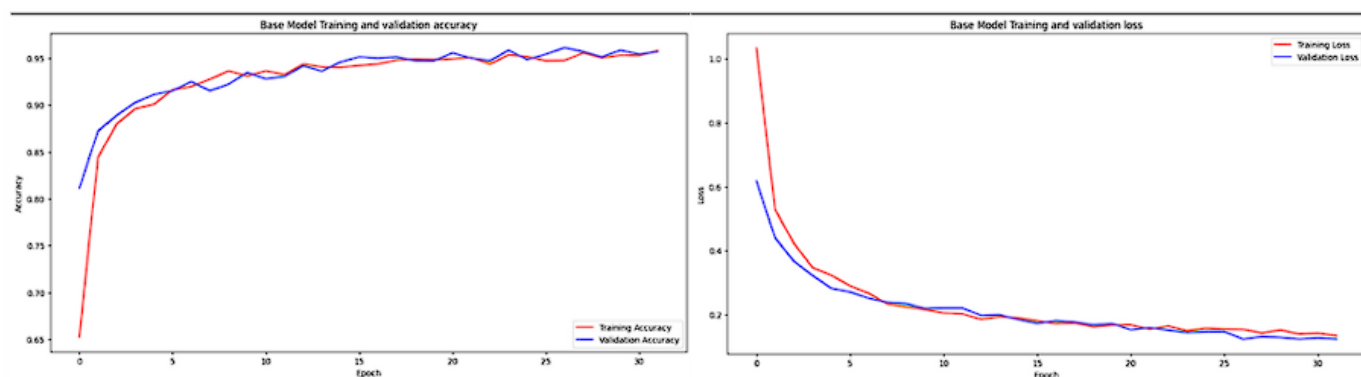


Fig 6: Accuracy and Loss Curve

1. EFFICIENTNETV2B0 BASE MODEL:

Figure 6 gives some indications of how well the EfficientNetV2B0 base model performs. Accuracy curve plots have a uniform trend of an increase in training accuracy and validation accuracy, with the model being an effective learner with little overfitting, since validation accuracy tracks closely to training accuracy. The validation accuracy doesn't exhibit any sharp drops, showing the model is not overfitting. The loss curve shows a consistent reduction in training and validation loss, indicating ongoing learning. Moreover, no sharp fluctuations exist, which means no extreme overfitting or underfitting. The small difference between the training and validation loss also indicates that the model has good generalizability, owing to proper regularization.

2. SUMMARY OF FINE-TUNING RESULTS:

Figure 7 plots the fine-tuning results for different numbers of unfrozen layers. With 20 unfrozen layers, accuracy and loss oscillate, indicating that learning is stable since validation accuracy closely tracks training. At 30 unfrozen layers, training accuracy gradually improves, but validation accuracy becomes more volatile, suggesting the possibility of overfitting. At 40 unfrozen layers, maximum accuracy is attained, but the higher divergence between training and validation accuracy suggests greater overfitting risk. Overall, the trend indicates that increased unfrozen layers enhance accuracy but also increase instability, necessitating sensitive tuning for best performance.

3. U-Net Segmentation Results:

a) Ground Truth vs Predicted Mask:

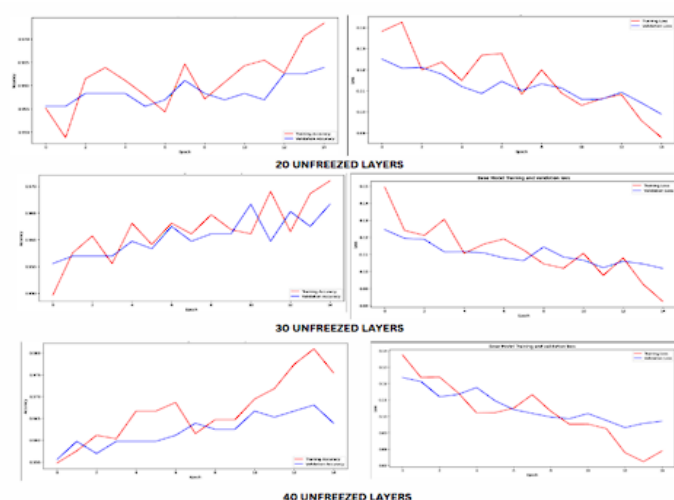


Fig 7: Accuracy and Loss Curves of Finetuned Model

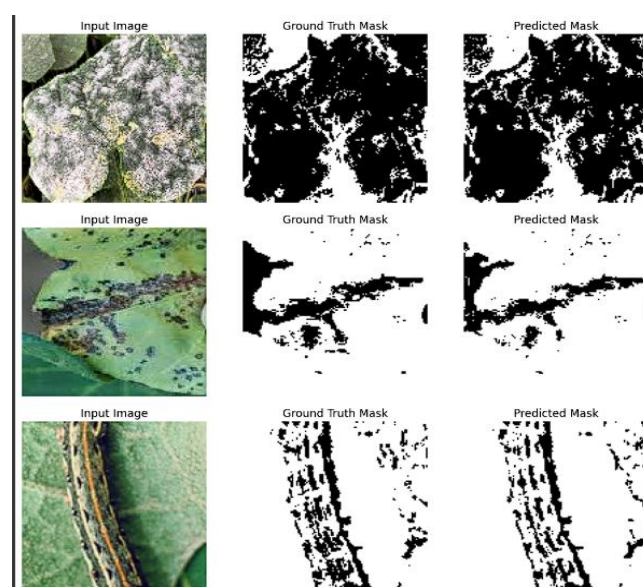


Fig 8: Ground Truth vs Predicted

b) Evaluation of UNET on Test Data

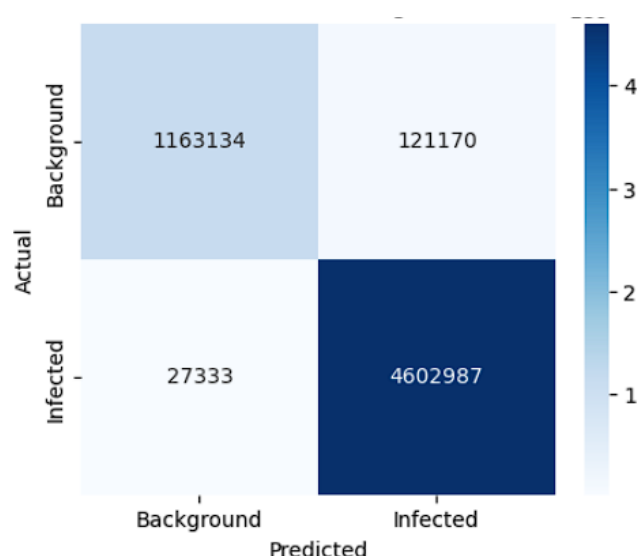


Fig 9: Confusion Matrix

Figure 9 shows the model performance measures. It accurately identified 1,163,134 background pixels (TN) and marked 4,602,987 infected pixels (TP). But it flagged 121,170 background pixels as infected incorrectly (FP), and 27,333 infected pixels as background incorrectly (FN). The model exhibits very good recall (0.9941), indicating that it finds infected pixels very efficiently with very few missed infections. Accuracy is also high (0.9744), meaning that the majority of the infected areas predicted are correct with few false positives.

c) Model Performance Metrics:

The performance metrics for the model, as depicted, illustrate good segmentation abilities. It has a 97.49% accuracy, classifying most pixels correctly. The precision is 97.44%, showing a high percentage of the predicted infected pixels indeed being infected. Its recall (sensitivity) of 99.41% captures the model's performance in identifying nearly all infected regions. The F1 score of 98.41% offers a balance of precision and recall, illustrating good segmentation. The IoU (Jaccard Index) of 96.87% means there is a high overlap between the predicted and true infected areas, and the Dice coefficient of 98.41% also ensures the high accuracy of the model's segmentation

d) Visual Results:

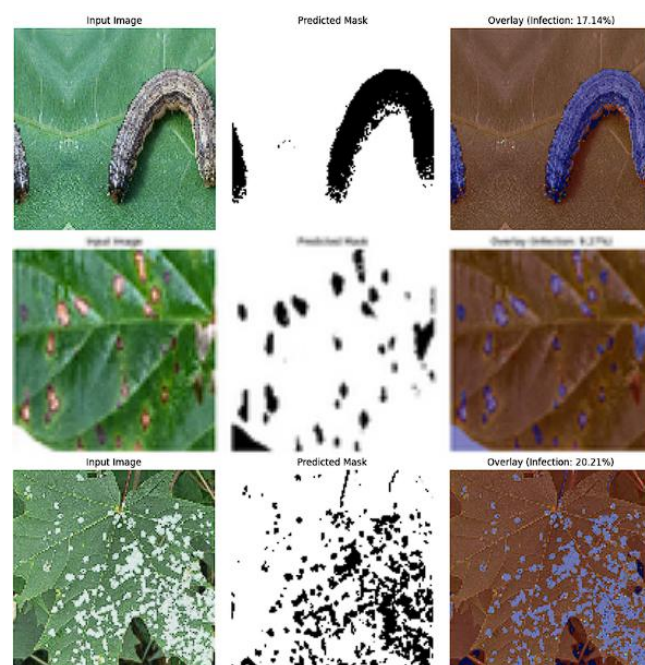


Fig 10: UNET Output

Figure 10 shows segmentation performance of the model. Input images, both healthy and infected leaves, are shown in the left column. The middle column shows the predicted masks, in which black areas point out detected infections. Overlaid infection segmentation on the original image, along with a percentage showing the extent of the infection affecting the image, appears in the right column.

4. YOLOV8 RESULTS:

a) Precision Recall Curve

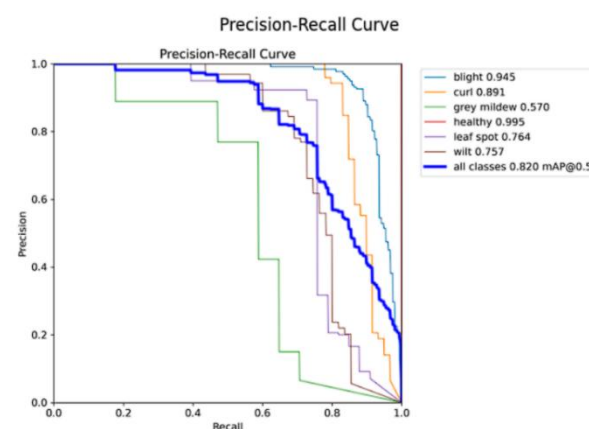


Fig 11: Precision Recall Curve

Figure 11 illustrates that the model attains a mAP@0.5 of 0.820 across all classes. A higher mAP@0.5 shows that the model is successfully detecting objects, with a good balance between precision and recall.

b) Precision-Confidence Curve

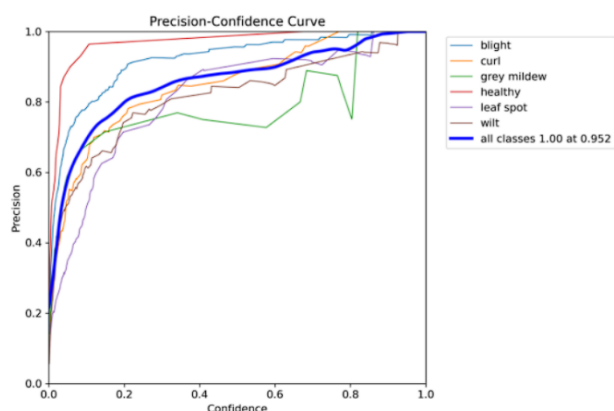


Fig 12: Precision-Confidence

Figure 12 shows a curve in which all classes attain 1.00 precision at 0.952 confidence. It shows that the model attains perfect precision with high confidence, implying that the predictions made by the model are extremely accurate.

c) Recall-Confidence Curve

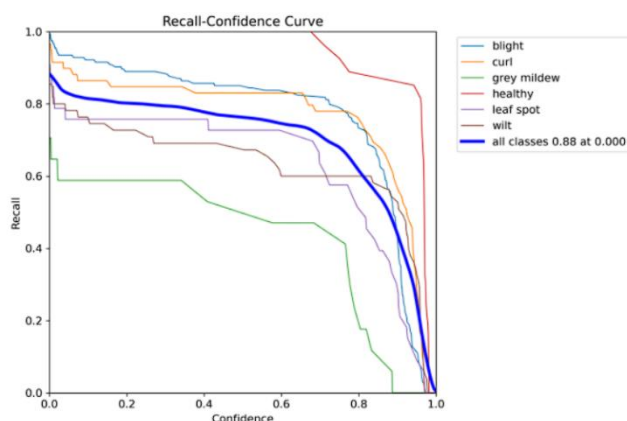


Fig 13: Recall Confidence

Figure 13 shows that the recall for all classes reaches 0.88 at a confidence level of 0. This indicates that the model maintains strong recall, ensuring good detection capability even at lower confidence thresholds.

d) F1 Score Curve

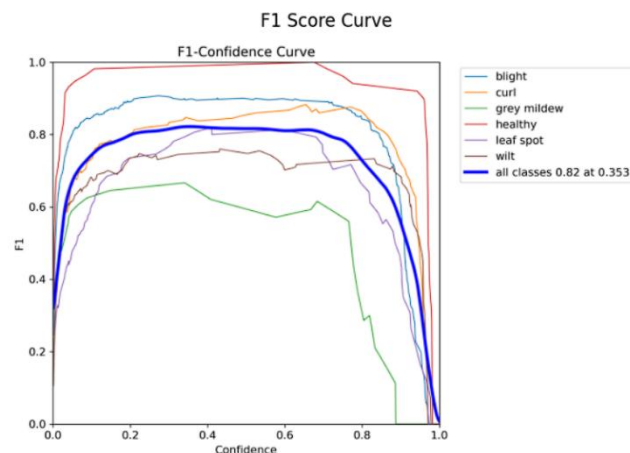


Fig 14: F1 Score Curve

Figure 14 shows the F1-score reaching 0.82 at a confidence level of 0.353. This reflects a well-balanced trade-off between precision and recall, confirming the model's robustness in detection performance.

e) Output



Fig 15: YOLOv8 Output

5. SAM RESULTS:

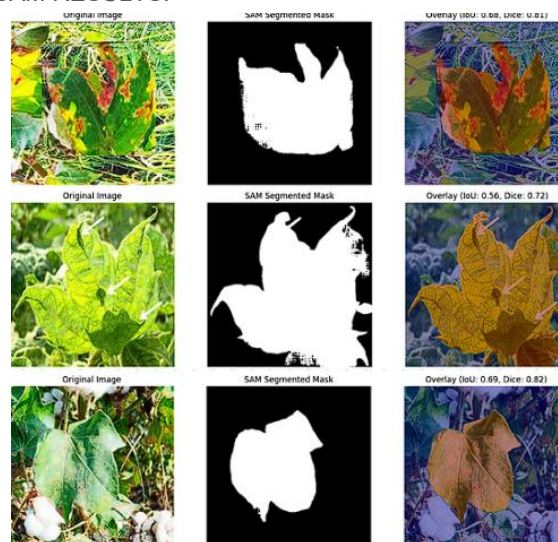


Fig 16: YOLO detects leaves, extracts regions, and generates corresponding infection masks.

6. PIPELINE-2 RESULT:

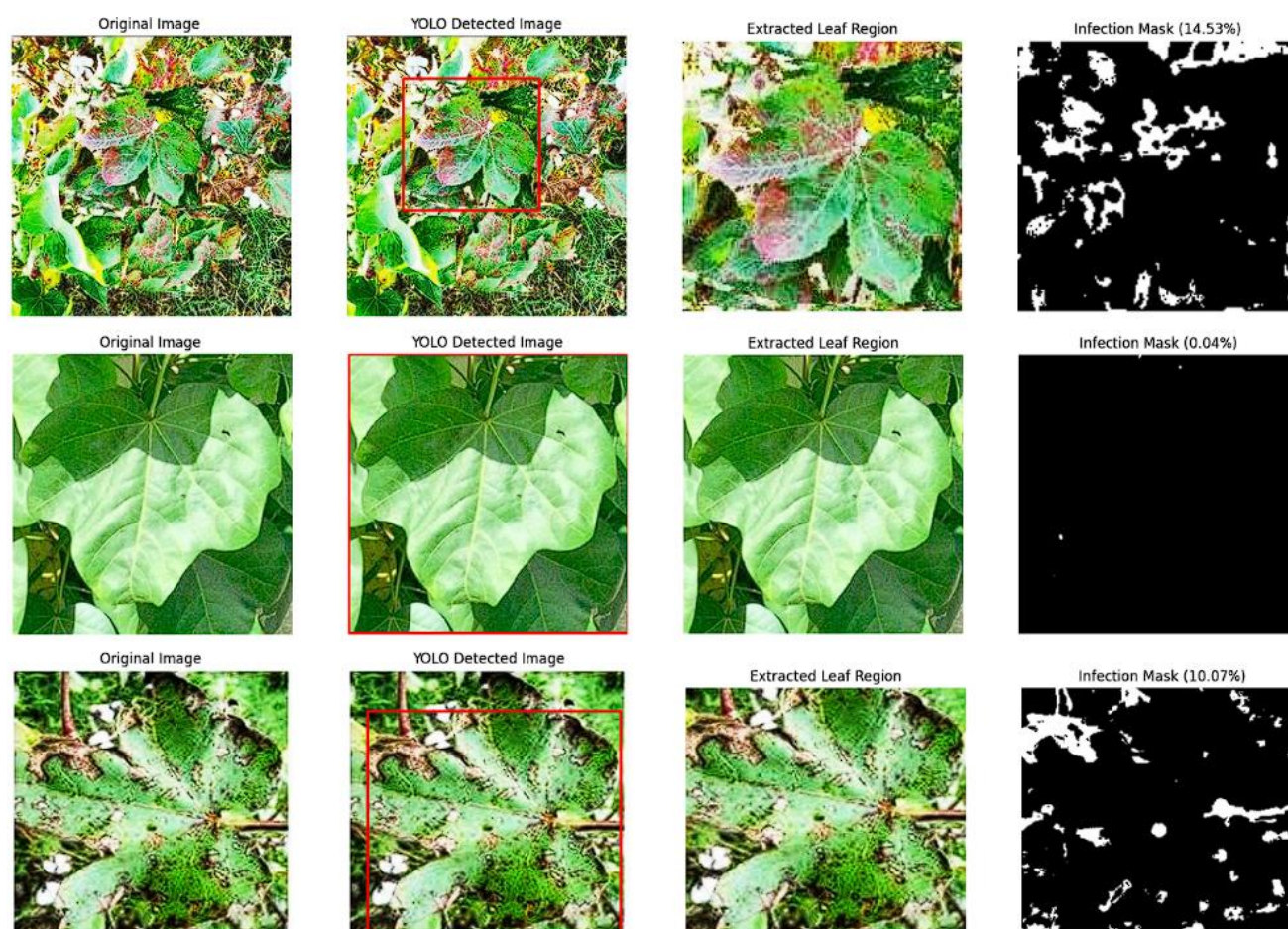


Fig 17: YOLO detects leaves, extracts regions, and generates infection masks with

VI. CONCLUSION AND FUTURE WORK

Here, we propose an automatic cotton leaf disease detection system based on deeplearning techniques such as Efficient Net, U-Net, YOLO, SAM and Explainable AI (LIME). Our contribution addresses the crucial task of disease detection at an early stage in cotton crops to enable farmers and agricultural experts to take preventive measures at the right time.

A. Future Work

In order to further improve the real-world practicability and scalability of our system, we suggest the following extensions:

1. CREATION OF A STREAMLIT-BASED WEB APPLICATION:

A user-friendly platform was developed using Streamlit, allowing farmers to upload leaf images and receive real-time disease classification, segmentation, and detection results. The application integrates LIME visualizations to enhance interpretability of the classification outcomes. Additionally, multi-language support was incorporated to ensure accessibility for a wider user base.

2. DATASET EXPANSION AND MODEL GENERALIZATION:

To improve real-world performance, the dataset is being expanded by collecting more diverse images captured under various lighting conditions, orientations, and disease severities. Additionally, efforts are underway to broaden the dataset to include a wider range of cotton diseases and extend coverage to other crops, enhancing the model's generalizability across agricultural contexts.

3. DEPLOYMENT ON EDGE AND IOT DEVICES:

The model is being optimized for real-time detection on low-power platforms like Raspberry Pi, NVIDIA Jetson Nano, and smartphones to allow on-field usage. Additionally, integration with smart agricultural drones is also being investigated to enable automated, large-scale crop disease monitoring.

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