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Precision diagnosis of tomato diseases for sustainable agriculture through deep learning approach with hybrid data augmentation

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ABSTRACT

Tomato is a key crop in global agriculture, yet it faces yield and quality challenges due to various diseases. Traditional disease identification methods are slow and require expertise, limiting their practicality in large-scale farming. Integrating automated disease detection with precision agriculture provides a timely, accurate diagnosis, promoting sustainable practices. However, the scarcity of real-world data hampers effectiveness. To address this issue, data augmentation techniques simulate variations in farm images, enriching datasets for improved detection of diseases. This investigation aims to identify seven different tomato diseases, such as bacterial spot, early blight, late blight, and others, while also detecting healthy plant leaves. Unlike previous studies that relied on the controlled PlantVillage dataset, this study utilizes the real-world PlantDoc dataset. The study addresses different challenges faced throughout the model development process, like data scarcity and imbalances. A hybrid data augmentation technique is introduced to increase the dataset size from 737 images to 6696 images, which improves the accuracy and robustness of the computer vision model. The study employs the YOLOv8n deep convolutional neural network, achieving 96.5 % mAP, 97 % precision, 93.8 % recall, and 95 % F1 score. The results demonstrate a significant improvement in disease detection, addressing challenges from inadequate datasets and advancing AI-driven precision agriculture. The proposed YOLOv8n model has the potential to be applied beyond its current scope by training it on datasets of other crops. The model can learn and generalize the unique image features associated with various crop types, expanding its utility in agricultural applications. This flexibility allows the model to detect and classify plant characteristics, diseases, or pests across different crops, enabling its use in diverse agricultural environments. As a result, the YOLOv8n model could serve as a robust tool for precision farming, helping to optimize crop management and enhance productivity on a broader scale.

1. Introduction

Frequently changing global climatic conditions coupled with the onset of a variety of biotic stress factors in the form of bacterial, fungal, viral and insect pest-related challenges posed a serious threat to global agriculture [1,2]. It has been observed that losses due to diseases are one of the most significant constraints on global food security [3]. Plant diseases alone incur an estimated annual loss of US$220 billion in the global economy [4], https://www.fao.org/plant-production-protection/about/en]. Timely disease detection remains challenging, often relying on limited options such as consulting peers or agricultural helplines [5,6]. Early identification of diseased plants requires specialized knowledge and often necessitates access to laboratory facilities. Over the last decade, computer vision has emerged as the most advanced tool for recognizing plant diseases. It is crucial for assessing both biotic and abiotic stress in tomato plants, since it analyzes photos to identify indicators such as alterations in fruit or leaf color, shape, or texture. By recognizing unique visual patterns, it enables the automatic detection of illnesses, pests, and environmental stressors. This facilitates real-time monitoring and differentiates between biotic stresses such as diseases

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Fig. 1. Illustration of a highly effective combination of data augmentation techniques for advanced image transformation. The images are annotated examples from the original PlantDoc dataset (available at https://public.roboflow.com/object-detection/plantdoc).

Table 1
List of tomato diseases and their extracted images with their respective instances.

Tomato disease	Extracted image count	Instance count
Tomato early blight	86	210
Tomato healthy	73	400
Tomato bacterial spot	111	263
Tomato late blight	110	218
Tomato mosaic virus	55	261
Tomato yellow virus	74	801
Tomato mold	92	295
Tomato septoria leaf spot	148	426

and pests, and abiotic stressors like drought and nutrient deficiency. Recent advancements in CNN have revolutionized computer vision, enabling rapid image classification and object detection even on personal devices like smartphones. Applying computer vision to plant disease detection integrates deep learning expertise with real-world agricultural challenges, potentially enhancing crop yield and disease management [7]. Unlike existing computer vision-based solutions that typically require high-resolution images with controlled backgrounds, the present research focuses on images captured under natural habitats with complex backgrounds and lighting variations. This approach will be helpful, particularly for small and marginal farmers who predominantly use low-end mobile devices [7].

Tomatoes thrive in well-drained soils, and they are extensively

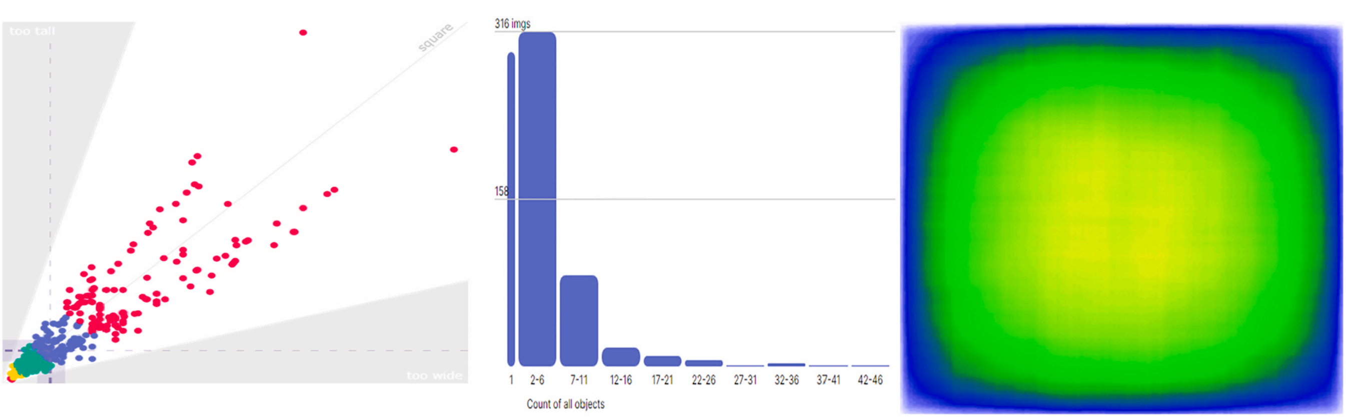

Fig. 2. Distribution of data set with different visualization tools like data distribution, histogram and heatmap: Data distribution (left), histogram (middle) and heatmap (left) of the dataset.

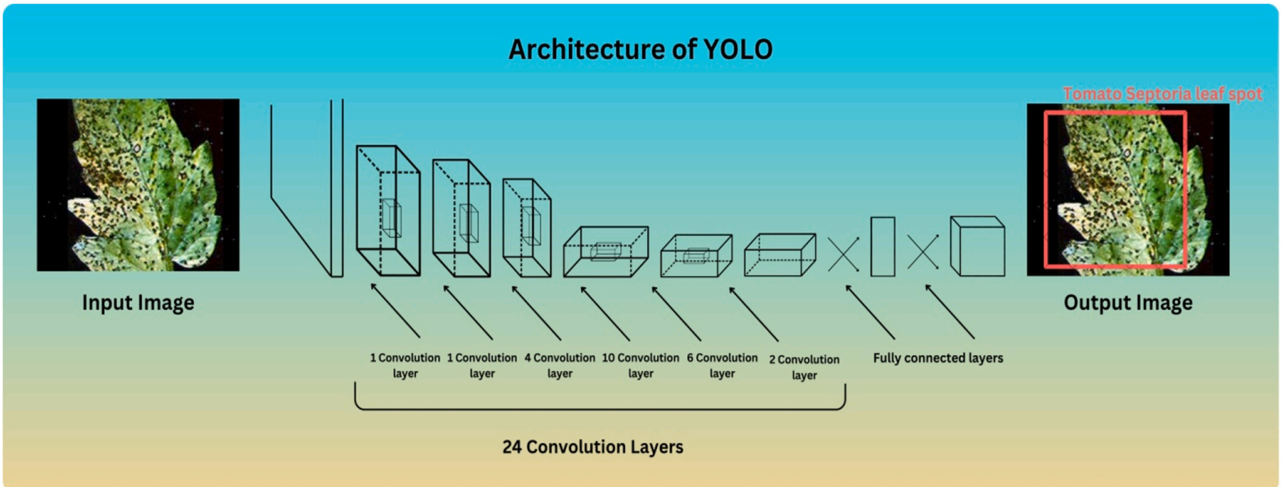

Fig. 3. Architecture of Yolo model that integrates state-of-the-art techniques in deep learning and computer vision, including advanced feature extraction layers, fully connected layers optimized anchor box clustering, and improved training strategies.

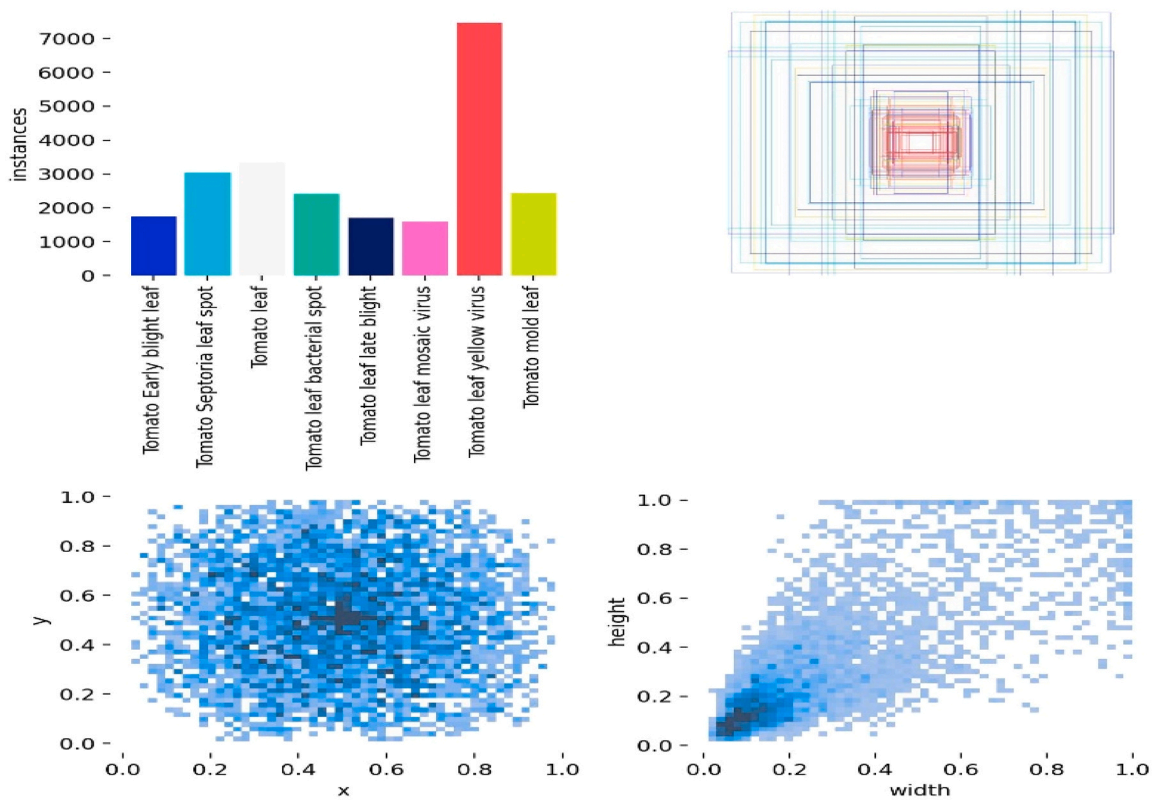

Fig. 4. Label plots related to the labels of the augmented dataset represent the top left plot shows the label distributions of different classes, the top right shows the size distribution of the labels, the bottom left is the plot of horizontal and vertical coordinates of the labels, and the bottom right plot is the height and width of the labels.

cultivated worldwide in open agriculture fields as well as in greenhouses under protected environments [8]. Diseases predominantly occur under both conditions, which causes significant losses [9]. Effective control measures of the disease need precise identification of the causal pathogen and stage of the disease. Identifying tomato plant diseases involves diagnosing areas of infection, observing symptoms like brown or black patches and holes, and examining for the presence of insects [10]. Tomato diseases can generally be categorized into two types: those caused by bacteria or fungi due to poor cultivation practices and those caused by insects. For instance, the bacterium *Ralstonia solanacearum* causes a severe form of bacterial wilt, surviving in soil for extended periods and entering plants through natural or man-made wounds during cultivation, transplanting, or even *via* insect vectors. Optimal conditions for disease development include high moisture and temperature, leading to bacterial proliferation within the water-conducting tissues of plants, disrupting the vascular system, whereas leaves may still appear healthy and green. Infected tomato stems show a characteristic cross-section appearance of brown with yellowish exudate.

The present research article proposes a novel method for identifying tomato crop diseases by analyzing leaf images. This approach aims to

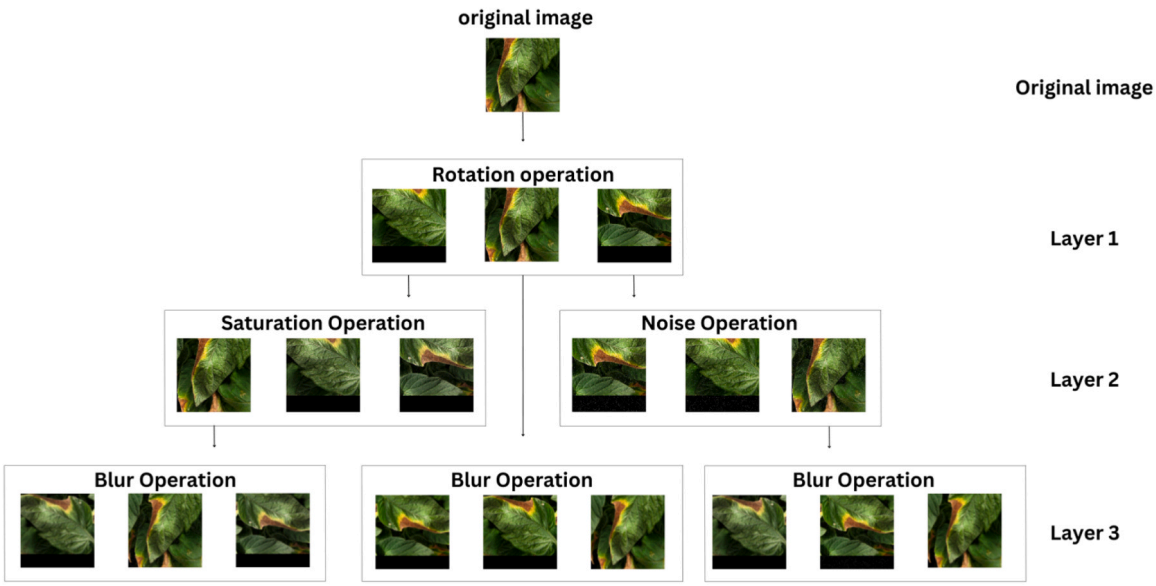

Fig. 5. Three Kernel-based layered augmentations scheme in a layered approach.

Table 2
Effect of various augmentations on mAP50.

S. No.	Augmentation applied	New image count	Epochs	mAP50 in %
1.	NA	737	30	37.55
2.	Resize (400 ×400)	737	30	34.23
3.	Flip	1247	30	37.83
4.	Rotate by 90	1247	30	42.26
5.	Saturation (−25 % to +25 %)	1247	30	38.48
6.	Gaussian Blur (up to 2px)	1247	30	39.79
7.	Noise (up to 0.5 %)	1247	30	39.64
8.	Proposed Approach	6696	100	96.57

alleviate farmers' challenges in disease identification, providing timely solutions without dependence on others. By improving the efficacy of disease management practices, our method will be helpful in improving both the quality and quantity of crop yields, thereby increasing the income of the farmer community. A dataset of tomato leaf images from PlantDoc [11] is used to conduct the experiments, and a Yolov8n model is employed for disease detection. The present investigation evaluated the performance of the model based on various attributes such as precision, recall, F1 curve, mAP50, mAP50–95, loss of function, precision confidence, precision-recall curve, and recall confidence.

2. Recent developments in DL-assisted disease diagnosis

A comprehensive search was conducted across various databases - Web of Science (WoS), SpringerLink, Frontiers, ScienceDirect, and IEEEXplore - using keywords such as "tomato disease," "deep learning," "data augmentation," "object detection," and "machine learning." The initial findings revealed limited publications related to disease detection in tomato leaves. ML algorithms are widely employed across diverse fields, but traditional feature engineering poses significant challenges. However, with the rise of DNNs, promising advancements have been made in plant pathology. DNNs have notably increased the accuracy of image classification in this domain. This part explores various DL techniques employed by researchers to identify plant diseases. Mohanty et al. [12] utilized AlexNet [13] to classify previously unseen plant diseases. However, they noted a significant decrease in model accuracy when testing images differed in conditions from those used in training. Rangarajan et al. [14] trained AlexNet and VGG16net, experimenting with hyper-parameters like minimum batch size and learning rates for weights and biases. They observed a negative correlation between accuracy and minimum batch size in the case of VGG16net. In another approach, convolutional and pooling layers were stacked in modules and applied to the GoogleNet architecture, known as Inception V4, for dimension reduction [15]. Too et al. [16] fine-tuned this architecture with weights pre-trained on ImageNet, utilizing an average pooling layer of 8 × 8 for further refinement. DenseNets [17] with 122 layers were fine-tuned for recognizing plant diseases.The [18,19] compared ResNet50 and Xception architectures using three optimizers: Adam, Nadam, and RMSProp, with learning rates of 0.0001, 0.002, and 0.04, on publicly available data. Data augmentation techniques such as rotation, zooming, and shifting were applied. Xception with the Adam optimizer and a 0.0001 learning rate achieved good accuracy, recall, precision, and F-score. CNN with a local contrast normalization layer and ReLU activation function was used for binary disease classification [20]. Furthermore, AlexNet and GoogleNet were trained and fine-tuned specifically for classifying disease regions and symptoms [21]. DeChant et al. [22] proposed a three-stage CNN training approach: the first stage detects lesions, the second produces heatmaps for infection identification, and the third classifies features based on these heatmaps. Li et al. [23] proposed FWDGAN-based data augmentation for tomato leaf disease identification, which uses a WDBlock in the generator to enhance image quality and a DSC-Discriminator to reduce model parameters. The SeLU activation function improves training stability. FWDGAN generates higher-quality images with better FID scores and has one-third fewer parameters than DCGAN. Ahmed et al. [24] compare YOLOv5 and YOLOv8 for detecting tomato diseases. After initial training, data augmentation from Roboflow was used to enhance the dataset. Retraining with this augmented data improved accuracy, with YOLOv8l performing slightly better than YOLOv5l, especially without background images [46]. Wang et al. [25] explored the impact of network depth on classification accuracy, finding that even with transfer learning, fewer convolutional layers can achieve high accuracy. Tan et al. [26] applied a variable momentum rule to CNNs for parameter learning from lesion images, resulting in quick convergence and good accuracy comparisons.The performance of various CNN architectures in plant disease identification depends on several factors: the availability of annotated data, the representation of disease symptoms, image background and capturing conditions, and the variability in disease symptoms [27]. Pattnaik et al. [28] focused on pest detection in tomato

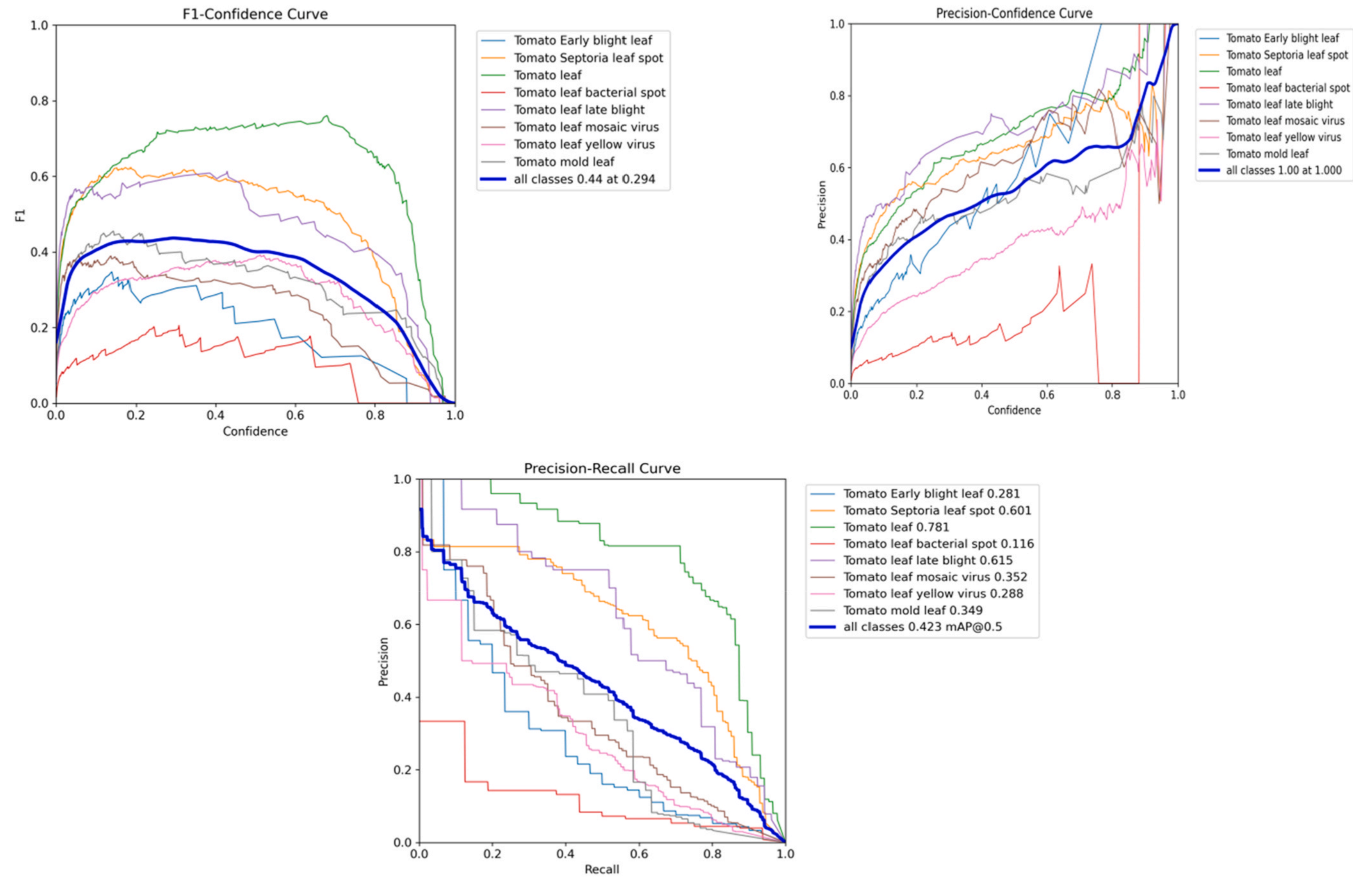

Fig. 6. Bottleneck in the case of the bacterial spot disease.

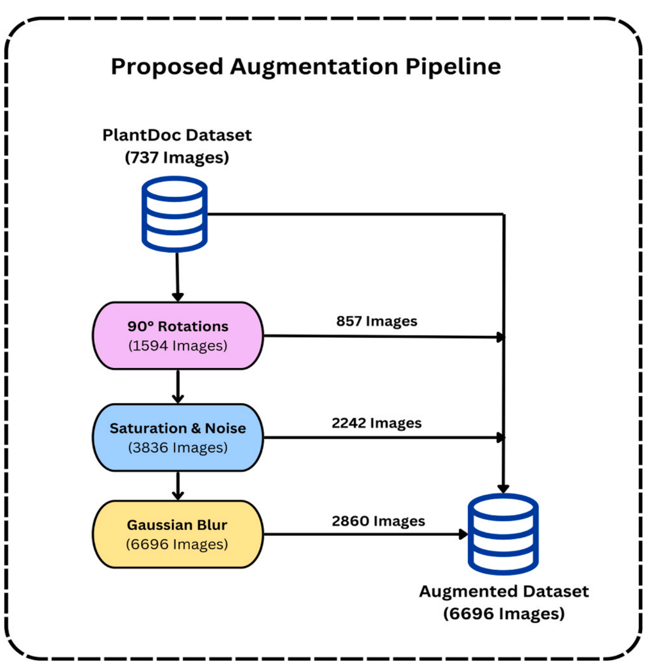

Fig. 7. Scematic augmentation pipeline.

plants, creating a dataset of 859 images categorized into ten classes. They tested their approach using 15 pre-trained CNN models. Turkoglu et al. [29] proposed models using deep features from pre-trained CNNs to detect plant diseases, achieving high accuracies with different ensemble techniques. Kalaivaniet al. [30] use machine learning and deep learning to detect tomato and potato leaf diseases, comparing SVM and ResNet algorithms. ResNet achieves 94 % accuracy, outperforming SVM's 88 %, making it suitable for real-time implementation. Kasinathan and Uyyala [31] explored various image feature extraction techniques and classifiers, demonstrating significant impacts on performance, particularly with the Random Forest classifier achieving accuracies up to 95.89 %. Sankaran et al. [32] proposed using reliable sensors to monitor plant health and diseases under field conditions. However, widespread sensor-based plant disease detection adoption is limited due to high hardware costs and the expertise required to operate such systems effectively [33]. Recent research has explored neural networks for identifying three legume species based on leaf vein morphological patterns. Feature extraction and Neural Network Ensemble (NNE) were employed to achieve 91 % testing accuracy in recognizing tea leaf diseases [34]. Several recent studies have also investigated convolutional neural network (CNN) variants for detecting diseases using plant leaf images [35]. However, these studies often focus on specific crops, limiting their generalizability. Moreover, the lack of publicly available datasets in these studies hinders reproducibility and broader adoption of the proposed methods.

This research aims to achieve the following objectives: 1. Development of a framework for data augmentation using various manipulation-based transformation techniques. 2. Creating a deep learning model utilizing Yolov8n object detection with enhanced, fully connected layers. 3. Assessing the impact of data augmentation on model evaluation. The study evaluates the effectiveness of data augmentation techniques in a machine vision system designed to detect tomato diseases. The developed system aims to help farmers quickly identify and manage crop diseases, ultimately improving crop yield management.

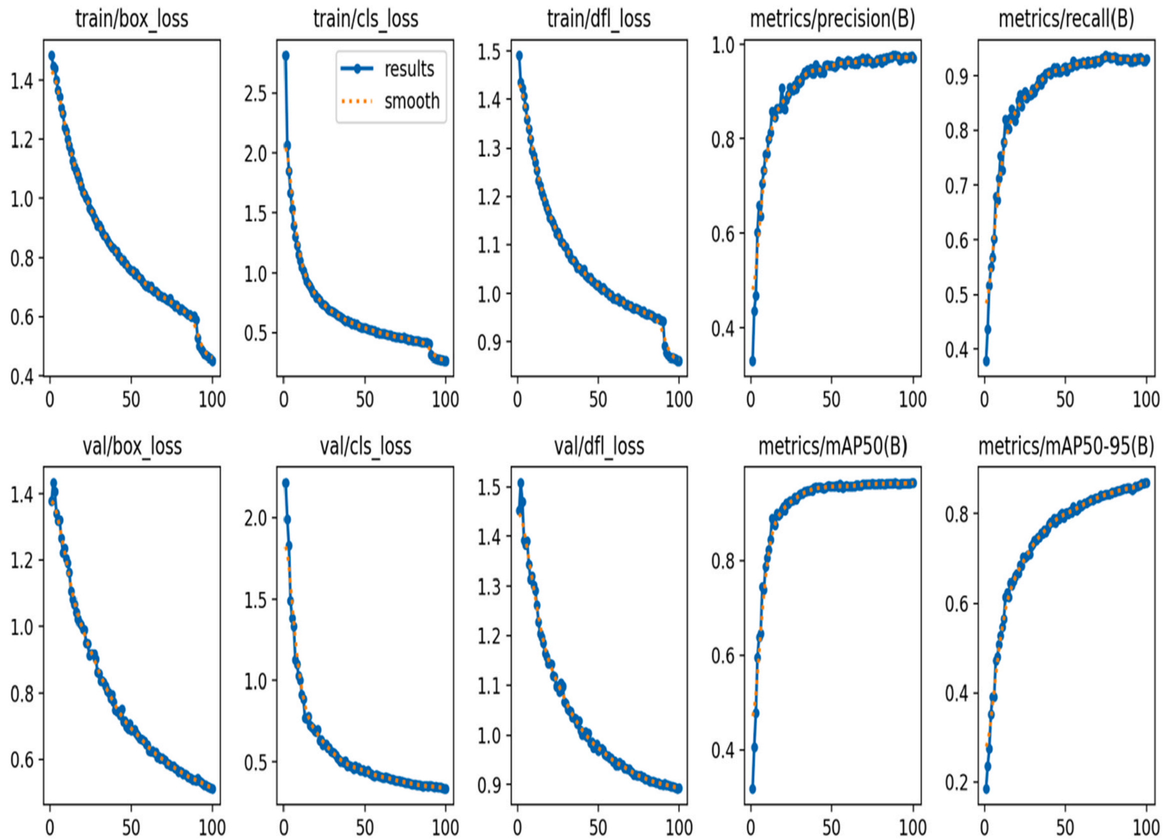

Fig. 8. Results of the proposed model indicate the performance and stability. All the training and validation loss functions decrease as the epochs increase. The mAP50 metric crossed 0.9 in the first 20 epochs, increased constantly, and finally reached 0.965.

3. Materials and methods

3.1. Dataset collection and preprocessing

The PlantVillage [36] dataset comprises images captured under controlled conditions. This setup limits the dataset's effectiveness in real-world disease detection, as plant images often include multiple leaves with diverse backgrounds and varying lighting conditions. In real situations, a camera may capture images of multiple diseases on the plant. To address these limitations, we utilized the PlantDoc dataset [37, 38]. To our knowledge, PlantDoc is the first dataset collected from non-controlled settings with annotation (see Fig. 1). It contains 27 classes of labelled data spanning over 13 species with 2598 images. The tomato data set was extracted from the plantDoc dataset and a total of 737 images across eight classes of diseases, which are tomato bacterial spot, tomato early blight, tomato healthy, tomato late blight, tomato mold, tomato mosaic virus, tomato septoria leaf spot, and tomato yellow virus were extracted. Table 1 shows the extracted images and their respective instances.

Researchers have introduced a manipulation-based data augmentation framework to tackle the issue of limited data in automated tomato disease detection. This study focuses on enhancing the diversity of image data to boost the learning capabilities of machine vision systems. These techniques involve applying mathematical transformations to generate new images while retaining important features. This approach diversifies the dataset, enhancing its randomness and thereby boosting the effectiveness of machine learning model training for accurate tomato disease detection (Fig. 2).

Despite the utility of the available image dataset, the limited dataset presents a significant challenge in developing a machine vision model for tomato disease detection. Additionally, the subtle differences between disease categories render techniques like image mixing, colour conversion, and random pixel erasing unsuitable for model training. An effective combination of data augmentation techniques for high-level image transformation is demonstrated in Fig. 1. Each sample of tomato disease images undergoes multiple operations, including filter and geometric-based transformations, such as rotation, noise addition, image enhancement, and scaling. The innovative aspect of the proposed method is its sequential pipeline, which applies multiple operations to each sample, thereby increasing the variability in the training dataset.

3.2. Experiment setup

This section focuses on the experimental investigation of the proposed methodology. The experiments carried out in this research were conducted on the Jupiter Notebook environment, and a GeForce RTX 3050 Ti (Laptop) GPU was used for training. Python and Ultralytics modules were used, which contain YOLO (You Only Look Once) models for implementation. The Nano version of Yolov8 with AdamW as the optimizer was trained. It was initialized with a momentum of 0.9 and a learning rate of 0.000833. Moreover, 225 layers, 3012408 parameters, 3012392 gradients, 8.2 GFLOPs, and 319/355 pre-trained weights were transferred.

3.2.1. Yolov8

In recent years, YOLO has emerged as a powerful and efficient object detection algorithm in computer vision. YOLOv8, an evolution in this series, represents a significant advancement with improvements in accuracy and speed over its predecessors. YOLOv8 builds on its predecessors, offering enhanced real-time detection accuracy. It leverages a single CNN to directly predict bounding boxes and class probabilities from full images in a single evaluation, distinguishing it from traditional two-stage detectors. The architecture of YOLOv8 integrates state-of-the-art techniques in deep learning and computer vision, including

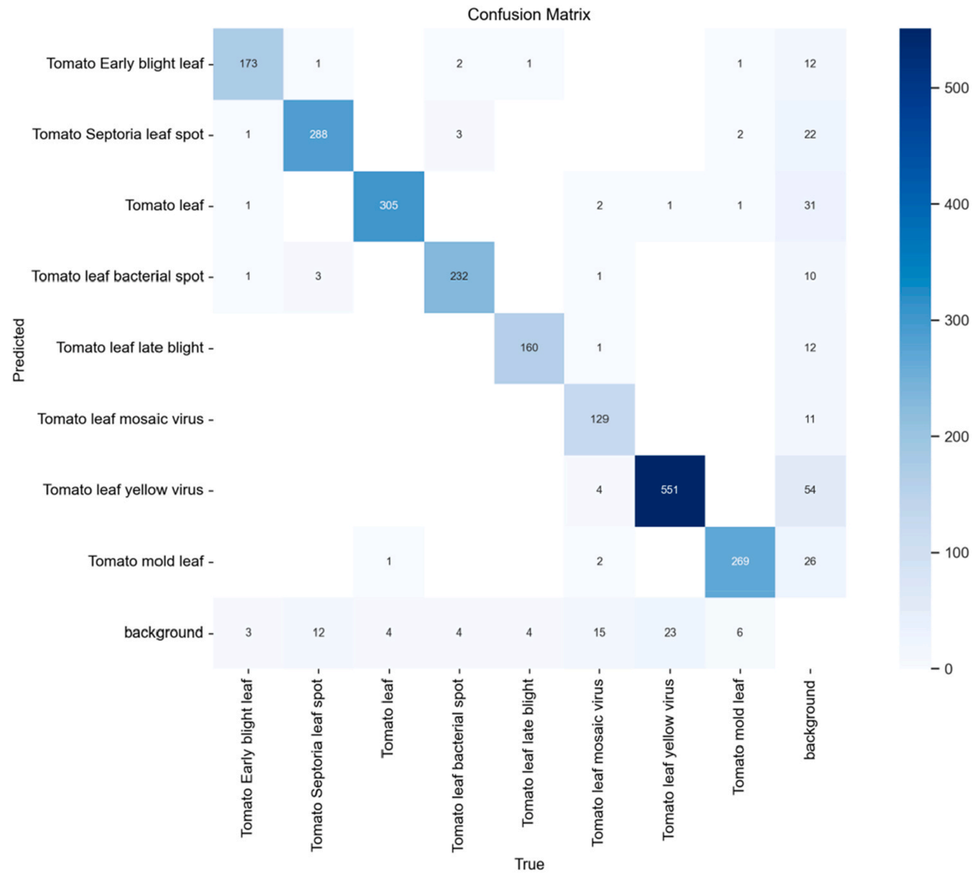

Fig. 9. Confusion matrix. The principle diagonal represents all the true predictions and contains most of the values. A small number of false positives and false negatives do not require much attention.

advanced feature extraction layers, optimized anchor box clustering, and improved training strategies (Fig. 3). These enhancements enable YOLOv8 to excel in detecting and localizing objects across various scales and categories, making it suitable for various applications in research and industry.

3.3. Data augmentation

When a dataset is insufficient or unbalanced for model training, data augmentation is the most effective approach to achieve accurate prediction results [39]. This technique enhances data diversity during the training process for machine vision algorithms, improving overall model performance and preventing overfitting. Researchers have developed various data augmentation techniques over the past few decades, generally categorized into operation-based manipulation approaches, synthetic data generator approaches, and hybrid techniques [40,41]. Operation-based manipulation is a straightforward data augmentation approach that enhances datasets by applying mathematical transformations to real-input images. Techniques such as rotation, flipping, cropping, edge enhancement, noise addition, and jittering are commonly used to generate new images with variations in orientation, perspective, composition, edge clarity, imperfections, and object positioning. These methods are crucial in improving the robustness and performance of machine learning models by exposing them to a diverse set of data conditions encountered in real-world applications [42]. Synthetic data generation methods like Generative Adversarial Networks (GANs), image registration, and PCA (Principal Component Analysis) create new images by altering existing ones, aiming to diversify data distributions. GANs generate artificial samples to enhance training data quality for CNN models with limited datasets in agriculture and other fields [43]. These approaches are pivotal for improving model accuracy in scenarios where traditional augmentation techniques may not suffice. Geometric-based transformations are popular in data augmentation due to their simplicity and ability to preserve the original characteristics of images. Techniques like scaling, rotation, translation, and flipping adjust image coordinates without altering the inherent content, making them effective for enhancing datasets. Kernel filtering uses effects such as blur, sharpening, and contrast enhancement to images. Blurring and sharpening are common techniques in the data augmentation process [44] introduced a patch shuffle regularization technique, using a filter that randomly swaps adjacent pixels to create a sharper image, achieving a better error ratio than traditional filters on the CIFAR dataset.

4. Results and discussion

4.1. Comparison and evaluation of various data augmentations

PlantDoc data set contains 2569 images of 13 plant species in 30 classes (diseased and healthy) with 8851 labels (https://public.roboflow.com/object-detection/plantdoc).

The diseased and healthy leaves of tomato species were extracted from the dataset (Fig. 4). The Yolov8 object detection model was then employed, which resulted in a Mean Average Precision (mAP) of 37.55 % on the unaugmented dataset. We observed that it decreased the mAP (37.55 %) and the performance when compared with the unaugmented data set shown in Table 1. As shown in Fig. 5, several augmentation techniques were applied to the training set to see their effect on the mAP, shown in Table 2. For the initial processing, we resized all the images into 400 x 400px dimensions. For the next step, we applied our first augmentation, rotating the training images to 90 degrees left and 90 degrees in the right direction. Thus, after removing

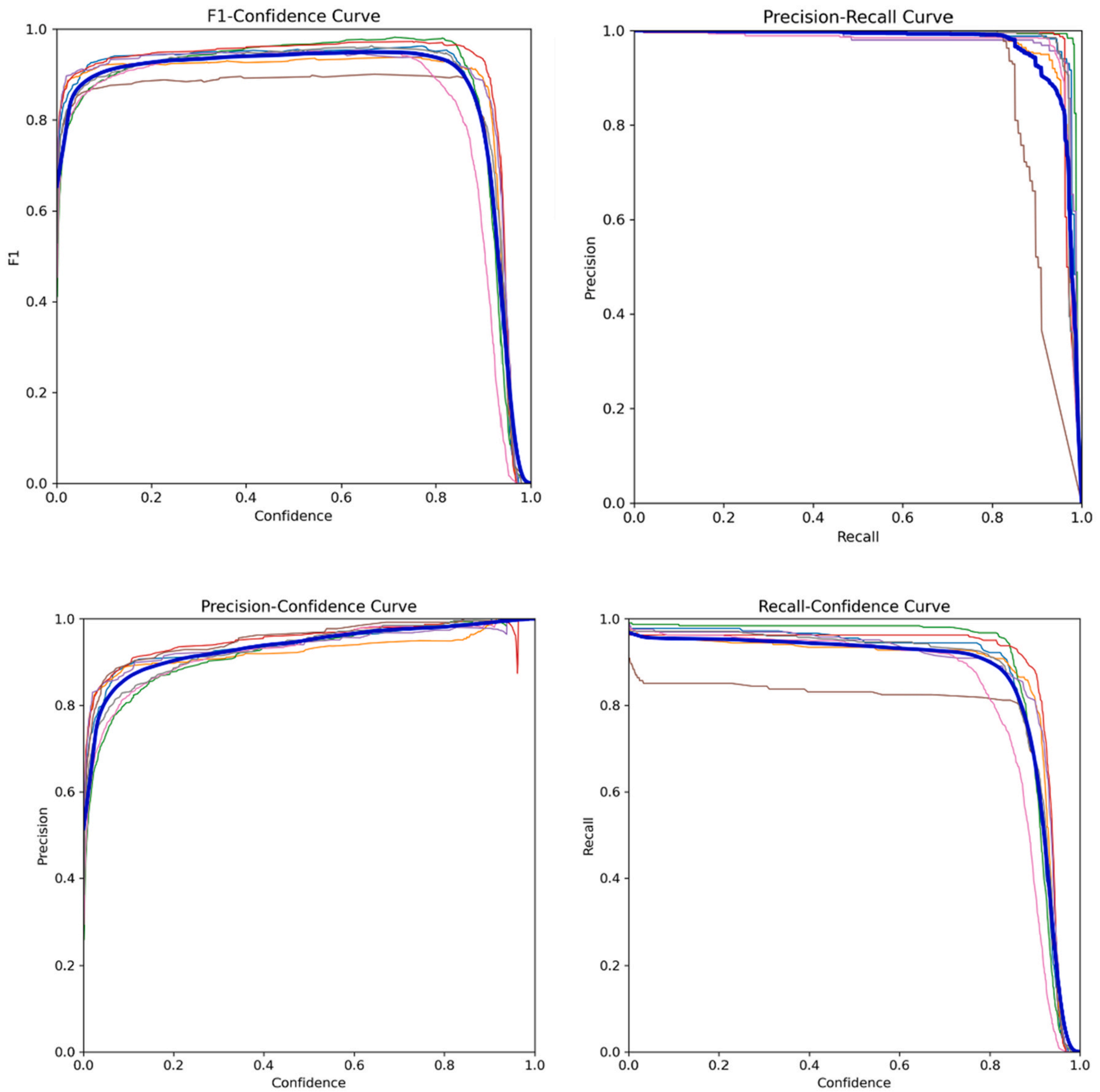

Fig. 10. The training graphs display the F1 confidence curve, precision-recall curve, precision confidence curve, and recall confidence curve.

duplicity, the image dataset is increased from 737 to 1594 images, including the original dataset. It resulted in a significant increase in the mAP (42.26 %) from 37.55 %. The model is now enriched and contains various versions of the original images. As shown in Fig. 5, we have used this augmentation as the first layer in our proposed framework.

The three Kernel-based augmentations were applied to the dataset, and their effects on the dataset and their results were evaluated. These filters increased the mAP graph's slope, indicating a potential increase in mAP if the training epochs were increased. These schemes will be very effective with new variations of training images with small adjustments. For the first filter, we applied random saturation adjustments from −25 % to + 25 % on training images after removing duplicity and increased the dataset images to 1247. As a result, we observed an increase in mAP (38.48 %) and performance of training graphs. However, the loss functions plot for the validation set is not normal and indicates overfitting on the training set. In the next filter, we applied salt and pepper noise in random proportions up to 0.5 % of the pixels. In this way, we doubled the training images and increased the dataset to 1247 images. It significantly increased the mAP to (39.64 %), and the training graphs also indicated better performance except for the loss functions. As indicated in Fig. 5, we have used this augmentation scheme as the second layer in our proposed augmentation framework.

The Gaussian Blur up to 2px was applied for the last augmentation and increased the dataset to 1247 images. This experiment resulted in mAP increment (39.79) and improved training graphs & loss function. We have used Gaussian Blur as the biggest layer in our proposed framework. We have used this augmentation scheme as the third layer in our proposed augmentation framework, as indicated in Fig. 5. Throughout all these experiments, we identified a bottleneck in the case of the bacterial spot disease, as shown in Fig. 6. It was constantly underperforming under all the augmentations. To optimize it, we rebalanced the class balances and increased the validation set to avoid overfitting. After this adjustment, the bacterial spot disease performed well. Two strategies were used to assess the effectiveness of the data augmentation process: (i) The original image dataset was split into training and validation sets in an 85:15 ratio to evaluate baseline performance. (ii) The augmented dataset, created using the proposed methods, was used for training, while the unmodified original dataset was used for validation. Table 2 shows the distribution of the original and augmented datasets with the corresponding mAP on different epochs using yolov8.

Fig. 11. Actual *vs* predicted labels: The left image contains the labels from the dataset, and the right image shows the predicted labels for the corresponding image.

Table 3
Outcomes of the proposed model on different parameters like mAP50, mAP50-95, precision, recall and F1 score.

Parameters	Values
mAP50	96.57
mAP50–95	86.92
Precision	97.75
Recall	93.84
F1	0.95
Boxloss	0.45
Class loss	0.26
Dfl loss	0.86

Table 4
Mean Average Precision (mAP) based comparison of leaf disease detection using different related deep learning models.

Model	Pretrained weights	mAP 50 in %
MobileNet	COCO	32.8
MobileNet	COCO + PVD	22.4
Fater-RCNN-Inception-resnet	iNaturalists	36.1
Fater-RCNN-Inception-resnet	iNaturalist	36.1
Yolov5l without data Augmentation [24]	Yolov5	67.9
Yolov8l without data Augmentation	Yolov8	78.9
Yolov5l with data augmentation [24]	Yolov5	85.2
Yolov8l with data augmentation [24]	Yolov8	85.2
Faster RCNN model with augmentation [24]	COCO	82.08
Faster RCNN with SGD optimizer [38]	COCO	91.33
Proposed approach	**Yolov8**	**96.5**

4.2. Proposed data augmentation framework

After carefully observing the effects and results of all the augmentations on our dataset, we calculated the betterment of all the augmentations. We combined the goodness of these experiments in one manual to create the proposed manual augmentation approach. Our proposed augmentation framework aims to increase input images without losing useful features while maintaining the randomness of the data. Each image from the dataset is passed through 3 layers of augmentation, and a sequential pipeline is followed, including multiple operations to be performed, as shown in Fig. 7. The augmentation layers in the framework were very carefully selected after doing proper analysis & evaluation in the first layer. The image is rotated to 90° left and 90° right to produce two new images. One set of both transformed and original images is stored in the augmented data, and two sets are passed to saturation (-10 % to + 10x) adjustments and Noise (up to 0.4 %) augmentation, respectively. After this, all the transformed images are stored in the augmented data. All the images are passed to the final layer of Gaussian Blur (up to 2px) augmentation to generate the complete augmented data set for the proposed model. The motivation behind selecting these manipulation techniques stems from a farmer's perspective, as farmers encounter various image conditions involving rotation, blurring, and changes in illumination. Thus, the initial dataset of 737 images is increased to 6696 images in the augmented set. Finally, this augmented dataset trains the Yolov8 model for the final experiment. (Fig. 8)

True Positives (TP): TP are the correct predictions where the actual class matches the predicted class (diagonal elements). For example, "tomato early blight leaf," 173 samples were correctly predicted as "tomato early blight leaf" (Fig. 9).

True Negatives (TN): TN are the correct predictions where the model correctly predicted other classes, but the true class was not predicted (all values outside the row and column of the class being considered). Example: For "tomato early blight leaf," all predictions that are not in the "tomato early blight leaf" row or column and are correct predictions fall under true negatives.

False Positives (FP): FP are the incorrect predictions where the model predicted a class, but the true class was something else (off-diagonal values in the row for the predicted class)

False Negatives (FN): FN are the missed predictions where the model failed to predict the true class and instead predicted something else (off-diagonal values in the column for the true class).

Figs. 9 and 10 exhibit various simulation results from the model in terms of F1 confidence, precision-recall curves, etc. All graphs indicate strong overall performance, with individual classes also showing favourable results.

From Fig. 11, it can be seen that there is almost no difference between the actual and predicted labels. The confidence scores corresponding to each predicted label are also shown in the right image with good confidence. Table 3 exhibits the outcomes of the proposed model on different parameters like mAP50, mAP50–95, precision, recall and F1 score. Table 4 shows the promising results when compared with the previous study based on the mAP50 parameter.

5. Conclusion and future perspective

The present study used the yolov8 model and investigated the efficiency of the proposed data augmentation scheme to detect tomato diseases. An evaluation was conducted across the PlantDoc dataset by extracting the tomato leaves datasets. Results demonstrated that the proposed data augmentation method improved mAP to 96.5 %, with 97 % precision, 93.8 % recall, and a 95 % F1 score. The study concludes that this approach enhances model performance in predicting tomato disease detection. This work highlighted challenges in deep learning tasks, particularly data imbalance, and proposed future research to optimize these techniques using genetic algorithms. Tomato disease detection will benefit from the ongoing integration of AI-driven technologies with precision agriculture. As automated systems like YOLOv8n become more sophisticated, they will play an increasingly vital role in enhancing crop yield and quality on a global scale. The use of real-world datasets like PlantDoc, coupled with advanced data augmentation techniques, will further refine these models, making them more robust against the variability of actual farming conditions. Future research may focus on expanding these methods to other crops and diseases, creating a more comprehensive and adaptable agricultural framework. Additionally, advancements in sensor technology and ML algorithms could lead to real-time disease monitoring, enabling farmers to take proactive measures, ultimately contributing to more sustainable and resilient agricultural practices.

CRediT authorship contribution statement

KJ, SSG, RG, NT conceived and designed the experiments; KJ, SH performed the experiments; KJ, SH, RG analyzed and interpreted the data; KJ, NT, RG, SSG wrote and revised the manuscript.

Declaration of Competing Interest

Authors declare no Conflicts of interest/Competing interests.

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Data availability

https://public.roboflow.com/object-detection/plantdoc

References

[1] B. Subedi, A. Poudel, S. Aryal, The impact of climate change on insect pest biology and ecology: implications for pest management strategies, crop production, and food security, J. Agric. Food Res. 14 (2023) 100733, https://doi.org/10.1016/j.jafr.2023.100733.
[2] B.K. Singh, M. Delgado-Baquerizo, E. Egidi, E. Guirado, J.E. Leach, H. Liu, P. Trivedi, Climate change impacts on plant pathogens, food security and paths forward, Nat. Rev. Microbiol 21 (2023) (2023) 640–656, https://doi.org/10.1038/s41579-023-00900-7.
[3] T. Afroz, Tazwar Mohammed Shoumik, H. Emon, S. Hossain, N. Nayla, An effective method for detecting tomato leaf disease using distributed neural networks. 2023 26th International Conference on Computer and Information Technology, ICCIT, 2023, p. 2023, https://doi.org/10.1109/ICCIT60459.2023.10441629.
[4] G.N. Agrios, Plant Pathology, Elsevier, 2004.
[5] M. Javaid, A. Haleem, R.P. Singh, R. Suman, Enhancing smart farming through the applications of Agriculture 4.0 technologies, Int. J. Intell. Netw. 3 (2022) 150–164, https://doi.org/10.1016/j.ijin.2022.09.004.
[6] S. Kalaivani, C. Tharini, Saran Sara, S.T. Abinaya, ResNet-based classification for leaf disease detection, J. Inst. Eng. (India): Ser. B 2 (4) (2024), https://doi.org/10.1007/s40031-024-01062-7.
[7] A. Singla, A. Nehra, K. Joshi, A. Kumar, Narendra Tuteja, R.K. Varshney, S.S. Gill, R. Gill, Exploration of machine learning approaches for automated crop disease detection, 100382–100382, Curr. Plant Biol. 40 (2024), https://doi.org/10.1016/j.cpb.2024.100382.
[8] Y. Tian, E. Li, Z. Liang, M. Tan, X. He, Diagnosis of typical apple diseases: a deep learning method based on multi-scale dense classification network, Front. Plant Sci. 12 (1) (2021), https://doi.org/10.3389/fpls.2021.698474.
[9] N. Ally, H. Neetoo, V. Ranghoo-Sanmukhiya, T. Coutinho, Greenhouse-grown tomatoes: microbial diseases and their control methods: a review, Int. J. Phytopathol. (2023), https://doi.org/10.33687/phytopath.012.01.4273.
[10] H. Moreno, A. Gómez, S. Altares-López, A. Ribeiro, D. Andújar, Analysis of stable diffusion-derived fake weeds performance for training convolutional neural networks, Comput. Electron. Agric. 214 (1) (2023), https://doi.org/10.1016/j.compag.2023.108324.
[11] R.S. Swapna, Kumar, F.S. Aurthy, G.S. Sankar, A. Choubey, R. Anitha, Development and evaluation of a distinctive cloud-based artificial intelligence system using deep learning techniques (AISDLT) for accurate detection of tomato plant leaf diseases, Int. J. Intell. Syst. Appl. Eng. 12 (12s) (2024) 12s.
[12] S.P. Mohanty, D.P. Hughes, M. Salathé, Using deep learning for image-based plant disease detection, Front. Plant Sci. 7 (1) (2016), https://doi.org/10.3389/fpls.2016.01419.
[13] A. Krizhevsky, I. Sutskever, G.E. Hinton, ImageNet classification with deep convolutional neural networks, Commun. ACM 60 (6) (2012) 84–90, https://doi.org/10.1145/3065386.
[14] A.K. Rangarajan, R. Purushothaman, A. Ramesh, Tomato crop disease classification using pre-trained deep learning algorithm, Procedia Comput. Sci. 133 (1) (2018) 1040–1047, https://doi.org/10.1016/j.procs.2018.07.070.
[15] X. Zhang, J. Bu, X. Zhou, X. Wang, Automatic pest identification system in the greenhouse based on deep learning and machine vision, Front. Plant Sci. 14 (1) (2023), https://doi.org/10.3389/fpls.2023.1255719.
[16] E.C. Too, L. Yujian, S. Njuki, L. Yingchun, A comparative study of fine-tuning deep learning models for plant disease identification, Comput. Electron. Agric. 161 (1) (2018), https://doi.org/10.1016/j.compag.2018.03.032.
[17] T. Afroz, Tazwar Mohammed Shoumik, H. Emon, S. Hossain, N. Nayla, An effective method for detecting tomato leaf disease using distributed neural networks. 2023 26th International Conference on Computer and Information Technology, ICCIT, 2023, p. 2023, https://doi.org/10.1109/ICCIT60459.2023.10441629.
[18] P. Goyal, D.K. Verma, S. Kumar, Diagnosis of plant leaf diseases using image based detection and prediction using machine learning approach, Econ. Comput. Econ. Cybern. Stud. Res. 57 (2) (2023) 4, https://doi.org/10.24818/18423264/57.4.23.18.
[19] N.B. Nageswararao, R. Malmathanraj, P. Palanisamy, Detection and classification of chilli leaf disease using a squeeze-and-excitation-based CNN model, Ecol. Inform. 69 (1) (2022), https://doi.org/10.1016/j.ecoinf.2022.101663.
[20] Arun M. Patokar, Vinaya V. Gohokar, Classification of tomato leaf diseases: a comparison of different optimizers, Lect. Notes Electr. Eng. 959 (1) (2023) 27–37, https://doi.org/10.1007/978-981-19-6581-4_3.
[21] M. Brahimi, K. Boukhalfa, A. Moussaoui, Deep learning for tomato diseases: classification and symptoms visualization, Appl. Artif. Intell. 31 (4) (2017) 299–315, https://doi.org/10.1080/08839514.2017.1315516.
[22] C. DeChant, T. Wiesner-Hanks, S. Chen, E.L. Stewart, J. Yosinski, M.A. Gore, R. J. Nelson, H. Lipson, Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning, Phytopathology® 107 (11) (2017) 1426–1432, https://doi.org/10.1094/phyto-11-16-0417-r.
[23] M. Li, G. Zhou, A. Chen, J. Yi, C. Lu, M. He, Y. Hu, FWDGAN-based data augmentation for tomato leaf disease identification, Comput. Electron. Agric. 194 (2) (2022), https://doi.org/10.1016/j.compag.2022.106779.

[24] R. Ahmed, E.H. Abd-Elkawy, Improved tomato disease detection with YOLOv5 and YOLOv8, Eng. Technol. Appl. Sci. Res. 14 (3) (2024) 13922–13928, https://doi.org/10.48084/etasr.7262.
[25] X. Zhang, J. Bu, X. Zhou, X. Wang, Automatic pest identification system in the greenhouse based on deep learning and machine vision, Front. Plant Sci. 14 (1) (2023), https://doi.org/10.3389/fpls.2023.1255719.
[26] W. Tan, C. Zhao, H. Wu, Intelligent alerting for fruit-melon lesion image based on momentum deep learning, Multimed. Tools Appl. 75 (24) (2015) 16741–16761, https://doi.org/10.1007/s11042-015-2940-7.
[27] K. Yamamoto, T. Togami, N. Yamaguchi, Super-resolution of plant disease images for the acceleration of image-based phenotyping and vigor diagnosis in agriculture, Sensors 17 (11) (2017) 2557, https://doi.org/10.3390/s17112557.
[28] G. Pattnaik, V.K. Shrivastava, K. Parvathi, Transfer learning-based framework for classification of pest in tomato plants, Appl. Artif. Intell. 1 (1) (2020) 1–13, https://doi.org/10.1080/08839514.2020.1792034.
[29] M. Turkoglu, B. Yanikoğlu, D. Hanbay, PlantDiseaseNet: convolutional neural network ensemble for plant disease and pest detection, Signal, Image Video Process. 1 (2) (2021), https://doi.org/10.1007/s11760-021-01909-2.
[30] S. Kalaivani, C. Tharini, Saran Sara, S.T. Abinaya, ResNet-based classification for leaf disease detection, J. Inst. Eng. (India): Ser. B 2 (4) (2024), https://doi.org/10.1007/s40031-024-01062-7.
[31] T. Kasinathan, S.R. Uyyala, Machine learning ensemble with image processing for pest identification and classification in field crops, Neural Comput. Appl. 33 (13) (2021) 7491–7504, https://doi.org/10.1007/s00521-020-05497-z.
[32] S. Sankaran, A. Mishra, R. Ehsani, C. Davis, A review of advanced techniques for detecting plant diseases, Comput. Electron. Agric. 72 (1) (2010) 1–13, https://doi.org/10.1016/j.compag.2010.02.007.
[33] M. Zedler, S. Tse, A. Ruiz-Gonzalez, J. Haseloff, Paper-based multiplex sensors for the optical detection of plant stress, Micromachines 14 (2023), https://doi.org/10.3390/mi14020314.
[34] G.L. Grinblat, L.C. Uzal, M.G. Larese, P.M. Granitto, Deep learning for plant identification using vein morphological patterns, Comput. Electron. Agric. 127 (1) (2016) 418–424, https://doi.org/10.1016/j.compag.2016.07.003.
[35] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, D. Stefanovic, Deep neural networks based recognition of plant diseases by leaf image classification, Comput. Intell. Neurosci. 2016 (1) (2016) 1–11, https://doi.org/10.1155/2016/3289801.
[36] Tairu Oluwafemi Emmanuel. (2018). PlantVillage Dataset. Retrieved July 25, 2024, from Kaggle.com website: ⟨https://www.kaggle.com/datasets/emmarex/plantdisease⟩.
[37] Pratikkayal. (2020). GitHub - pratikkayal/PlantDoc-Dataset: Dataset used in "PlantDoc: A Dataset for Visual Plant Disease Detection" accepted in CODS-COMAD 2020. Retrieved July 25, 2024, from GitHub website: ⟨https://github.com/pratikkayal/PlantDoc-Dataset⟩.
[38] Singh, D., Jain, N., Jain, P., Kayal, P., Kumawat, S., & Batra, N. (n.d.). PlantDoc: A Dataset for Visual Plant Disease Detection. Retrieved from ⟨https://arxiv.org/pdf/1911.10317⟩.
[39] M. Xu, S. Yoon, A. Fuentes, J. Yang, Dong Sun Park, Style-consistent image translation: a novel data augmentation paradigm to improve plant disease recognition, Front. Plant Sci. 12 (1) (2022), https://doi.org/10.3389/fpls.2021.773142.
[40] C. Shorten, T.M. Khoshgoftaar, A survey on image data augmentation for deep learning, J. Big Data 6 (1) (2019), https://doi.org/10.1186/s40537-019-0197-0.
[41] F. López, J.L. Gómez-Sirvent, R. Sánchez-Reolid, R. Morales, A. Fernández-Caballero, Geometric transformation-based data augmentation on defect classification of segmented images of semiconductor materials using a ResNet50 convolutional neural network, Expert Syst. Appl. 206 (1) (2022), 117731–117731.
[42] C. Shorten, T.M. Khoshgoftaar, A survey on image data augmentation for deep learning, J. Big Data 6 (1) (2019), https://doi.org/10.1186/s40537-019-0197-0.
[43] Y. Tian, E. Li, Z. Liang, M. Tan, X. He, Diagnosis of typical apple diseases: a deep learning method based on multi-scale dense classification network, Front. Plant Sci. 12 (1) (2021), https://doi.org/10.3389/fpls.2021.698474.
[44] S. Kang, Rotation-invariant wafer map pattern classification with convolutional neural networks, IEEE Access 8 (1) (2020) 170650–170658, https://doi.org/10.1109/ACCESS.2020.3024603.