# DM-YOLOv8: Cucumber Disease and Insect Detection using Detailed Multi-Intensity Features

Ji-Yuan Ding[1], Wang-Su Jeon[2] and Sang-Yong Rhee[2*]
Department of IT Convergence Enineering[1], Department of Computer Engineering[2]
University of Kyungnam, South Korea, Changwon City.
Dinggjiyuan1116@gmail.com[1], jws2218@naver.com[2], syrhee@kyungnam.ac.kr[2]

**Abstract—In light of the prevalent pest and disease issues faced by greenhouse cucumbers, a staple vegetable during the winter season, this study introduces a detection method based on the enhanced YOLOv8s model. This method aims to provide technical support for the detection and classification of pests and diseases in cucumber agricultural production. The model integrates the 'MultiCat' module for multiscale feature fusion and employs the 'C2fe' and 'ADC2f'modules to strengthen both spatial and channel attention. Additionally, the 'Block2d' function facilitates the choice between average pooling and attention-based spatial pooling. Channel fusion is achieved through additive and multiplicative operations, allowing the model to delve deeper into feature learning. Experimental results confirm that our approach outperforms the original YOLOv8s model in pest detection, particularly excelling in the identification of small-scale and overlapping afflictions.**

***Keywords— ADC2f , C2fe, Component, MultiCat, Pest detection, Yolov8s***

## I. Introduction

In today's globalized world, e nsuring food safety and high yields has become a central issue in agricultural research. Cucumber is a member of the Cucurbitaceae family, which has 90 genera and 750 species. It is one of the oldest cultivated vegetable crops and is grown in almost all temperate countries. It is a warm-loving, frost-tolerant plant that grows best at temperatures above 20°C [1]. Cucumber pests and diseases are one of the main reasons for the decrease in cucumber yield [2]. Outbreaks of agricultural pests not only affect crop production but also the use of pesticides not only causes ecological destruction but also further increases the risk of food safety [3]. Therefore, it is particularly important to develop a method that can detect cucumber pests and diseases in a timely and accurate manner.

Traditional methods of detecting pests and diseases on cucumber leaves mainly rely on human visual recognition, that is, directly observing the morphology, texture, and color of leaves with the naked eye [4]. Although this method is simple to operate, its accuracy is affected by the differences in the observer's experience and knowledge, and it is highly subjective, often leading to misdiagnosis, causing irreversible losses to farmers. Therefore, in addition to being time-consuming and costly, it is difficult to achieve the precise detection requirements for cucumber leaf pests. This is difficult to implement in large-scale agricultural production.

With the rapid development of technology, especially in the field of computer vision, deep learning provides a new direction for the identification and detection of pests and diseases in the agricultural field [5]. Against this background, object detection has become a core topic in computer vision research, aiming to accurately identify and locate specific objects in images. To achieve this goal, scholars have developed many innovative strategies. Among them, the one-stage (One-stage) and two-stage (Two-stage) methods stand out and have become the two mainstream technologies in this field.

Representatives of one-stage object detection algorithms include SSD (Liu et al., 2016) [6], RetinaNet (Lin et al., 2017) [7], YOLOv4 (Bochkovskiy et al., 2020) [8], YOLOv5 (Jocher et al., 2021) [9], DETR (Carion et al., 2020) [10], FCOS (Tian et al., 2019) [11], and YOLOX (Ge et al., 2021) [12]. In contrast, two-stage object detection algorithms such as R-CNN (Girshick et al., 2014) [13], Fast R-CNN (Girshick, 2015) [14], Faster-RCNN (Ren et al., 2016) [15], Mask R-CNN (He et al., 2017) [16], and Cascade R-CNN (Cai and Vasconcelos, 2018) [17] have a longer computational process.

Two-stage models first generate a series of candidate regions and then use a classifier to refine the classification of these regions. Although they are usually superior in accuracy, the two-step process makes them relatively slow [18,19]. On the other hand, one-stage models directly predict bounding boxes and categories from feature maps without generating candidate areas, providing the advantage of real-time detection. However, this speed sometimes comes at the expense of accuracy. Considering the need to make the model more practical and suitable for deployment on mobile devices, we chose the YOLO model as our object detection algorithm.

To solve the problem of low accuracy in small target detection of one-stage models, this paper proposes a new YOLOv8s model for cucumber pest identification and tests it on a newly built dataset. This study plans to adopt and improve the latest YOLOv8s model for the detection of cucumber pests and diseases. To compensate for the accuracy loss of lightweight models, we also adopted an attention mechanism to assign different weights to each part of the input feature layer, thereby more effectively extracting key features and improving classification performance.

The main contributions of this paper are two-fold:

- We propose a lightweight one-stage YOLOv8 model, referred to as the Detail and Multi-scale YOLO Network (DM-YOLO), built upon YOLOv8, for real-time cucumber pest and disease identification. Utilizing the MultiCat module by merging features of different scales, the model's detection capability for pests and diseases of varying sizes on cucumbers is enhanced. We introduced the C2fe module, a modification based on C2f, as a new feature fusion method aiming to more effectively combine multi-scale features. With an attention mechanism based on adaptive average pooling, we constructed a new module named AD-C2f, which intensifies the model's focus on crucial features, thereby increasing detection accuracy and overall model performance.

- We extracted a portion of data from the ai-hub's Integrated Plant Disease Induction Data public dataset to construct a new cucumber pest and disease dataset. To ensure data quality, we manually re-annotated the leaves in each image and carefully filtered the original images. After eliminating some unorganized data, we concentrated on two main cucumber afflictions: downy mildew and powdery mildew, culminating in this optimized new dataset.

## II. RELATED WORKS

### A. Traditional Machine Learning Methods

Traditional disease identification methods in machine learning typically rely on manually extracting designed features from images, such as color, texture, and shape. Classifiers like Support Vector Machines (SVM), Decision Trees, or K-Nearest Neighbors (KNN) are then employed to distinguish between healthy and damaged plants.

For instance, Ebrahimi et al. (2017) proposed an insect detection system based on SVM, successfully applied in strawberry greenhouse crop canopy images with an error rate of less than 2.25% [20]. Mondal et al. (2017) combined image processing and soft computing techniques for a disease recognition system, achieving high-accuracy disease classification in okra and bitter gourd leaves by selecting specific morphological features [21].

Additionally, Xu et al. (2020) used BP neural networks and random forest models to detect damage from forest caterpillars, with the random forest model outperforming and emphasizing the importance of balanced sample data [22]. Amirruddin et al. (2020) assessed chlorophyll sufficiency levels in mature oil palms using hyperspectral remote sensing and achieved high-accuracy chlorophyll classification, particularly on younger leaves, through a random forest classifier [23].

However, traditional machine learning methods may struggle to capture complex patterns in high-dimensional and large-scale data, leading to suboptimal performance. They often require extensive preprocessing and feature engineering, adding to development time and cost. In contrast to the adaptive learning capability of deep learning, traditional methods may underperform when facing data changes and uncertainties. In summary, while traditional machine learning methods may excel in specific situations, they might not be suitable for tasks requiring the capture of intricate patterns and relationships in high-dimensional and large-scale data.

### B. Deep Learning Methods

Deep learning offers significant advantages in crop pest and disease identification and classification. In contrast to traditional machine learning methods, deep learning automatically extracts features from data, eliminating the need for manual feature design and accommodating complex, high-dimensional data. Various advanced deep learning models, including Convolutional Neural Networks and pre-trained models, have proven successful in diverse crop pest and disease identification tasks.

Sethy et al. (2020) effectively identified four rice leaf diseases by combining deep convolutional neural networks with SVM, achieving an impressive F1 score of 0.9838 [24]. Yin et al. (2022) developed a grape leaf disease identification method using an improved MobileNetV3 model and deep transfer learning, achieving a recognition accuracy of 99.84% with a modest computational footprint and dataset size (30 MB) [25].

Sankareshwaran et al. (2023) introduced the Cross Enhanced Artificial Hummingbird Algorithm based on AX-RetinaNet (CAHA-AXRNet) for optimizing rice plant disease detection, outperforming existing methods with an accuracy of 98.1% [26]. Liu Shiyi et al. (2023) presented the DCNSE-YOLOv7 deep learning algorithm, enhancing the detection accuracy of cucumber leaf pests and diseases, particularly for minute features on early-stage diseased leaves. This algorithm exhibited significant improvements over mainstream object detection models, supporting precise detection of cucumber leaf pests and diseases [27].

Additionally, Yang et al. (2023) introduced a tomato automatic detection method based on an improved YOLOv8s model, achieving an mAP of 93.4%. This method meets real-time detection requirements and provides technical support for efficient and accurate operations of tomato-picking robots [28]. Collectively, these studies highlight the continuous optimization and improvement of deep learning models, demonstrating remarkable success in crop pest and disease detection and identification.

## III. MATERIALS AND METHODS

### A. Materials

The data required for this study was sourced from ai-hub translated as "Integrated Data on Plant Disease Induction" public dataset (Figure 1). To construct a dataset specifically targeting cucumber pests and diseases, we extracted a subset of data from this collection and deeply integrated it. In order to ensure the model's broad adaptability and robustness, we manually annotated each leaf in the images and meticulously filtered the original photos. After removing some irregular data, our primary focus was on the two prevalent ailments of cucumbers: downy mildew and powdery mildew. We selected 2,000 images of cucumber pests and diseases to form a new dataset.

(a)Powdery Mildew (b)Downy Mildew

Fig. 1. Example of plant leaf disease dataset

The entire dataset was split in an 8:2 ratio for training and validation sets, respectively. The specific data distribution is illustrated in Figure 2.

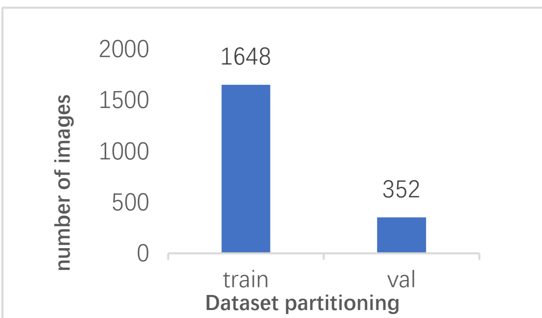


Fig. 2. Dataset distribution results. The dataset is mainly divided into train, val,, as shown on the horizontal axis. The vertical axis mainly represents the number of images in each dataset.

## B. Standard YOLOv8

YOLOv8 is a part of the YOLO lineage, not only offering the latest State Of The Art (SOTA) models but also incorporating a multitude of innovations and optimizations to enhance performance and adaptability. Firstly, this model introduces a variety of resolution and scale target detection networks, thoroughly considering the demands of different scenarios. Secondly, from the backbone network to the head structure, YOLOv8 underwent a series of meticulous fine-tuning, including adopting a gradient flow enriched C2f structure and introducing a decoupled head structure, making classification and detection more independent and efficient. Moreover, it transitioned from an Anchor-Based structure to Anchor-Free, aligning with a major trend in recent years. On the loss function, YOLOv8 combined the TaskAlignedAssigner and Distribution Focal Loss, these novel strategies assist the model in achieving more precise detection across various targets. Lastly, in terms of data augmentation, the model also adopted effective strategies, such as disabling Mosaic augmentation in the final training phase. Figure 3 illustrates the architecture of the YOLOv8 model.

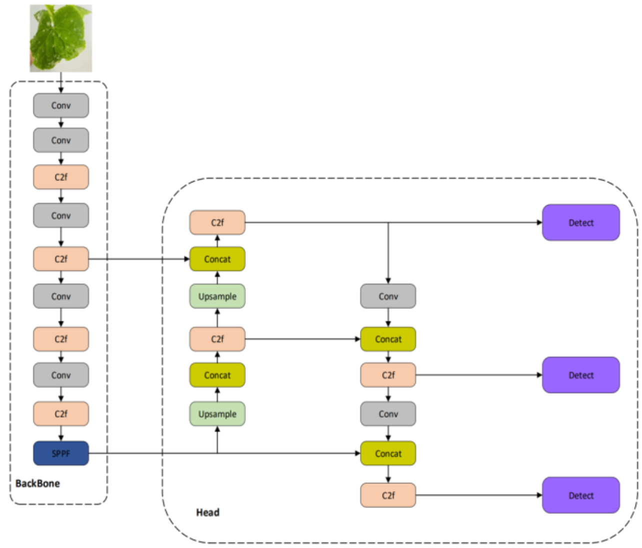


Fig. 3. Standard yolov8 model

## C. Proposed model

To accommodate the detection of small targets, we proposed and refined the YOLOv8 model as depicted in Figure 4, where one of the c2f modules was altered to an AD-c2f module. A multi-scale feature fusion module, termed Mult module, was constructed. By extracting and merging information from three distinct levels of the backbone, the model is capable of capturing and utilizing features from multiple scales and levels. Further optimization and extension were conducted on the c2f basis, forming a C2fe module. Besides conducting feature extraction in the channel dimension, this module also performs in-depth feature processing spatially. This dual operation mode on two dimensions ensures a comprehensive and profound feature extraction by the model.

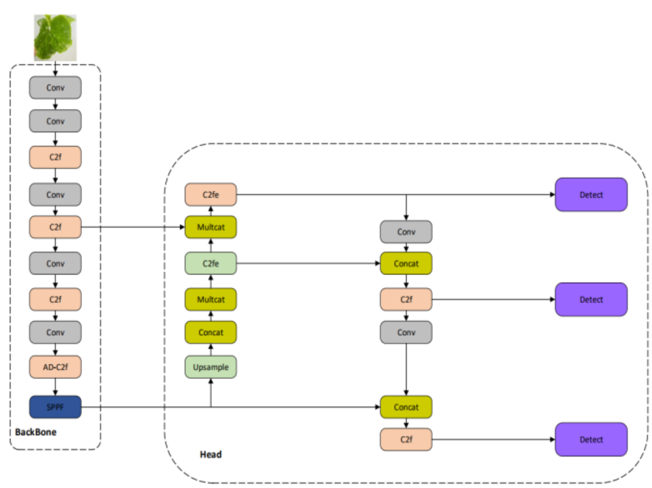


Fig. 4. Proposed model (DM-YOLOv8)

### 1) *MultiCat Module*

An improved model for cucumber disease and pest detection addresses challenges like varying lighting conditions and object occlusions through a specially designed module called MultiCat. This module employs meticulous multi-scale feature processing and fusion to enhance the model's ability to detect smaller target diseases and pests on cucumber leaves. The MultiCat module decomposes input feature maps into three scaled maps (L, M, S) for capturing disease features from various angles. Adaptive pooling and interpolation techniques are applied to explore global and regional disease features, while channel concatenation operation fuses the scaled feature maps into a unified output, ensuring rich local disease feature details are preserved.

### 2) *AD-C2f Module*

An ADC2F module is introduced to enhance the detection of downy mildew and powdery mildew during cucumber cultivation. Combining attention mechanisms and depthwise separable convolution, the model focuses on crucial elements for accurate disease identification. The attention mechanism enables selective concentration on infected areas, disregarding irrelevant background noise, contributing to improved detection accuracy. The ADC2F module decomposes input features, applies adaptive average pooling and convolution layers to two separate parts, and uses a sigmoid activation function to obtain adaptive weights. This adaptive filtering aims to emphasize useful features while suppressing unnecessary or interfering elements in the identification process.

## IV. Experiments and Environment

### A. *Environment setup*

The experimental operating system used in this study is Windows 10, with PyTorch serving as the framework for developing the deep learning model. The table 1. provides specific details regarding the experimental environment.

TABLE I. EXPERIMENTAL ENVIRONMENT CONFIGURATION

| | Configuration |
|---|---|
| CPU | AMD Ryzen 5 3600 6-core |
| GPU | NVIDIA GeForce RTX 3060 |
| GPU memory | 32GB |
| Operating systems | Windows 10 |
| Deep learning framework | Pytorch1.9.2 |

Training Parameter Settings: The image input size is 640×640, batch size (Batch_size) is 16, multi-threading is set to 4, the initial learning rate is 0.01, with a total of 120 training iterations (Epochs). The specific parameter settings are shown in Table 2.

### B. *Experimental results*

We compared the improved model with the original YOLOv8 model to evaluate whether our improvements could enhance the performance of the model. To showcase the detection results of the algorithm proposed in this study, we randomly selected images from the test subset for comparison. The specific comparison results are shown in Table 3, and the visual outcomes of the selected images are illustrated in Figure 8.

TABLE II. PERFORMANCE COMPARISON RESULT OF YOLOV8 AND DM-YOLOV8 FOR DIFFERENT CLASSES AND METRICS

| | Class | Precision (%) | Recall (%) | mAP50 (%) | Param (MB) | FPS (m/s) |
|---|---|---|---|---|---|---|
| Yolov8 | All | 0.834 | 0.794 | 0.874 | 11.47 | 181.8 |
| | A3 | 0.875 | 0.778 | 0.903 | | |
| | A4 | 0.793 | 0.81 | 0.845 | | |
| DM-Yolov8 | All | 0.842 | 0.815 | 0.8825 | 12.19 | 178.6 |
| | A3 | 0.851 | 0.83 | 0.910 | | |
| | A4 | 0.834 | 0.80 | 0.855 | | |

The DM-Yolov8 model demonstrates superior performance over the standard YoloV8 model in key metrics crucial for cucumber pest and disease detection. With a higher recall of 0.81 versus 0.76, DM-YoloV8 effectively reduces the likelihood of missing actual pest and disease instances. Its MAP50 score of 0.90 in the "A3" category, compared to Yolov8 is 0.89, reflects better accuracy and precision. Despite a slightly lower frame rate, the significant improvements in recall and MAP50, along with consistent performance across various categories, underscore A-Yolov8 is enhanced suitability and reliability for cucumber pest and disease detection tasks, making it a preferable choice over the original Yolov8 model.

During the training process, we are concerned not only with the model's final performance, but also with the training and validation process to ensure the model is progressing in the right direction. For this purpose, we decided to plot some key metrics during the training and validation process, so we could have a visual understanding of the model's learning situation, as shown in Figure 8.

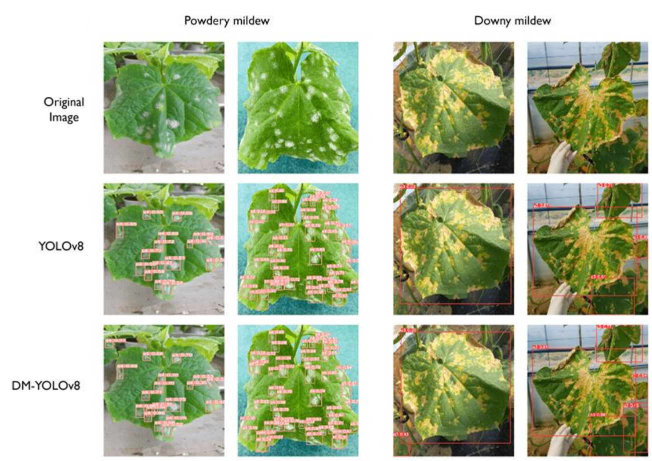


Fig. 5. Cucumber Disease Detection and Algorithm Comparison

In Figure 5, our investigation revealed that the enhanced DM-YOLOv8 model exhibits notable performance enhancements in the detection of foliar diseases, specifically Powdery Mildew and Downy Mildew. When benchmarked against the baseline YOLOv8s model, the DM-YOLOv8 variant demonstrated superior accuracy in bounding box delineation and augmented confidence scores, signaling a refined capability for precise pathogen feature recognition.

In particular, the DM-YOLOv8 model consistently yielded elevated confidence scores across a multitude of test instances, denoting a heightened proficiency in differentiating healthy leaf tissue from that afflicted by disease. Despite these advancements, the model occasionally generated detection boxes in healthy tissue zones, indicative of potential false positives. Furthermore, there were instances where prominent disease manifestations were not encapsulated within detection boxes, pointing to possible false negatives.

The performance of the DM-YOLOv8 model also varied when processing images characterized by intricate backgrounds and overlapping leaf structures. This variability suggests that the model's robustness in complex visual environments may require additional refinement. Notably, the model exhibited uncertainty in regions of leaf margin and vein convergence, likely attributed to the feature representation similarities between these areas and diseased segments.

Summarily, while the DM-YOLOv8 model demonstrates a distinct advantage in the domain of leaf disease detection, there is an evident imperative for enhancement in minimizing false positives and fortifying detection consistency in multifaceted scenarios. Consequently, this necessitates the development of further optimization strategies to align the model's capabilities with the pragmatic demands of accurate disease detection.

### C. *Comparative Experiments*

To demonstrate the superiority of our proposed YOLO model in image classification tasks, we compared it with four popular image classification models. The experimental results are shown in the Table 3.

TABLE III. PERFORMANCE COMPARISON RESULTS OF EXISTING MODELS

| | **Precision (%)** | **Recall (%)** | **mAP50 (%)** | **Param (MB)** | **FPS (m/s)** |
|---|---|---|---|---|---|
| Yolov5 | 84.2% | 81.0% | 87.6% | 26.76 | 153.84 |
| Retinanet | 90.63% | 60.40% | 84.17% | 144.84 | 25.93 |
| SSD | 85.16% | 30.77% | 56.45% | 100.27 | 65.8 |
| Faster-RCNN | 43.1% | 86.58% | 86.58% | 108 | 11.94 |
| DM-yolov8 | 84.2% | 80.8% | 88.2% | 12.2 | 178.57 |

In our comparative analysis, we evaluated the DM-YOLOv8 against four leading-edge image classification models: YOLOv5, RetinaNet, SSD, and Faster R-CNN. Data delineated in Table 4 corroborates that DM-YOLOv8 not only showcases exceptional real-time processing capability but also establishes a significant equilibrium among precision, recall, and mean Average Precision (mAP).

While YOLOv5 exhibited a formidable overall performance with an mAP of 87.6%, DM-YOLOv8 surpassed this benchmark, registering an mAP of 88.1%, and concurrently demonstrated a substantial increase in processing speed, with a frame rate (FPS) of 178.57, in comparison to YOLOv5's 153.84. This positions DM-YOLOv8 as a more apt choice for real-time applications where both precision and speed are of paramount importance.

RetinaNet, although reaching a precision of 90.63%, displayed deficiencies in recall and FPS. In contrast, DM-YOLOv8 offered a more balanced configuration with a significantly elevated recall rate of 80.6% and an FPS more than six times higher. SSD, with its FPS at 65.8, lagged in terms of mAP and recall, metrics critical for robust object detection.

Faster R-CNN, with a high recall rate of 86.58%, outperformed DM-YOLOv8 in this respect. However, when juxtaposed with the larger model size of Faster R-CNN (108MB), the considerably smaller size of DM-YOLOv8 (12.2MB) highlights the efficiency and optimization of our model, rendering it highly suitable for deployment in environments with limited computational resources.

## V. CONCLUSIONS

This study delved into the detection of diseases and pests in cucumbers within greenhouse environments, successfully proposing an optimized YOLOv8 algorithm tailored for this purpose. Despite the reduced detection accuracy due to interference from complex backgrounds, the introduction of specific modules significantly enhanced the algorithm's feature extraction and representation capabilities. The integration of the C2fE and AD-C2f modules, in particular, collectively strengthened the network's feature extraction prowess, markedly boosting the model's detection capabilities. Additionally, in cucumber disease and pest detection tasks, this model demonstrated a higher recall rate and mean Average Precision (mAP) with an extremely high processing speed, while maintaining a relatively small model size compared to other algorithms. These attributes make it an ideal choice for fast and accurate real-time object detection tasks.

In future research, we plan to enhance feature extraction accuracy and detection robustness by introducing more advanced network structures, increasing inter-layer connections, and utilizing deeper networks. We aim to expand the training dataset and adjust and test the algorithm to cater to different types of crops. Integrating the algorithm with hardware platforms such as drones and automated mobile robots, we intend to develop an automated and intelligent disease monitoring system for on-site testing and to optimize the model's real-time application performance. Through these research and development plans, we anticipate not only scientific progress but also significant technological transformation and industrial advancement in practical applications.

## ACKNOWLEDGMENT

This result was supported by "Regional Innovation Strategy (RIS)" through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (MOE) (2021RIS-003).

## REFERENCES

[1] Staub, J. E.; Robbins, M. D.; Wehner, T. C. Cucumber. In Vegetables I: Asteraceae, Brassicaceae, Chenopodicaceae, and Cucurbitaceae; Prohens, J., Nuez, F., Eds.; Springer: New York, NY, USA, 2008; pp. 241–282.

[2] M.Rur, B.Rämert, M.Hökeberg, RR.Vetukuri, L.Grenville-Briggs.Scree ning of alternative products for integrated pest management of cucurbit p owdery mildew in Sweden.Eur J Plant Pathol, vol.150, pp.127–138, 201 8. https://doi.org/10.1007/s10658-017-1258-x

[3] B.Wan, E.Zhou, P.Xiao, X.Sun, J.Yang. Pesticide overuse in vegetable production: A case study of urban agriculture in city x, China. Environ. Res. Commun. vol.5, no. 085012, 2023.

[4] Y.Li, Scientific Identification and Control Measures of Several Diseases of Greenhouse Cucumbers. Grassroots Agricultural Technology Extension ,vol.9, pp. 40-42, 2021.

[5] M.Türkoğlu, D.Hanbay. Plant disease and pest detection using deep learning-based features. Turkish J. Electr. Eng. Comput. Sci, vol.27, pp.1636-1651, 2019.

[6] W.Liu, D.Anguelov, ED.rhan, C.Szegedy, S.Reed, C.-Y.Fu, A. C.Berg. SSD: Single shot multibox detector. In Proceedings of the European Conference on Computer Vision (ECCV), 2016.

[7] T.-Y.Lin, P.Dollár, R.Girshick, K.He, B.Hariharan, S.Belongie. Focal Loss for Dense Object Detection. In Proceedings of the ICCV, 2017.

[8] A.Bochkovskiy, C.Y.Wang, H.Y.M.Liao. YOLOv4: Optimal Speed and Accuracy of Object Detection. arXiv preprint arXiv:2004.10934, 2020.

[9] G.Jocher, A.Stoken, J.Borovec, F.F.Fomin, L.Q.V.Hoang, M.Eskenazi, J.Anselmo, Z.Zhang, A.A.Borkowski. YOLOv5. GitHub repository, 2021.

[10] N.Carion, F.Massa, G.Synnaeve, N.Usunier, A.Kirillov, S.Zagoruyko. End-to-end object detection with transformers. In Proceedings of the ECCV, pp.213-219, 2020.

[11] Z.Tian, C.Shen, H.Chen, T.He. FCOS: Fully Convolutional One-Stage Object Detection. In Proceedings of the ICCV, pp.9627-9636, 2019.

[12] X.Ge, Y.Li, Z.Wang, H.Wang, R.Tang, P.Luo. YOLOX: Exceeding YOLO Series in 2021. arXiv preprint arXiv:2107.08430, 2021.

[13] S.Ren, K.He, GR.irshick, J.Sun. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. In Proceedings of the NeurIPS, 2016.

[14] R.Girshick, J.Donahue, T.Darrell, J.Malik. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. In Proceedings of the CVPR, pp.580-587, 2014.

[15] R.Girshick. Fast R-CNN. In Proceedings of the ICCV, 2015.

[16] K.He, GG.kioxari, DP.ollár, R.Girshick. Mask R-CNN. In Proceedings of the ICCV, 2017.

[17] Z.Cai, N.Vasconcelos. Cascade R-CNN: Delving into High Quality Object Detection. In Proceedings of the CVPR, 2018.

[18] U.Sirisha, S.P.Praveen, P.N.Srinivasu, P.Barsocchi, A.K.Bhoi. Statistical Analysis of Design Aspects of Various YOLO-Based Deep Learning Models for Object Detection. Int. J. Comput. Intell. Syst., vol.16, no.1, p. 126, 2023. https://doi.org/10.1007/s44196-023-00302-w

[19] D.S. Bacea, F. Oniga, "Single stage architecture for improved accuracy r eal-time object detection on mobile devices," Image Vision Comput., vo l. 130, 2023, Art. no. 104613, ISSN 0262-8856, https://doi.org/10.1016/j.imavis.2022.104613.

[20] M.A. Ebrahimi, M.H. Khoshtaghaza, S. Minaei, B. Jamshidi, "Vision-ba sed pest detection based on SVM classification method," Comput. Electr on. Agric., vol. 137, pp. 52-58, 2017, https://doi.org/10.1016/j.compag.2017.03.016.

[21] D.Mondal, D.K.Kole, & K.Roy. Gradation of yellow mosaic virus diseas e of okra and bitter gourd based on entropy based binning and Naive Bay es classifier after identification of leaves. Computers and Electronics in Agriculture, vol.142(Part B), pp.485-493, 2017. https://doi.org/10.1016/j.compag.2017.11.024

[22] Z.Xu, X.Huang, L.Lin, Q.Wang, J.Liu, K.Yu, C.Chen. BP neural networks and random forest models to detect damage by Dendrolimus punctatus Walker. J. For. Res. Vol.31, pp.107–121, 2020. https://doi.org/10.1007/s11676-018-0832-1

[23] A. D.Amirruddin, F.M.Muharam, M.H.Ismail, M. F.Ismail, N. P.Tan, D. S.Karam. Hyperspectral remote sensing for assessment of chlorophyll su fficiency levels in mature oil palm (Elaeis guineensis) based on frond nu mbers: Analysis of decision tree and random forest. Computers and Elect ronics in Agriculture, vol.169, pp.105221, 2020. https://doi.org/10.1016/j.compag.2020.105221

[24] P.K. Sethy, N.K. Barpanda, A.K. Rath, S.K. Behera, "Deep feature based rice leaf disease identification using support vector machine," Comput. Electron. Agric., vol. 173, Art. no. 105527, 2020, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2020.105527.

[25] Yin, X.; Li, W.; Li, Z.; Yi, L. Recognition of Grape Leaf Diseases Using MobileNetV3 and Deep Transfer Learning. Int. J. Agric. & Biol. Eng. V ol.15, no.3, pp.184–194, 2022. https://doi.org/10.25165/j.ijabe.20221503.7062.

[26] S.P.Sankareshwaran, G.Jayaraman, P.Muthukumar, A.Krishnan. Optimi zing Rice Plant Disease Detection with Crossover Boosted Artificial Hu mmingbird Algorithm Based AX-RetinaNet. Environ. Monit. Assess. Vo l.195, pp.1070, 2023. https://doi.org/10.1007/s10661-023-11612-z.

[27] S.Liu, B.Hu, C.Zhao. Detection and Identification of Cucumber Leaf Dis eases Based Improved YOLOv7. Trans. Chin. Soc. Agric. Eng. vol.39, p p.164–172, 2023. https://doi.org/10.11975/j.issn.1002-6819.202305042

[28] G.Yang, J.Wang, Z.Nie, H.Yang, S.Yu. A Lightweight YOLOv8 Tomat o Detection Algorithm Combining Feature Enhancement and Attention. Agronomy, vol.13, pp.1824, 2023. https://doi.org/10.3390/agronomy13071824