

# CapsNet-Yolo : A Novel Deep Learning Approach For Real Time Tomato Disease Identification Synergised With Drone Technology And Pesticide Spraying

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**Abstract**— Precision agriculture is transforming crop management by leveraging technology to optimize yields and minimize environmental impact. This research presents a cutting-edge system, CapsNet-Yolo, which integrates Capsule Networks (CapsNet) and YOLO v8 models for real-time tomato disease identification and targeted pesticide application using drones. The approach employs drones equipped with advanced sensors to capture detailed aerial imagery of tomato crops. The captured images are processed by deep learning models, combining the strengths of CapsNet for robust feature extraction and YOLO v8 for efficient object detection. Upon identifying diseased plants, the system autonomously triggers precise pesticide spraying, ensuring efficient resource utilization and reducing environmental harm.

**Keywords**— *Precision agriculture, Drone technology, Deep learning, Crop disease detection, Sustainable farming, Disease management.*

## I. INTRODUCTION

The evolution of agriculture has undergone transformative phases since the Industrial Revolution. Initially characterized by the introduction of machinery such as tractors and implements, the agricultural landscape continued to evolve until the 1940s with the advent of synthetic chemicals. This marked a crucial juncture, setting the stage for increased global production but also raising concerns about the reliance on these chemicals.

Precision Agriculture stands as a response to the evolving needs of modern agriculture. Its roots in understanding and harnessing the variability of crops, coupled with technological advancements, have positioned it as a key player in the current agricultural revolution [1].

### A. Significance of Disease Management in Agriculture

Comprehensive training and awareness initiatives, targeting farmers, are crucial for immediate disease management effectiveness. Farmers must be empowered with a practical understanding of the ecology, aetiology, and epidemiology of major crop diseases. This understanding is attained through extensive training using participatory approaches, ensuring farmers possess the necessary knowledge to effectively manage their fields. This knowledge is then translated into practical decision-making tools and

control strategies, enabling farmers to actively engage in disease management within their agricultural systems [2].

### B. Technological reforms in Agriculture

Amidst the ongoing transformative period in agriculture known as Farming 4.0, the integration of Information and Communication Technologies (ICTs) has ushered in the fourth revolution. This evolution encompasses innovative technologies such as Remote Sensing, the Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs) [3], Big Data Analytics (BDA), and Machine Learning (ML), all holding the promise to revolutionize age-old farming practices.

Smart farming utilizes IoT and UAVs (drones) for precise crop monitoring and resource management. Deep learning is essential for analyzing agricultural data efficiently. Our system aims to reduce crop losses through early disease detection, improve resource use by minimizing pesticides, and promote environmental conservation by reducing chemical dispersion.

## II. LITERATURE REVIEW

Yamaha Motor Co. Ltd.'s early work laid the foundation for UAV-based spraying, leading to recent advancements by Martinez-Guanter et al. and Karan Kumar Shaw et al., incorporating adaptive control, genetic algorithms, and AI (Artificial Intelligence) for variable spray systems [4].

Chen et al. harnessed edge intelligence and the Tiny-YOLOv3 algorithm for real-time pest detection, highlighting the successful integration of edge computing into smart farming practices [5]. The study, utilizing the APD-616X agricultural spray drone, demonstrated significant reductions in pesticide consumption, operating time, and workforce needs compared to traditional methods [5].

General trends in drone applications for agriculture are outlined by Hafeez et al., providing an encompassing review [6]. The study emphasizes the transition from semi-controlled to fully automated pesticide spraying systems, underscoring drones' potential in creating safer and more economical agricultural solutions [6].

Abouelmagd et al. contribute to precision agriculture with an optimized Capsule Neural Network (CapsNet) for tomato leaf disease classification [7]. The proposed CapsNet achieves remarkable accuracy, outperforming traditional Convolutional Neural Networks (CNNs) and laying the groundwork for employing unmanned aerial vehicles for efficient disease monitoring [7].

Stamford et al. introduced NDVIpi, a cost-effective dual camera system connected to a Raspberry Pi for NDVI imagery, showing robust performance compared to commercial alternatives [8]. The study highlights the significance of red wavelengths in NDVI calculation and NDVIpi's sensitivity to chlorophyll content [8].

Soetedjo and Hendrianti developed a low-cost infrared camera system for leaf detection and counting, showing effectiveness in handling illumination changes and shadows [9]. The proposed method, evaluated against benchmark datasets, shows comparable performance and real-time execution feasibility for future applications in diverse natural environments [9].

The literature review focuses on transformative advances in crop monitoring and pesticide spraying through drone integration. Researchers use sensors such as digital color infrared and multispectral cameras to perform precise monitoring and disease detection. Deep learning supported breakthroughs in automatic disease monitoring systems have the potential to improve disease identification. Advances in drone-mounted sprayers, including adaptive control and artificial intelligence, address pesticide application uniformity issues. Overall, the literature emphasizes drone's critical role in shifting agriculture towards safer, more cost-effective, and environmentally sustainable practices, along with potential research gaps in perfecting the Deep learning model's performance.

### III. METHODOLOGY

The methodology of the proposed project is illustrated in Fig. 1, which presents the overall block diagram for the proposed system. The drone hovers above the farm, capturing images of each plant with an onboard camera [18]. These images are transmitted to a base station where the proposed CapsNet-Yolo model identifies unhealthy plants. If a plant is detected as diseased, a motor activates to spray pesticide. This process is repeated sequentially for each plant until all are inspected. After completing the monitoring, the drone returns to the base station for storage and charging.

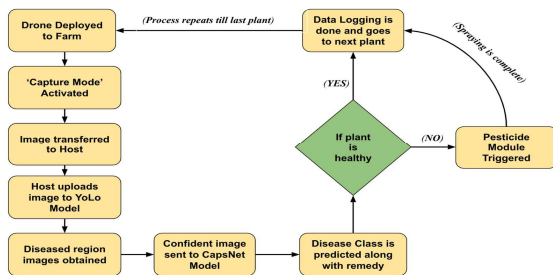


Fig. 1. Block Diagram of the proposed system

In this research, the Capsule Network model for image classification is implemented using TensorFlow and Keras within a controlled HPC environment. The research uses the computational power of NVIDIA GEFORCE RTX 2080 Ti GPU, PyTorch 2.2.1 and CUDA 12.1, for seam-less execution and collaboration

### IV. MODEL ARCHITECTURE

#### A. Capsule Network (CapsNet)

A Capsule Neural Network is intended to mimic the operation of biological neural networks, with a particular emphasis on improving recognition and segmentation skills.

These networks, classified as a subtype of Artificial Neural Networks [17], introduce a novel feature known as capsules, which are effectively nested layers beneath the central capsule layer. CapsNet addresses CNN's limitations by capturing relative spatial and orientation relationships crucial for accurate disease detection [14].

In the proposed Capsule Network architecture, a sequential model is instantiated using the Keras framework. The architecture comprises several layers tailored to extract and manipulate features hierarchically. Initially, a convolutional layer with 256 filters and a kernel size of 3x3 is employed to convolve input images, using the rectified linear unit (ReLU) activation function to introduce non-linearity. Subsequently, primary capsules are formed through another convolutional layer with 32\*8 filters and a stride of 2x2 to ensure spatial down-sampling. This layer, also activated by ReLU, aims to detect basic visual patterns within localized receptive fields (Fig. 2, Fig. 3).

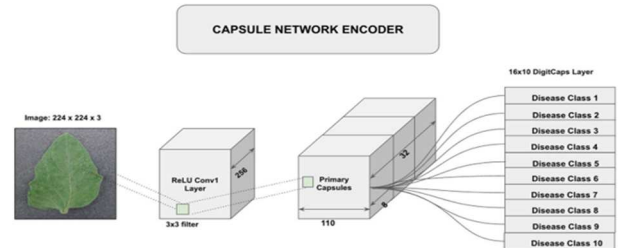


Fig. 2. Design of Encoder Component

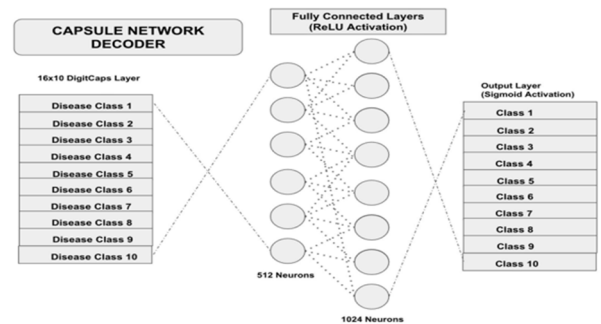


Fig. 3. Design of Decoder Component

#### B. Object Detection: Yolo v8

YOLOv8, the latest evolution in the "You Only Look Once" (YOLO) series, offers significant advancements in

real-time object detection through its enhanced architecture. It uses a more efficient backbone network, typically a CSPDarknet53 variant, to extract rich features, and employs the Path Aggregation Network (PANet) to capture multi-scale features effectively [16]. The model's anchor-free mechanism simplifies detection, improving localization and classification accuracy.

YOLOv8 integrates advanced loss functions to better align training with performance metrics and incorporates ultramodern data augmentation techniques like Mosaic and CutMix for superior generalization (Fig. 4). These improvements ensure that YOLOv8 maintains a high throughput, making it ideal for real-time applications requiring reliable and precise object detection.

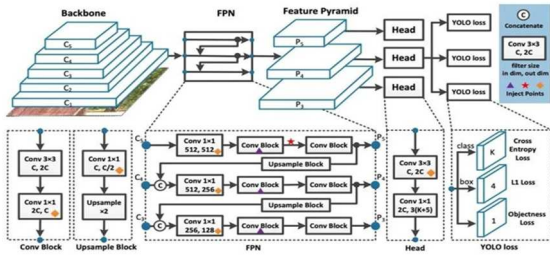


Fig. 4. Yolo Network Architecture

## V. DATASET ANALYSIS

The datasets were obtained from Kaggle [11] [12] and RoboFlow [13]. The Plant Village Dataset is renowned for its extensive use in plant disease identification. It offers a collection of over 54,300 high-quality images spanning over 26 disease categories, making it a rich and diverse dataset. This dataset has been curated with precision by David Hughes and Marcel Salathe at Cornell University in New York, USA, ensuring its trust- worthiness. Thanks to its well-labelled content and diversity, this dataset is an excellent choice for researchers in machine learning and agricultural projects, providing a reliable foundation. The “New Plant Diseases Dataset” (Fig. 5) has been recreated using offline augmentation from the original dataset.

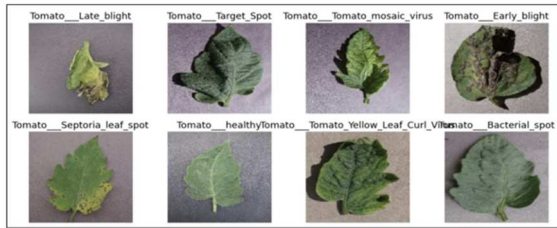


Fig. 5 Tomato Plant Images from New Plant Diseases Dataset

Tomato object image dataset (Fig. 6) is publicly available dataset which is curated and modified and taken from the authors RoboFlow workspace [13] which consists of 18369 images which are accurately labelled and available in different download formats ensuring easy deployment for different model architectures.



Fig. 6. Tomato object dataset Images from Tomato object Image Dataset (Version 2)

### A. Data Pre-processing and Augmentation for CapsNet

In the field of machine learning, efficient data pre-processing is critical. The code uses the *ImageDataGenerator* class to carefully curate the dataset for training. This class excels at data augmentation, a technique that dynamically improves a dataset to aid model learning. To address the various blurs encountered in drone-captured images, Gaussian blur (Fig. 7) and Motion blur (Fig. 8) have been incorporated into the pre-processing pipeline. Scaling pixel values to ensure they uniformly span the normalized range of 0 to 1 is an important aspect of deep learning model convergence and performance.

Gaussian blur stands as a prominent non-uniform low-pass filtering operation employed to mitigate input image noises and achieve a smoother representation of edges. The two-dimensional Gaussian kernel function, mathematically defined as:

$$Gaussian(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (1)$$

Motion blur is a technique applied to create a sense of movement or dynamism in images [10]. It simulates the effect of rapid motion, resulting in blurred streaks along the direction of the motion. The motion blur operation involves capturing an object in motion over a specific period, causing its appearance to smear across the image. Mathematically, the motion blur can be represented as the convolution of the image with a motion kernel.

$$G(x, y) = \frac{1}{N} \sum_{i=0}^N \delta(x - i \cdot \cos(\theta), y - i \cdot \sin(\theta)) \quad (2)$$

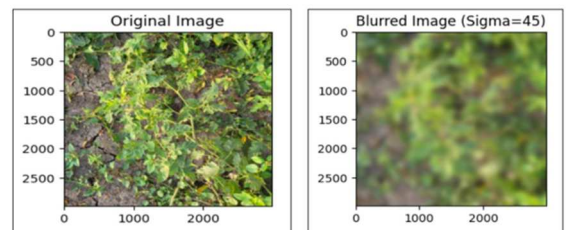


Fig. 7. Data Pre-processing - Gaussian Blur application

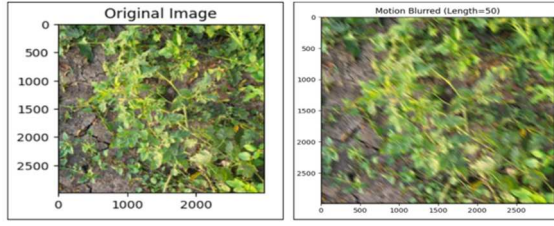


Fig. 8. Data Pre-processing - Motion Blur application

In addition to traditional techniques, Gamma correction is applied to adjust the lighting in leaf images, while diverse zoom and shear transformations account for variations in the distance between the drone and the captured image. Flip and rotation range augmentations handle multiple orientations, resulting in a more robust dataset. The dataset is stratified, with 80% for training and 20% for validation, allowing for the evaluation of the model's ability to generalize to new and previously unseen data.

### B. Data Pre-processing and Augmentation for YoLo v8

This section details the architecture, data pre-processing, augmentation, and training strategies of YOLOv8 for object detection. YOLOv8 comprises a backbone, Feature Pyramid Network (FPN), and task-specific subnetworks. Preprocessing involves image orientation and resizing. Augmentation includes flips, saturation, brightness adjustments, and blur.

A comprehensive data augmentation strategy is employed to enhance the robustness of YOLOv8 model for plant disease detection. The augmentation techniques included horizontal and vertical flips, saturation adjustments within a range of -25% to +25%, brightness variations from -15% to +15%, and Gaussian blur with a radius up to 1.1 pixels. Additionally, mosaic augmentation, which was applied during the initial training phases and disabled towards the end of training to stabilize learning. These augmentations aimed to improve the model's ability to generalize across diverse visual conditions, thereby enhancing its performance and reliability in real-world scenarios.

## VI. COMBINED MODEL

Combining YOLO object detection with Capsule Network classification offers a synergistic approach to enhance object understanding and accuracy. YOLO swiftly detects objects but lacks detailed insights, which are provided by Capsule Network's discernment of hierarchical feature relationships. Integrating YOLO's bounding boxes with Capsule Network's detailed classification refines object recognition, minimizing false positives and elevating detection accuracy.

Capsule Networks excel in capturing spatial relationships and pose intricacies within objects, making them ideal for analyzing cropped regions of interest (ROIs) identified by YOLO. Targeting only the ROIs marked by YOLO reduces computing needs (Fig. 9), speeding up inference, improving resource usage, and proving beneficial for tasks requiring quick analysis or running on resource-constrained devices like drones.

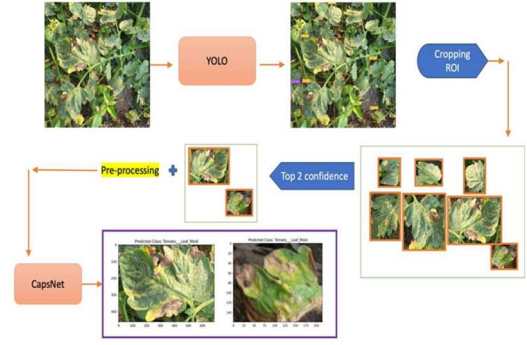


Fig. 9. Overall Workflow of the Caps – Yolo Model

The YOLOv8 model is characterized by its anchor-free architecture, representing a departure from traditional anchor-based object detection methods. Instead of predicting offsets from predefined anchor boxes, YOLOv8 directly predicts the centre of an object.

Only the high-confidence images detected by the YOLOv8 model are selected from the JSON format list of dictionaries returned by the model. These selected images will then be cropped using the specified ROI formulas (3)(4). Focusing on high-confidence images ensures the reliability and accuracy of the detected objects, minimizing false positives and enhancing the overall precision of the model's performance. This approach is particularly important for applications where accuracy is critical, such as disease diagnostics or autonomous driving.

The corner points for cropping the ROI's can be calculated from the centre co-ordinates (x, y) by using the following formulas.

$$x1 = x - \left(\frac{width}{2}\right), y1 = y - \left(\frac{height}{2}\right) \quad (3)$$

$$x2 = x + \left(\frac{width}{2}\right), y2 = y + \left(\frac{height}{2}\right) \quad (4)$$

The Caps-Yolo model shows promising performance in both the classification of plant diseases and object detection tasks. By addressing challenges found in the confusion matrix and perfecting training dynamics using accuracy and loss plots, the model shows potential for enhancing accuracy and robustness in real-world scenarios. This concise summary encapsulates the key findings and insights derived from the provided content, offering a comprehensive understanding of the model's effectiveness in both classification and object detection tasks.

## VII. RESULTS AND DISCUSSIONS

### A. CapsNet Model

The diagonal elements of the confusion matrix represent the instances where the predicted class aligns with the true class labels. Looking at the values along the diagonal in Fig. 10, the model performs well for several classes, such as

Tomato bacterial spot, Tomato healthy, Tomato late blight, Tomato leaf Mold, and Tomato Septoria leaf spot, where most predictions fall on the diagonal, indicating accurate classification. For instance, Tomato\_bacterial\_spot has 1770 correct predictions out of 1814 instances (97.57%), displaying a strong predictive capability.

The graph shown in Fig. 11, depicting the training and validation accuracy of our Capsule Neural Network model, reveals several significant observations. Notably, the training accuracy consistently outperforms the validation accuracy, especially after 25 epochs, indicating the model's ability in learning from the training data and its potential for making accurate predictions on previously unseen data.



Fig. 10. Confusion Matrix for CapsNet Model

The provided classification report illustrated in Table. 1 offers a comprehensive evaluation of the Capsule Neural Network model's performance across ten classes of plant diseases.

Table. 1. Classification Report for CapsNet Model

Classification report	precision	recall	F1-score	support
0	0.99	0.98	0.98	1814
1	0.93	0.91	0.92	861
2	0.99	1.00	0.99	1336
3	0.96	0.96	0.96	1630
4	0.96	0.96	0.96	814
5	1.00	0.98	0.99	320
6	0.97	0.98	0.97	1546
7	0.98	0.96	0.97	1428
8	0.95	0.98	0.97	1184
9	0.99	0.99	0.99	2733
accuracy			0.97	13666
Macro avg	0.97	0.97	0.97	13666
Weighted avg	0.97	0.97	0.97	13666

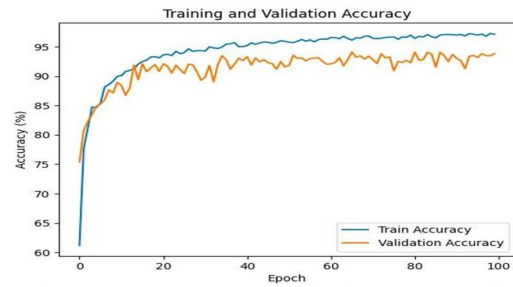


Fig. 11. Accuracy Vs No. of Epochs for CapsNet Model

## B. Yolo v8 Model

The training results of the YOLOv8 model are depicted in Fig. 12. Different lines in the graph represent various loss functions that the model aims to minimize during training.

The loss curves illustrate the model's performance improvement on the training set as the training iterations progress. Ideally, these curves should consistently decrease over time. Additionally, the bottom-left corner of the image displays the model's mean Average Precision (mAP) on a validation set. mAP is a vital metric for evaluating object detection models, considering both precision and recall. The increasing trend of mAP throughout training suggests the model's effective generalization to unseen data.

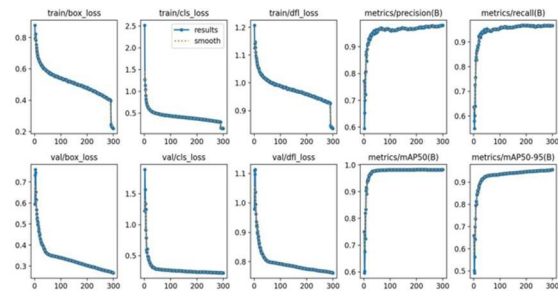


Fig. 12. Training Graphs for Trained Yolo v8 Model

The mAP results of the YOLOv8 model are visualized in Fig. 13. The line in the graph is purple and exhibits an upward trend throughout. The y-axis is labelled "mAP," ranging from 0.55 to 1.00, while the x-axis is labelled "Epochs," ranging from 0 to 300. At the bottom-left corner of the graph, there is text indicating "1.00." The graph portrays that the model's mean Average Precision (mAP) increases as training progresses, indicating effective generalization to unseen data.

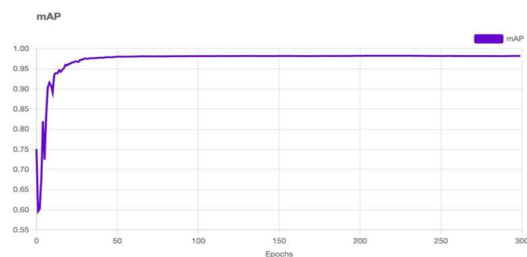


Fig. 13. mAP Result of Yolo v8 Model

## VIII. DRONE IMPLEMENTATION AND MODEL DEPLOYMENT

### A. Drone Communication and Website Deployment

The drone (Fig. 14), which is outfitted with Crossflight flight control, a F450 frame, Flysky 1100kv motors [15], ReadytoSky 40A ESC, FlySky FS-i6 Transmitter, TS100 GPS and 10-inch propellers, achieves the project's primary goal of carrying 1.5 to 2kg thrust, capturing images, and transmitting them to a local server for analysis.

Loiter mode is a flight mode featured on many drones, especially those with autopilots or flight controllers. It enables the drone to keep a reasonably constant position in the air, including height, location, and direction. This makes it extremely handy for a variety of drone applications.



Fig. 14. Image after assembling all parts of drone

The webpage allows image capture using a Pi Camera with Capture and Transfer buttons. Captured images are displayed after a 5-second delay and can be transferred to a local laptop for analysis Fig. 15. The site integrates Capsule Networks (CapsNet) and You Only Look Once (YOLO) for advanced image processing, powered by Django. It features secure image storage, user authentication, and displays remedies for detected plant diseases. An admin page provides secure data management and download capabilities. Django's MVC framework supports robust web applications with built-in features like authentication and URL routing.

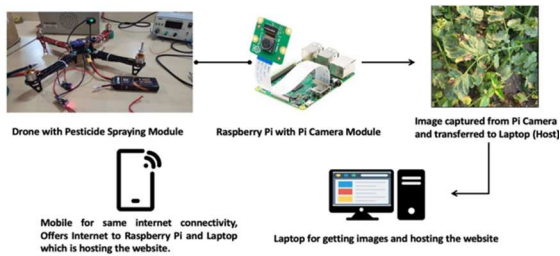


Fig. 15. Communication Setup – Block Diagram

### B. Comparison with Existing Results

This research involved developing and comparing different architectures for Capsule Network Models, focusing on their training accuracy, testing accuracy, and the number of epochs required. The main goal was to minimize the number of epochs needed to attain peak accuracy.

The implementation of Capsule Networks (CapsNet) has surpassed the results reported in the most recent research in [7]. The existing study achieved an accuracy of 96.39%, whereas the proposed model has attained a higher accuracy of 97.41% (Table. 2.). This improvement underscores the effectiveness of the training and approach in enhancing image processing capabilities for plant disease detection.

Table. 2. Comparative Study - Capsule Network Model

S. No	No. of Epochs	Training Accuracy (%)	Testing Accuracy (%)
1	10	70.14	68.32
2	30	90.96	85.96
3	50	95.54	96.06
4	100	97.11	97.41

Table 2 demonstrates how varying epoch numbers affect the Capsule Network Model's performance. Increasing epochs enhances training and testing accuracy initially. However, beyond 50 epochs, test accuracy improvements slow down, indicating diminishing returns and potential overfitting. The optimal balance between efficiency and accuracy is typically achieved within 50-100 epochs, emphasizing the critical role of epoch selection for model effectiveness.

## IX. CONCLUSION

This research demonstrates the effectiveness of reducing epochs in deep learning training, resulting in higher accuracy with lower computational demands, and utilizing the key advantages of different deep learning models to improve the prediction results. This optimisation provides a practical solution for accurate disease detection in precision agriculture. The integrated system, which includes manual drone control and deep learning models such as Yolo and CapsNet, achieves high accuracy rates while easing farm management.

This research presents a disease prediction method for tomato leaf disease detection and classification that combines Yolo v8 with Capsule Neural Network. The suggested method addresses the convenience and effectiveness of disease detection in agricultural settings by providing a GUI based, user-friendly web platform for uploading the images of Tomato leaves from a farm, that were captured using a drone and obtaining real-time disease forecasts. Its speedy processing of a high number of photos

makes it a useful tool for a wide range of agricultural applications.

The results demonstrate that the proposed model excels in both precision and speed proving that it is well-suited for real-world agricultural applications, delivering accurate and rapid inference results.

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