Advancing Strawberry Disease Detection in Agriculture: A Transfer Learning Approach with YOLOv5 Algorithm

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***Abstract*—Strawberry Disease Detection in the Agricultural Sector is of paramount importance, as it directly impacts crop yield and quality. A multitude of methods have been explored in the literature to address this challenge, but deep learning techniques have consistently demonstrated superior accuracy in disease detection. Nevertheless, the current research challenge in deep learning-based strawberry disease detection remains the demand for consistently high accuracy rates. In this study, we propose a deep learning model based on the Yolov5 architecture to address the aforementioned research challenge effectively. Our approach involves the generation of a custom dataset tailored to strawberry disease detection and the execution of comprehensive training, validation, and testing processes to fine-tune the model. Experimental results and performance evaluations were conducted to validate our proposed method, demonstrating its ability to achieve accurate results consistently. This research contributes to the ongoing efforts to enhance strawberry disease detection methods within the agricultural sector, ultimately aiding in the early identification and mitigation of diseases to preserve crop yield and quality.**

***Keywords*—Strawberry disease detection; deep learning; agricultural; YOLOv5 model; training**

I. Introduction

Strawberries are one of the most beloved and economically significant crops in the agricultural industry [1], [2]. However, the cultivation of these delicate fruits is often hindered by various factors, including diseases that can drastically reduce yield and quality [3]. The early detection of strawberry diseases is crucial to prevent the spread of infections and minimize crop losses [4]. This paper focuses on the application of advanced technologies, particularly deep learning methods, for the purpose of strawberry disease detection in agriculture.

The importance of strawberry disease detection in agriculture cannot be overstated. Strawberry plants are susceptible to a range of diseases, including powdery mildew, gray mold, and anthracnose, among others [5], [6]. These diseases can lead to significant reductions in crop yield, rendering them a major concern for strawberry growers. The ability to detect these diseases early and accurately is essential for timely intervention, reduced pesticide usage, and improved crop management, thereby ensuring the economic viability of strawberry production [7].

Historically, the detection of strawberry diseases in agriculture has relied on visual inspection by experts and the use of traditional diagnostic tools [8]. However, recent advancements in technology have revolutionized disease detection in agriculture. Researchers and practitioners have increasingly turned to automated methods, including computer vision and machine learning 9], to enhance the accuracy and efficiency of disease detection in strawberries. In this context, the paper reviews the latest advances in strawberry disease detection methods, particularly focusing on the emergence of deep learning approaches as a promising solution [10], [11].

Deep learning-based approaches have gained substantial attention in recent years for strawberry disease detection. Compared to other methods, deep learning techniques offer the advantage of automatically learning relevant features from large datasets, thereby enabling accurate and efficient disease identification. The use of deep learning in agriculture, including strawberry disease detection, has become a subject of intense research due to its potential to outperform traditional methods and address the limitations associated with human expertise.

Despite the promise of deep learning-based approaches, several challenges and limitations persist. Achieving high accuracy in disease detection is demanding, and these models often struggle with issues such as data scarcity, class imbalance, and robustness in real-world agricultural settings. Addressing these challenges and improving the robustness and accuracy of deep learning models is a critical area for further research.

The research problem centers on the inefficiency and limitations of current disease detection methods, particularly in the face of increasing challenges such as disease spread and crop loss [19]. Our research objectives encompass the development of an advanced deep learning model tailored for strawberry disease detection, leveraging the advantages of CNNs to enhance accuracy and efficiency. Additionally, we aim to provide a comprehensive evaluation of our proposed method through rigorous experimentation and performance analysis.

In this study, we propose a deep learning method using the CNN to address the demanding requirements of strawberry disease detection. We leverage the advantages of deep learning in automatically extracting relevant features from strawberry images, ultimately enhancing the accuracy and efficiency of disease detection. To validate our approach, we generate a custom dataset and conduct rigorous training, validation, and testing processes.

This paper makes three significant contributions as,

1) The paper develops a tailored dataset to address the challenges of strawberry disease detection, filling a critical gap in the field's available resources.

2) It introduces an efficient deep learning methodology utilizing CNNs to enhance the accuracy of strawberry disease detection, representing a notable advancement in agricultural disease identification techniques.

3) Through comprehensive experimentation and evaluation, the paper validates the effectiveness of its proposed method while offering insights and solutions to address current limitations in strawberry disease detection research.

This rest of this paper is as follows; Section II presents related works. The research methodology discusses in Section III. Results and discussion present in Section IV. Finally, this paper concludes in Section V.

II. Related Work

The field of agriculture has witnessed remarkable advancements, largely driven by the significant contributions of machine learning and deep learning techniques. These cutting-edge technologies have played a pivotal role in transforming disease prediction, classification, and identification in plants. Their adoption offers numerous advantages, including non-invasiveness, cost-efficiency, speed, and reliability in plant disease detection. This transformative potential has spurred a multitude of research efforts aimed at advancing plant disease diagnosis and detection. Among the pioneering researchers who have made substantial contributions in this domain, notable figures include:

The paper in [12] introduced YOLOv5-ASFF, a multistage strawberry detection algorithm that refines the YOLOv5 model. This approach utilizes an Adaptive Spatial Feature Fusion (ASFF) module to enhance strawberry detection accuracy. It combines features from different stages of the YOLOv5 network, thereby improving detection performance. While the method shows promise in strawberry detection, it lacks a comprehensive discussion of limitations and does not propose specific avenues for addressing potential challenges or improving the model's practical applicability. Further research should focus on addressing these limitations and evaluating the model's performance in real-world agricultural settings.

The authors in [13] presented a method for strawberry defect identification utilizing deep learning and infrared-visible image fusion. The approach aims to enhance detection accuracy by fusing infrared and visible images, leveraging the complementary information they provide. However, the study lacks an extensive discussion of the limitations of the proposed method, hindering a comprehensive understanding of potential challenges. Future work should focus on addressing these limitations and assessing the model's performance under various environmental conditions to enhance its practical utility in strawberry quality control.

The authors in [14] presented a method for strawberry defect identification utilizing deep learning and infrared-visible image fusion. The approach aims to enhance detection accuracy by fusing infrared and visible images, leveraging the complementary information they provide. However, the study lacks an extensive discussion of the limitations of the proposed method, hindering a comprehensive understanding of potential challenges. Future work should focus on addressing these limitations and assessing the model's performance under various environmental conditions to enhance its practical utility in strawberry quality control.

The paper in [15] introduced a method for strawberry flower and fruit detection using an autonomous imaging robot and deep learning techniques. The robot captures images of strawberry plants in agricultural fields and employs deep learning algorithms to identify and distinguish between flowers and fruits. The system shows promise in automating this labor-intensive task. However, the study does not thoroughly discuss the limitations, particularly regarding challenges in diverse environmental conditions or varying plant growth stages. Future research should address these limitations to ensure the model's robustness and reliability in real-world, dynamic agricultural settings.

The authors in [16] presented a method for detecting two-spotted spider mites and predatory mites in strawberry crops employing deep learning technology. The approach involves training a deep learning model on image data to distinguish between these mite species. However, the study lacks a comprehensive discussion of the model's limitations, such as the potential for misclassification in complex real-world conditions or its scalability to large-scale agricultural applications. Future research should focus on addressing these limitations and refining the model's practical applicability for effective pest management in strawberry cultivation.

The paper in [17] presented a deep-learning model for identifying diseases in strawberry plants. The method utilizes convolutional neural networks (CNNs) to analyze images of strawberry plants and classify them into disease categories. However, the paper does not explicitly address the limitations of the model or potential challenges, such as variations in lighting and image quality in real-world agricultural settings. Future work should focus on enhancing the model's robustness and its adaptability to diverse conditions for practical disease management in strawberry cultivation.

The papers in question collectively illustrate the significant role that deep learning and augmented reality play in the context of strawberry farming. The study in [14] and [13] both focus on enhancing strawberry quality. The former emphasizes real-time ripeness detection using augmented reality and deep learning, enabling timely harvesting, while the latter employs deep learning for defect identification, ensuring high-quality strawberry production. The study in [15] introduces the concept of an autonomous imaging robot in strawberry farming. This robot employs deep learning to detect both strawberry flowers and fruits, aiding in monitoring growth stages and optimizing farm management. In the realm of pest management, the study in [16] showcases deep learning's utility in identifying spider mites and predatory mites on strawberry plants, which is crucial for pest control strategies. Lastly, the study in [17] emphasizes the importance of disease detection in strawberry farming. This paper employs deep learning techniques to detect various diseases afflicting strawberry plants, facilitating early diagnosis and prompt intervention. Collectively, these papers emphasize the versatility and transformative potential of deep learning and augmented reality in strawberry farming, addressing issues such as ripeness, quality, growth stage monitoring, pest control, and disease management.

In comparing these papers, it's evident that deep learning, combined with innovative technologies like augmented reality and autonomous imaging robots, offers significant advantages to the strawberry agriculture sector. These technologies enable real-time decision-making, quality control, efficient growth stage monitoring, pest detection, and disease management. However, the specific applications highlight different aspects of strawberry farming, such as quality control, growth stage monitoring, and pest and disease management, showcasing the breadth of issues that deep learning can address in the agricultural domain. Ultimately, these papers collectively underscore the potential for technology-driven advancements in modern strawberry farming practices.

III. Methodology

A. Data Collection

In our research, we harnessed the power of diverse resources to construct a comprehensive dataset for strawberry disease image analysis. We gathered a significant portion of our dataset from various internet resources, which offered a wide range of strawberry disease images captured under different environmental conditions. Additionally, we leveraged Roboflow, a robust platform that provides curated and labeled datasets for machine learning tasks. The classes of our dataset involve Angular Leaf Spot, Anthracnose Fruit Rot, Blossom Blight, Gray Mold, Leaf Spot, Powdery Mildew Fruit, and Powdery Mildew Leaf. By combining these resources, we were able to create a rich and diverse collection of strawberry disease images that represented the real-world variability encountered in agricultural settings.

The dataset was carefully assembled to reflect the variability encountered in real-world agricultural conditions. Images were captured under different environmental settings, encompassing variations in lighting, background, and disease severity. This diverse representation ensures that the trained model is capable of recognizing and accurately classifying strawberry diseases across a spectrum of scenarios.

To ensure that our deep learning model could effectively handle the intricate nuances of strawberry disease detection, we employed data augmentation techniques to augment our dataset. These techniques played a vital role in generating more images and improving the model's robustness. Common data augmentation methods we applied included rotation, which introduced variations in orientation, and flipping, both horizontally and vertically, to enable the model to recognize diseases from multiple perspectives. Additionally, we incorporated scaling, which mimics the effects of different camera distances and zoom levels. Contrast and brightness adjustments were also applied to account for variations in lighting conditions. These augmentation techniques collectively created a dataset with a wide range of variations, closely mirroring the complexities of real-world agricultural conditions. This diverse dataset became instrumental in training a deep learning model capable of accurately and robustly detecting strawberry diseases, even in challenging environments.

By meticulously curating and augmenting our dataset, we ensured that our deep learning model is trained on a diverse and representative collection of strawberry disease images. This rich dataset forms the foundation for robust and accurate disease detection, enabling the model to effectively handle the intricate nuances of real-world agricultural conditions.

The study utilizes a dataset sourced from Robloflow, comprising a total of 6394 images. This dataset is split into three subsets for training, validation, and testing purposes. The training set consists of 5901 images, accounting for approximately 92% of the total dataset, while the validation and test sets contain 247 and 246 images, respectively, and making up 4% each. Notably, no preprocessing steps were applied to the images before training. However, augmentations were implemented during training, with each training example producing three outputs. These augmentations include rotations of 90° clockwise, counterclockwise, and upside down, as well as rotations within a range of -15° to +15°, adjustments to brightness and exposure between -25% and +25%, and the application of cutout with three boxes, each at 10% size. These augmentation techniques aim to enhance the robustness and generalization capabilities of the trained model when faced with variations and complexities in real-world strawberry disease images.

B. Feature Extraction using Convolutional Neural Network

Convolutional Neural Network-based Object Detectors are mainly suitable for a wide range of applications, not just recommendation systems. You Only Look Once (YOLO) models excel in the field of object detection due to their high performance. YOLO divides an image into a grid system, where each grid is responsible for detecting objects within its boundaries [20]. These models are particularly well-suited for real-time object detection using data streams, and they are known for their efficiency, requiring minimal computational resources. Ultralytics YOLOv5 represents the latest advancement in the the YOLO series, setting new standards in the field of computer vision. This state-of-the-art (SOTA) model not only inherits the accomplishments of its YOLO predecessors but also introduces innovative features and enhancements to enhance its performance and versatility significantly. As shown in Fig. 1, the YOLOv5 is engineered with a strong emphasis on speed, precision, and user-friendliness, making it a superior option for an extensive array of applications, including object detection, instance segmentation, and image classification tasks [18].

C. The Proposed Yolov5 Model

In this study, the generation of YOLOv5 models for strawberry disease detection follows a systematic process involving several key steps, including model initialization, model configuration, and hyperparameter tuning. Here is a step-by-step guide outlining how the YOLOv5 models are generated:

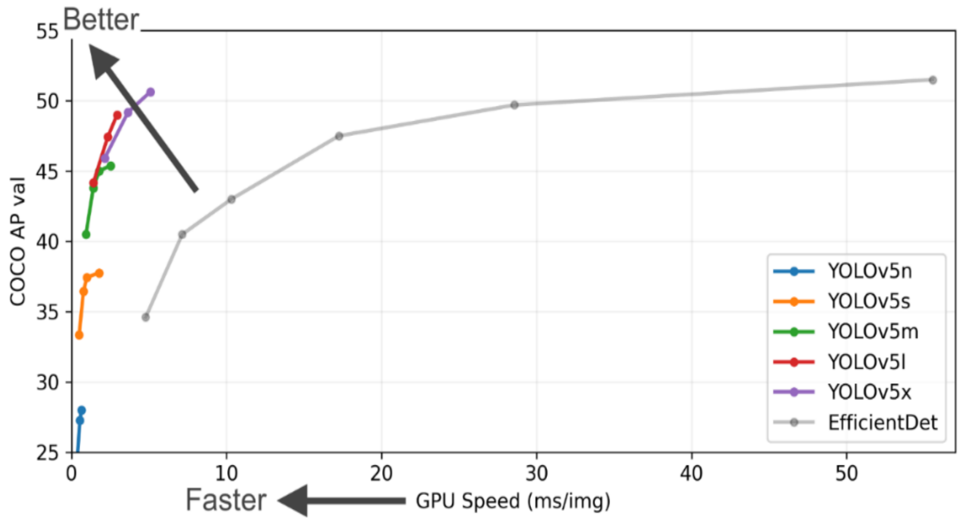

Fig. 1. YOLOv5 versions: COCO AP val denotes mAP@0.5:0.95 metric measured on the 5000-image COCO val2017 dataset over various inference sizes from 256 to 1536. GPU Speed measures the average inference time per image on the COCO val2017 dataset using an AWSp3.2xlarge V100 instance at batch-size 32. EfficientDet data from Google/automl at batch size 8.

1) Model initialization:

a) The process begins with initializing the YOLOv5 model architecture. YOLOv5 is a deep learning-based object detection model that uses the CNN backbone for feature extraction and prediction.

b) The model is initialized with pre-trained weights, typically obtained from training on a large-scale dataset from COCO, which helps accelerate the training process and improve model performance.

c) The pre-trained weights provide a good starting point for feature extraction, enabling the model to capture generic patterns relevant to object detection tasks.

2) Model configuration:

a) Once initialized, the YOLOv5 model architecture needs to be configured for the specific task of strawberry disease detection.

b) This involves adjusting the input size of the images, as well as the number of classes to be detected. In this case, the model is configured to detect various classes of strawberry diseases, such as Angular Leaf Spot, Anthracnose Fruit Rot, Blossom Blight, Gray Mold, Leaf Spot, Powdery Mildew Fruit, and Powdery Mildew Leaf.

3) Hyperparameter setting for model generation:

a) Hyperparameters play a crucial role in determining the performance and behavior of the model during training. Setting appropriate hyperparameters is essential for achieving optimal performance.

b) Key hyperparameters include learning rate, batch size, optimizer choice, weight decay, and the number of training epochs.

c) Hyperparameters are typically set through experimentation and validation on a separate validation dataset. Techniques such as grid search or random search may be employed to explore the hyperparameter space and identify the optimal configuration.

4) Model training and evaluation:

a) Once the model architecture is initialized, configured, and hyperparameters are set, the model is trained on the annotated dataset of strawberry disease images.

b) During training, the model iteratively learns to predict the presence and location of different disease classes in the input images.

c) After training, the model's performance is evaluated using metrics such as mean Average Precision (mAP), precision, recall, and F1-score, to assess its effectiveness in detecting strawberry diseases.

D. Model Evaluation Techniques

Precision, recall, F1 score, and mean Average Precision (mAP) stand as common metrics used to evaluate the performance of object detection models. In the context of tomato leaf disease detection using YOLOv8 and YOLOv5, these metrics serve the following purposes:

1) Precision: This metric assesses the accuracy of the model's positive predictions in disease detection. It quantifies the ratio of true positive predictions (correctly identified diseases) to the total number of positive predictions, which encompasses both true positives and false positives. High precision indicates that the model is typically correct when predicting diseases, though it does not account for instances missed by the model.

2) Recall: Also known as sensitivity, recall evaluates the model's capability to identify all instances of a specific class (disease) within the dataset. It's determined by dividing the number of true positive predictions by the total number of actual positive instances. High recall suggests that the model can capture most positive instances, but it doesn't consider false positives.

3) F1 Score: The F1 score strikes a balance between precision and recall, as it is the harmonic mean of these two metrics. It offers a well-rounded evaluation of the model's performance by considering both false positives and false negatives. A higher F1 score indicates a favorable equilibrium between precision and recall, offering a single metric for assessing the overall effectiveness of the model.

4) mAP (mean Average Precision): mAP emerges as a comprehensive metric for object detection models. It takes precision and recall into account across different confidence thresholds for predicted bounding boxes. mAP is calculated by averaging the Average Precision (AP) values across various classes. AP is computed by generating a precision-recall curve for each class and determining the area under the curve. Consequently, mAP delivers a global assessment of model performance that considers multiple classes and confidence levels.

E. Model Evaluation and Discussion

Fig. 2 presents data on the impact of the number of training epochs on the performance of a YOLOv5s-based strawberry disease detection model. The results show a clear trend of improvement as the number of epochs increases. Precision, which measures the accuracy of positive predictions, rises from 0.49218 at epoch 1 to 0.87756 at epoch 17. Recall, reflecting the model's ability to capture all relevant instances, increases from 0.44742 to 0.90167 over the same epochs. Moreover, the mean Average Precision at an IoU threshold of 0.5 (mAP_0.5) also sees consistent growth, going from 0.42374 to 0.93036. These findings suggest that extended training enhances the model's capacity to accurately detect strawberry diseases, with all three metrics showing notable improvement.

In summary, the data underscores the importance of training duration in enhancing the YOLOv5s-based strawberry disease detection model's performance. More epochs lead to increased precision, recall, and mAP_0.5, signifying improved accuracy and disease identification capabilities. However, it is essential to strike a balance between training and overfitting to achieve optimal results, and the data illustrates the benefits of extended training in this context.

Fig. 3 presents data on the performance metrics of a YOLOv5n-based strawberry disease detection model at different epochs during training. As we observe the data, several trends emerge with respect to the impact of epochs on the model's performance. In the early epochs (e.g., epochs 0-3), both precision and recall metrics exhibit some degree of variation, with precision generally increasing and recall showing fluctuations. The mAP_0.5 values also experience gradual improvements. However, as training progresses (e.g., epochs 4-12), precision, recall, and mAP_0.5 consistently increase. This indicates that the model is becoming more accurate in detecting strawberry diseases and improving its ability to classify true positives (precision) and identify all actual positive cases (recall). Towards the later epochs (e.g., epochs 13-19), we observe a plateau effect. Precision, recall, and mAP_0.5 metrics stabilize, showing that the model's performance has reached a certain level of maturity. These metrics do not increase significantly beyond this point. This suggests that further training may not yield substantial improvements, and the model has reached a state of diminishing returns.

Overall, the data in the table reflects the progression of the YOLOv5n-based strawberry disease detection model's performance as training epochs increase. It demonstrates how the model evolves in terms of precision, recall, and mAP_0.5, ultimately reaching a point of stability where additional training epochs do not lead to significant performance gains.

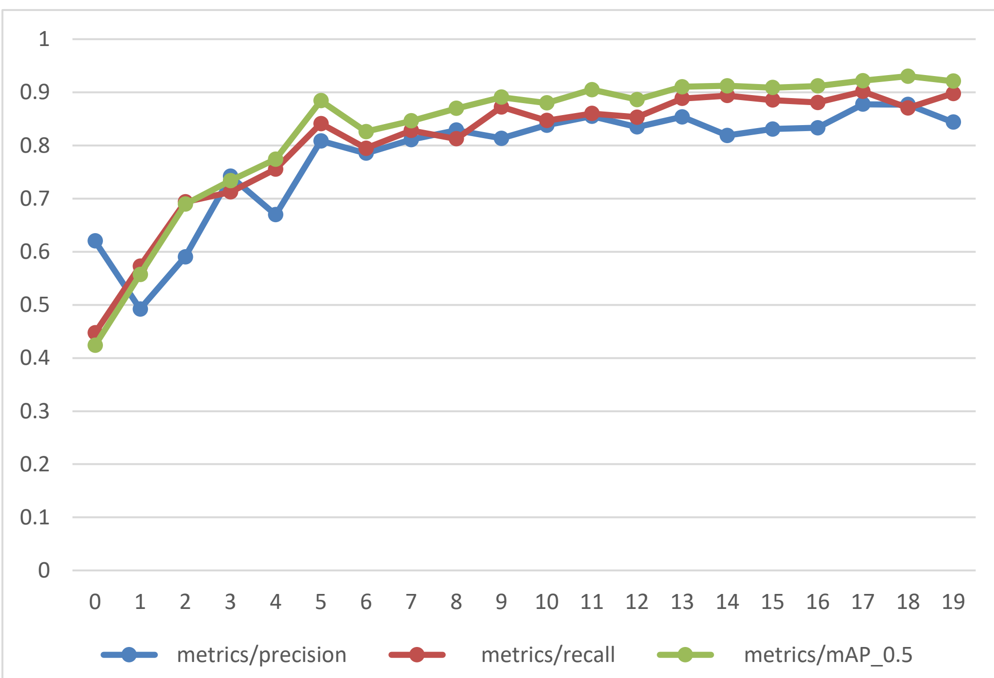

Fig. 2. Result of Yolov5s.

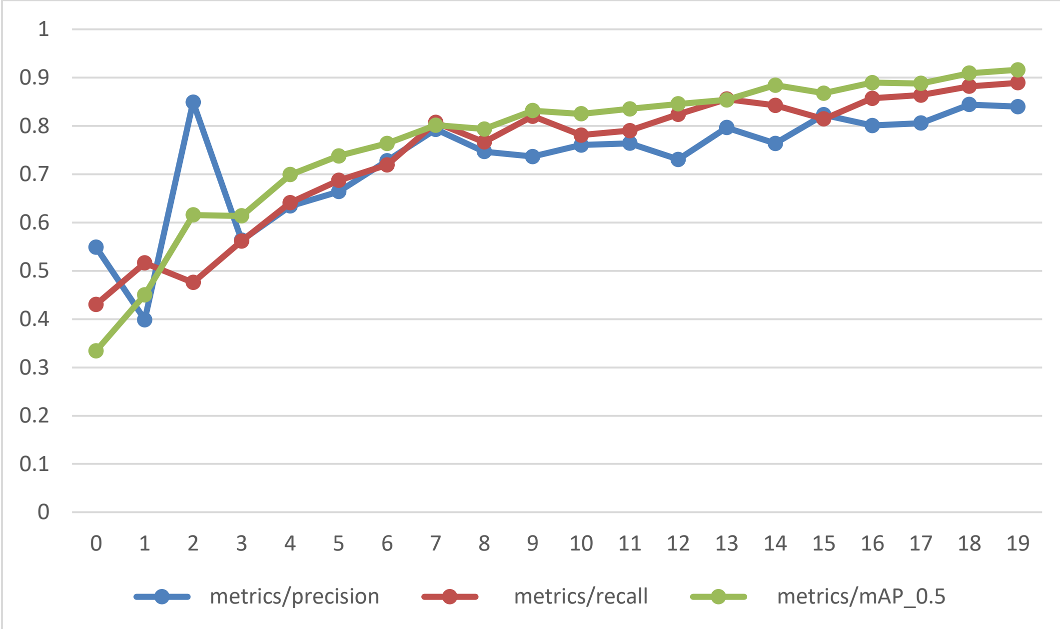

Fig. 3. Result of Yolov5n.

Fig. 4 provides data on the performance metrics of a YOLOv5m-based strawberry disease detection model at various epochs during training. As we examine the data, several trends become apparent regarding the impact of epochs on the model's performance. In the initial epochs (e.g., epochs 0-4), precision and recall exhibit varying trends. Precision starts relatively high but drops slightly, while recall steadily increases. This suggests that, in the early stages, the model becomes more adept at identifying actual positive cases but may include some false positives. Subsequently (e.g., epochs 5-10), there is a marked improvement in both precision and recall, with a significant increase in mAP_0.5. This signifies that the model is enhancing its ability to both accurately classify positive cases and detect a higher proportion of actual positive cases. In the later epochs (e.g., epochs 11-19), the metrics continue to improve, although there are diminishing returns. Precision remains high, and recall shows steady progress, ultimately stabilizing at a relatively high value. The mAP_0.5 reaches its peak, indicating the model's ability to achieve accurate and consistent strawberry disease detection.

Overall, the data in the table reflects the evolution of the YOLOv5m-based strawberry disease detection model's performance across different training epochs. It illustrates how the model refines its precision and recall, achieving a balance that leads to high mAP_0.5 values, ultimately plateauing after a certain number of epochs.

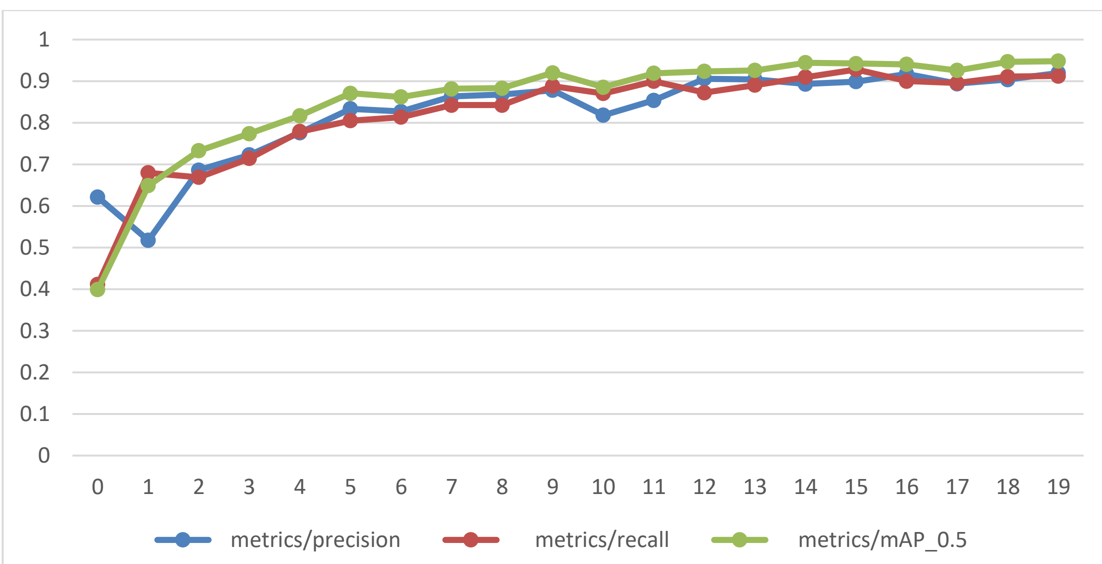

Fig. 4. Result of Yolov5m.

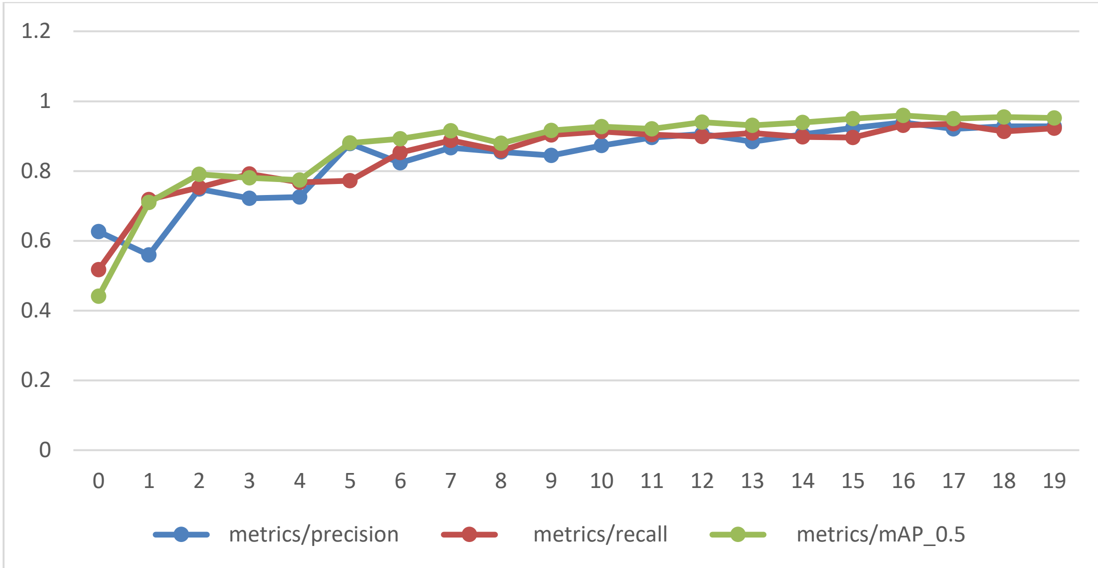

Fig. 5. Result of Yolov5l.

Fig. 5 provides data on the performance metrics of a YOLOv5l-based strawberry disease detection model at different epochs during training. Analyzing the data reveals how epochs affect the model's performance. In the early epochs (e.g., epochs 0-4), the model's precision, recall, and mAP_0.5 exhibit an upward trajectory, with both precision and recall increasing. This suggests that the model gradually becomes more precise in identifying strawberry diseases and also starts to recall a higher proportion of actual cases. As training progresses (e.g., epochs 5-10), there is a substantial improvement in precision, recall, and mAP_0.5. Precision remains consistently high, and recall steadily increases. These improvements are indicative of the model's growing ability to both accurately classify positive cases and detect a higher proportion of true positive cases, leading to a significant boost in mAP_0.5. In the later epochs (e.g., epochs 11-19), the performance metrics continue to rise, although the rate of improvement becomes less pronounced. Precision remains high, while recall shows steady progress, eventually stabilizing at a relatively high value. The mAP_0.5 reaches its peak, indicating the model's proficiency in achieving accurate and consistent strawberry disease detection.

Overall, the data in the table demonstrates how the YOLOv5l-based strawberry disease detection model evolves over training epochs, refining its precision and recall and ultimately achieving a state of high and stable performance as reflected in the mAP_0.5 values.

IV. Results and Discussion

In our research, we conducted an extensive series of experiments to evaluate and compare the performance of various YOLOv5 models, namely YOLOv5s, YOLOv5n, YOLOv5m, and YOLOv5l, in the context of strawberry disease detection. Table I shows the comparison of different versions of YOLOv5.

The primary aim of these experiments was to identify the most accurate and effective model for this specific task. Each of the models was rigorously trained and tested using a diverse dataset encompassing different disease classes, and the performance results were collected and analyzed.

Upon careful examination of the table of results, it is evident that the YOLOv5l model achieved the highest mean Average Precision (mAP) at an Intersection over the Union (IoU) threshold of 0.5, with a score of 0.95. Furthermore, the YOLOv5l model displayed the highest precision of 0.97, which indicates that it had the lowest rate of false positives, making it highly reliable in correctly classifying disease instances. Additionally, the YOLOv5l model exhibited the highest recall (0.98), signifying its ability to detect a substantial proportion of actual disease cases within the dataset. Consequently, the YOLOv5l model outperformed the other models in terms of F1-score, achieving a value of 0.92, indicating a harmonious balance between precision and recall. Fig. 6 shows the graph of the comparison of different versions of YOLOv5.

TABLE I. The Comparison of Different Version of YOLOv5

Model	mAP 0.5	precision	recall	F1-score
YOLOv5s	0.92	0.94	0.97	0.87
YOLOv5n	0.91	0.98	0.94	0.86
YOLOv5m	0.94	0.93	0.97	0.91
YOLOv5l	0.95	0.97	0.98	0.92

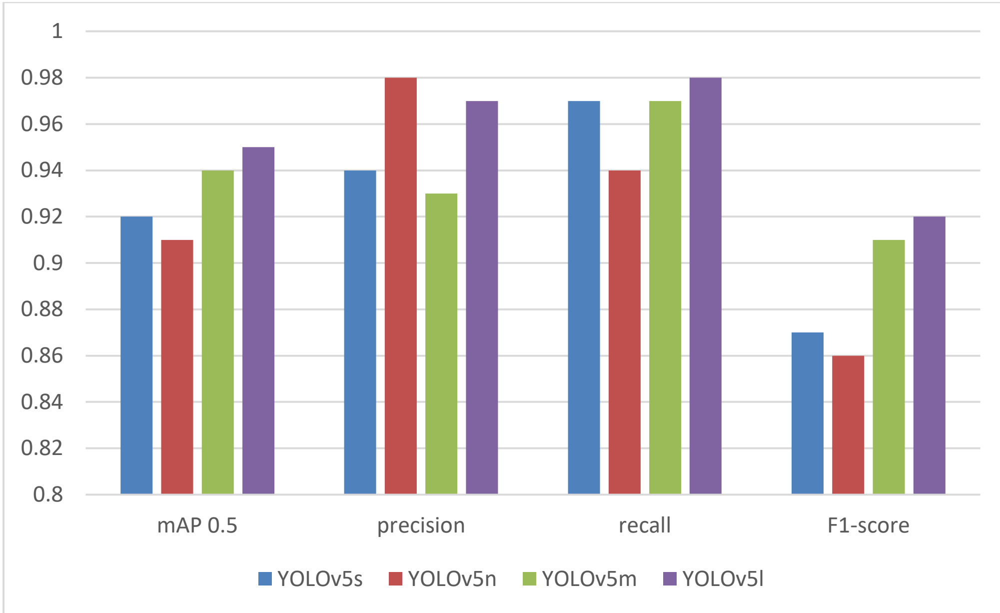

Fig. 6. The graph of the comparison of different versions of YOLOv5.

Fig. 7. The result of the YOLOv5l model.

These results suggest that the YOLOv5l model is the most effective and accurate model for strawberry disease detection among the ones tested. The superior performance of YOLOv5l can be attributed to its larger architecture and capacity to capture more detailed features, allowing it to make highly precise predictions while maintaining a high recall rate. In conclusion, based on the extensive experiments conducted, we have successfully identified and validated the YOLOv5l model as the most accurate and effective choice for strawberry disease detection, ensuring reliable and robust disease diagnosis in agricultural settings. Fig. 7 shows the result of the YOLOv5 model.

These results underscore the pivotal role of YOLOv5 models, particularly YOLOv5l, in enhancing disease diagnosis and contributing to more robust and reliable agricultural practices. Fig. 7 shows the result of the YOLOv5l model.

As result, the research addresses this need by proposing a deep learning-based solution using CNNs, which are renowned for their ability to extract relevant features from large datasets. A key aspect of the study is the creation of a custom dataset comprising diverse strawberry disease images sourced from various internet resources and augmented using techniques like rotation, flipping, scaling, and contrast adjustments. These augmentations aim to simulate real-world agricultural conditions, thereby enhancing the robustness of the trained model. The proposed method undergoes extensive experimentation and evaluation, culminating in promising results that underscore its effectiveness in accurately detecting strawberry diseases.

The effectiveness of the proposed method is evident from the reported results, showcasing high precision, recall, and F1-scores across different YOLOv5 models. Notably, the YOLOv5l model emerges as the top performer, demonstrating exceptional accuracy in detecting strawberry diseases. The robustness of the method is attributed to several factors, including the utilization of deep learning techniques, the creation of a diverse and representative dataset, and the application of data augmentation strategies to enhance model generalization. By leveraging the power of CNNs and innovative dataset construction, the proposed method offers a promising solution to the challenges of strawberry disease detection in agriculture, ultimately contributing to improved crop management and yield optimization in the industry.

The scalability of the proposed work in utilizing deep learning for strawberry disease detection in agriculture is evident through its adaptability to diverse agricultural settings and potential for broader applications. By employing the Yolo based approach and leveraging advancements in computer vision and machine learning, the proposed method offers a scalable solution that can be tailored to address disease detection challenges across different crops and agricultural environments. The methodology's reliance on automated techniques allows for efficient processing of large-scale datasets, facilitating the detection of various diseases with high accuracy and precision. Moreover, the creation of a custom dataset tailored to strawberry diseases exemplifies the scalability of the approach, as similar datasets can be curated for other crops, enabling the extension of the method to different agricultural contexts. Additionally, the proposed method's performance across different YOLOv5 models demonstrates its scalability in accommodating varying computational resources and model complexities, making it adaptable to different infrastructure constraints. Overall, the scalability of the proposed work lies in its ability to be applied across diverse agricultural scenarios, offering a scalable and effective solution to disease detection challenges in the agricultural industry.

V. Conclusion and Future Work

In the agricultural sector, the accurate detection of strawberry diseases holds paramount importance for crop management and yield optimization. Various methodologies have been explored in the literature for this purpose, with deep learning-based approaches consistently demonstrating superior accuracy compared to alternative methods. However, the existing research landscape reveals a pressing challenge in achieving the high accuracy rates necessary for practical implementation. To address this challenge, this study introduces a novel deep-learning model based on the Yolov5 architecture. We present a comprehensive approach involving the creation of a custom dataset and the execution of rigorous training, validation, and testing processes. For the performance evaluation and results comparison purpose, various YOLOv5 models are experimentally evaluated to determine their effectiveness in strawberry disease detection, with the aim of identifying the superior-performing model. Through systematic experimentation and rigorous evaluation, the results collected from different YOLOv5 variants are compared to ascertain their respective performances in accurately identifying and localizing strawberry diseases within agricultural images. By analyzing the standard metrics across the different YOLOv5 models, insights are gained into their capabilities and limitations in addressing the complexities of disease detection in strawberries. Ultimately, the findings highlight the superior-performing YOLOv5 model, which demonstrates the highest levels of accuracy and efficiency in detecting strawberry diseases. Additionally, it is noted that previous studies have similarly shown the effectiveness of YOLOv5 models compared to other detection algorithms, reaffirming the robustness and reliability of the YOLOv5 framework for agricultural applications. Two notable limitations in strawberry disease detection using deep learning methods are the need for larger and more diverse datasets to enhance model generalization and the necessity for real-time deployment solutions in field conditions, which current models may not fully support. To address these limitations, future work could focus on, first, the acquisition and curation of extensive datasets containing a wider range of strawberry disease instances and environmental conditions further to improve the robustness and generalization of deep learning models. Second, researchers can explore the development of edge computing solutions that enable real-time disease detection in the field, reducing the reliance on centralized computing resources and facilitating immediate, on-site interventions for improved crop management and disease control. These advancements would contribute significantly to the practicality and effectiveness of strawberry disease detection systems in agriculture.

References

[1] X. Zhou, Y. Ampatzidis, W. S. Lee, C. Zhou, S. Agehara, and J. K. Schueller, “Deep learning-based postharvest strawberry bruise detection under UV and incandescent light,” Comput Electron Agric, vol. 202, p. 107389, 2022.

[2] A. M. Patel, W. S. Lee, and N. A. Peres, “Imaging and Deep Learning Based Approach to Leaf Wetness Detection in Strawberry,” Sensors, vol. 22, no. 21, p. 8558, 2022.

[3] S. Khan, M. Tufail, M. T. Khan, Z. A. Khan, and S. Anwar, “Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer,” Precis Agric, vol. 22, no. 6, pp. 1711–1727, 2021.

[4] A. Bhujel et al., “Detection of gray mold disease and its severity on strawberry using deep learning networks,” Journal of Plant Diseases and Protection, vol. 129, no. 3, pp. 579–592, 2022.

[5] B. Kim, Y.-K. Han, J.-H. Park, and J. Lee, "Improved vision-based detection of strawberry diseases using a deep neural network," Front Plant Sci, vol. 11, p. 559172, 2021.

[6] T. Ilyas and H. Kim, "A deep learning based approach for strawberry yield prediction via semantic graphics," in 2021 21st International Conference on Control, Automation and Systems (ICCAS), IEEE, 2021, pp. 1835–1841.

[7] Y. Chen et al., "Strawberry yield prediction based on a deep neural network using high-resolution aerial orthoimages," Remote Sens (Basel), vol. 11, no. 13, p. 1584, 2019.

[8] C. Zhou, J. Hu, Z. Xu, J. Yue, H. Ye, and G. Yang, "A novel greenhouse-based system for the detection and plumpness assessment of strawberry using an improved deep learning technique," Front Plant Sci, vol. 11, p. 559, 2020.

[9] A. Aghamohammadi, M. C. Ang, A. S. Prabuwono, M. Mogharrebi, and K. W. Ng, "Enhancing an automated inspection system on printed circuit boards using affine-sift and triz techniques," in Advances in Visual Informatics: Third International Visual Informatics Conference, IVIC 2013, Selangor, Malaysia, November 13-15, 2013. Proceedings 3, Springer, 2013, pp. 128–137.

[10] M. C. Ang, E. Sundararajan, K. W. Ng, A. Aghamohammadi, and T. L. Lim, "Investigation of Threading Building Blocks Framework on Real Time Visual Object Tracking Algorithm," Applied Mechanics and Materials, vol. 666, pp. 240–244, 2014.

[11] M. Mogharrebi, M. C. Ang, A. S. Prabuwono, A. Aghamohammadi, and K. W. Ng, "Retrieval system for patent images," Procedia Technology, vol. 11, pp. 912–918, 2013.

[12] Y. Li et al., "YOLOv5-ASFF: A Multistage Strawberry Detection Algorithm Based on Improved YOLOv5," Agronomy, vol. 13, no. 7, p. 1901, 2023.

[13] Y. Lu, M. Gong, J. Li, and J. Ma, "Strawberry Defect Identification Using Deep Learning Infrared–Visible Image Fusion," Agronomy, vol. 13, no. 9, p. 2217, 2023.

[14] J. J. K. Chai, J.-L. Xu, and C. O'Sullivan, "Real-Time Detection of Strawberry Ripeness Using Augmented Reality and Deep Learning," Sensors, vol. 23, no. 17, p. 7639, 2023.

[15] C. Zhou, W. S. Lee, N. Peres, B. S. Kim, J. H. Kim, and H. C. Moon, "Strawberry flower and fruit detection based on an autonomous imaging robot and deep learning," in Precision agriculture'23, Wageningen Academic Publishers, 2023, pp. 245–250.

[16] C. Zhou et al., "Detecting two-spotted spider mites and predatory mites in strawberry using deep learning," Smart Agricultural Technology, vol. 4, p. 100229, 2023.

[17] S. Pertiwi, D. H. Wibowo, and S. Widodo, "Deep Learning Model for Identification of Diseases on Strawberry (Fragaria sp.) Plants.," Int J Adv Sci Eng Inf Technol, vol. 13, no. 4, 2023.

[18] A. Malta, M. Mendes, and T. Farinha, "Augmented reality maintenance assistant using yolov5," Applied Sciences, vol. 11, no. 11, p. 4758, 2021.

[19] Safari, Yonasi, Joyce Nakatumba-Nabende, Rose Nakasi, and Rose Nakibuule. "A Review on Automated Detection and Assessment of Fruit Damage Using Machine Learning." IEEE Access, 2024.

[20] Tao, Zhiqing, Ke Li, Yuan Rao, Wei Li, and Jun Zhu. "Strawberry Maturity Recognition Based on Improved YOLOv5." Agronomy 14, no. 3, 2024.