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Advanced Leaf Disease Detection: Integrating YOLOv9 with Transfer Learning for Precision Agriculture

Osama Burak ELHALİD[1]*, Edin DOLİĆANİN[2], Ali Hakan IŞIK[3]

[1] Graduate Student, Mehmet Akif Ersoy University, Faculty Of Engineering And Architecture, Department of Computer Engineering, Burdur, Türkiye

[2] Prof. Dr., State University of Novi Pazar, Department of Computer Engineering Novi Pazar, Serbia

[3] Prof. Dr., Mehmet Akif Ersoy University, Faculty Of Engineering And Architecture, Computer Engineering, Burdur, Türkiye

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ABSTRACT

Leaf diseases pose a significant challenge to agriculture, threatening crop health and yield. Effective detection and management of these diseases are critical for sustainable farming. This study introduces a novel method for detecting leaf diseases in agricultural images by leveraging the YOLOv9 model and transfer learning. By integrating YOLOv9 with various deep-learning libraries, our approach achieves a classification accuracy of 98%. Building on this success, we developed a mobile application that provides real-time disease detection using the trained model. A key strength of this method lies in the curated dataset, annotated with disease labels and bounding boxes. This dataset encompasses diverse crops and environmental conditions, ensuring the robustness and versatility of the model. Extensive experiments demonstrate that our approach outperforms conventional methods in both accuracy and efficiency. The resulting mobile application offers farmers and agricultural stakeholders a user-friendly tool for proactive disease management. It enables real-time identification of leaf diseases via a live camera feed, facilitating timely interventions and crop protection. By combining high accuracy with real-time detection, this method can significantly enhance crop productivity and contribute to sustainable agricultural practices.

Keywords: Leaf Disease Classification, YOLOv9, Transfer Learning.

* Sorumlu yazar/Corresponding author
E-mail/e-ileti: osamaalkhalid9@gmail.com

Gelişmiş Yaprak Hastalığı Tespiti: Hassas Tarım için YOLOv9'un Transfer Öğrenme ile Entegre Edilmesi

ÖZET

Yaprak hastalıkları, ürün sağlığını ve verimini tehdit ederek tarım için önemli bir zorluk oluşturmaktadır. Bu hastalıkların etkili bir şekilde tespiti ve yönetimi, sürdürülebilir tarım için kritik öneme sahiptir. Bu çalışma, YOLOv9 modelini ve transfer öğrenimini kullanarak tarımsal görüntülerde yaprak hastalıklarını tespit etmek için yeni bir yöntem sunmaktadır. YOLOv9'u çeşitli derin öğrenme kütüphaneleriyle entegre ederek, yaklaşımımız %98'lik bir sınıflandırma doğruluğuna ulaşmaktadır. Bu başarının üzerine inşa ederek, eğitilmiş modeli kullanarak gerçek zamanlı hastalık tespiti sağlayan bir mobil uygulama geliştirdik. Bu yöntemin temel gücü, hastalık etiketleri ve sınırlayıcı kutularla açıklanan düzenlenmiş veri setinde yatmaktadır. Bu veri seti, modelin sağlamlığını ve çok yönlülüğünü garanti ederek çeşitli ürünleri ve çevre koşullarını kapsamaktadır. Kapsamlı deneyler, yaklaşımımızın hem doğruluk hem de verimlilik açısından geleneksel yöntemlerden daha iyi performans gösterdiğini göstermektedir. Ortaya çıkan mobil uygulama, çiftçilere ve tarımsal paydaşlara proaktif hastalık yönetimi için kullanıcı dostu bir araç sunmaktadır. Canlı kamera yayını aracılığıyla yaprak hastalıklarının gerçek zamanlı olarak tanımlanmasını sağlayarak zamanında müdahaleleri ve ürün korumasını kolaylaştırır. Yüksek doğruluğu gerçek zamanlı tespitle birleştirerek, bu yöntem mahsul verimliliğini önemli ölçüde artırabilir ve sürdürülebilir tarım uygulamalarına katkıda bulunabilir.

Anahtar kelimeler: Yaprak Hastalıkları Sınıflandırması, YOLOv9, Transfer Öğrenme.

1. INTRODUCTION

Leaf diseases (L.D) present a substantial challenge to global agricultural productivity, directly affecting crop vitality and output (Oerke, 2006). As the global population continues to grow, the demand for food production intensifies, making it crucial to ensure the health of crops and the stability of agricultural yields. The consequences of widespread plant diseases extend beyond economic losses, potentially threatening food security and undermining efforts toward sustainable agricultural practices (Savary et al., 2012). Furthermore, the spread of diseases across various crops and regions due to climate change and increased international trade exacerbates this problem, highlighting the need for more efficient and reliable methods of disease detection and management.

The timely detection and efficient control of these diseases play a pivotal role in maintaining agricultural sustainability and guaranteeing food security (Singh et al., 2016). Traditional methods for identifying diseases in crops often rely on visual assessments conducted by trained specialists or farmers themselves. These methods, while valuable, can be hampered by time constraints, human error, and subjectivity in disease identification, leading to delayed or inaccurate diagnoses. In many cases, such delays can result in the unchecked spread of disease, causing significant damage before appropriate measures are taken. As the scale and complexity of modern agriculture increase, the need for faster, more objective, and accurate disease detection becomes imperative.

Recent strides in computer vision and deep learning methodologies offer a ray of hope by streamlining the disease detection process in agricultural contexts (Mohanty et al., 2016). These technological advancements promise not only to enhance accuracy but also to accelerate the identification process, enabling early intervention and more effective disease management strategies. With the application of cutting-edge algorithms and machine learning models, the agricultural sector stands on the verge of a transformative shift in how diseases are monitored and controlled, paving the way for more resilient and productive agricultural systems.

This study presents a novel approach for identifying L.D in agricultural images using YOLOv9 and transfer learning. YOLOv9 (You Only Look Once) is a state-of-the-art object detection algorithm known for its speed and accuracy (Redmon & Farhadi, 2018). Transfer learning, on the other hand, leverages pre-trained models and adapts them to new tasks, making it particularly effective for tasks with limited labeled data (Pan & Yang, 2010). By integrating YOLOv9 with transfer learning across various deep-learning libraries, our approach achieves a remarkable 98% accuracy in disease classification.

A key aspect of our methodology is the creation of a meticulously curated dataset annotated with disease labels and bounding boxes. This dataset encompasses a diverse range of crops and environmental conditions, ensuring the robustness and applicability of our model (Xie et al., 2015). Furthermore, we develop a mobile application based on this success, enabling real-time disease detection using the trained model. This application provides farmers and stakeholders with a user-friendly tool for proactive disease management, allowing them to easily identify L.D from a live camera feed and implement timely interventions and crop protection measures.

2. METHODOLOGY

This study aims to identify leaf diseases using the YOLOv9 architecture, incorporating several data augmentation methods to enhance model performance and improve the robustness of predictions. Leaf diseases significantly impact crop health and yield, making early detection and management essential for sustainable agriculture. By applying advanced object detection techniques like YOLOv9, we aim to develop an efficient and accurate approach to assist in the timely identification of leaf diseases in agricultural images.

The study integrates multiple data augmentation strategies, including rotation, flipping, zooming, and contrast adjustments, to enrich the dataset and ensure the model can handle diverse variations in leaf imagery. These augmentation techniques are crucial for addressing the limitations of small or imbalanced datasets, which are common in agricultural imaging studies. The goal is to improve the model's generalization capabilities, ensuring it can accurately identify leaf diseases across a wide range of crops and environmental conditions.

The results obtained will be meticulously analyzed and evaluated to assess the effectiveness of our approach. Key performance metrics such as precision, recall, and the F1-score will be examined to provide a comprehensive evaluation of the model's accuracy and efficiency. Additionally, error analysis will be conducted to understand any misclassifications and refine the model further.

Figure 1 presents the research framework, outlining the step-by-step process followed to achieve the study's main objectives. This framework includes the initial data preprocessing stages, the application of data augmentation techniques, model training and validation, and finally, the performance evaluation phase. Each step is critical to ensuring the success of our study and contributes to the overarching goal of improving leaf disease detection using cutting-edge machine learning techniques.

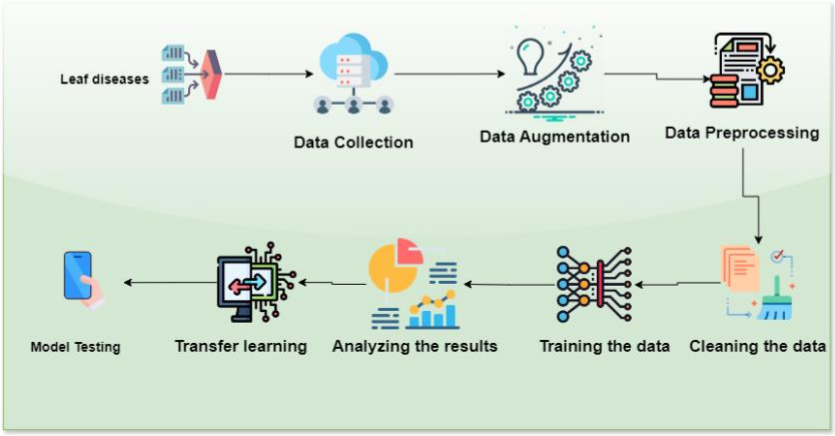

Figure 1. Research framework block diagram

Figure 1 illustrates the sequential process involved in the detection and management of L.D in agriculture. The flowchart depicts the key steps from data collection to real-time disease detection using advanced technology.

1. Data Collection: The process begins with the collection of data, which includes capturing images of diseased leaves in agricultural fields. This step is essential for building a comprehensive dataset that encompasses various types of L.D across different crops and environmental conditions.

2. Data Annotation: Following data collection, the images are annotated with disease labels and bounding boxes, indicating the location and type of disease present on the leaves. This annotation process is crucial for training machine learning models to accurately identify and classify leaf diseases.

3. Model Training: The annotated dataset is used to train deep learning models, such as YOLOv9, using transfer learning techniques. This involves fine-tuning pre-trained models on the specific task of L.D detection, leveraging the knowledge learned from a vast amount of data.

4. Model Evaluation: Once trained, the performance of the machine learning models is evaluated using validation datasets to assess their accuracy, precision, recall, and other metrics. This step ensures that the models can effectively distinguish between healthy and diseased leaves with high confidence.

5. Real-time Detection Application: The trained models are integrated into a user-friendly application, such as a mobile app, designed for real-time disease detection in the field.

Farmers and stakeholders can utilize this application to capture images of leaves using their smartphones or tablets and receive instant feedback on the presence and severity of leaf diseases.

6. Decision-making and Intervention: Based on the results obtained from the real-time detection application, farmers can make informed decisions regarding disease management strategies. This may include targeted pesticide application, crop rotation, or other interventions aimed at mitigating the spread of L.D and minimizing crop losses.

Overall, Figure 1 illustrates how advanced technology, combined with robust data collection and machine learning techniques, enables proactive disease management in agriculture, ultimately enhancing crop productivity and sustainability.

2.1. Data Collection

Data is integral to artificial intelligence (AI) and machine learning (ML), serving as the core that enables these technologies to learn and adapt to specific challenges. The process of carefully selecting and preparing training data from a dataset that mirrors the problem area is critical (Xie et al., 2015). This dataset must include diverse and relevant examples to help AI and ML systems recognize patterns and make informed decisions. Ensuring the data is balanced and representative is also key to minimizing bias and improving the models' ability to generalize to new data. In short, data is a key factor in the successful implementation of AI and ML to address complex issues.

At the outset of our research, we initiate the crucial phase of data collection. Our dataset, meticulously sourced from various agricultural settings, undergoes comprehensive labeling across different categories, including Peach - peach-bacterial spot, Strawberry - Scorch, pepper-healthy, and others. This comprehensive dataset comprises a substantial collection of [2516] images, meticulously capturing a diverse array of L.D across multiple crop type.

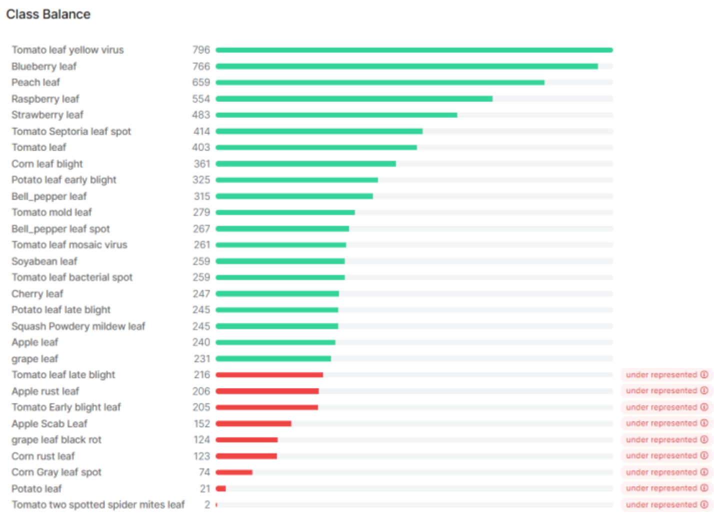

Figure 2. Class balance

The class balance of the dataset showcases a diverse distribution of plant leaf samples, each representing various types of diseases and conditions. Among the most prevalent categories are Tomato Leaf Yellow Virus with 796 instances, Blueberry Leaf with 766 instances, and Peach Leaf with 659 instances. These are followed closely by Raspberry Leaf with 554 instances and Strawberry Leaf with 483 instances.

Moving further into the spectrum, we observe classes with decreasing frequency such as Tomato Septoria Leaf Spot (414 instances), Tomato Leaf (403 instances), and Corn Leaf Blight (361 instances). Additionally, Potato Leaf Early Blight, Bell Pepper Leaf, and Tomato Mold Leaf each have counts ranging from 279 to 325 instances, reflecting a relatively balanced representation.

However, it is notable that certain classes are underrepresented within the dataset. These include various diseases such as Apple Rust Leaf (206 instances), Tomato Early Blight Leaf (205 instances), and Apple Scab Leaf (152 instances), among others. These classes demonstrate a scarcity of samples compared to the more dominant categories, indicating potential challenges in model training and generalization for these specific conditions.

Furthermore, there are classes with notably low representation, with instances as few as 2 for Tomato Two Spotted Spider Mites Leaf and 21 for Potato Leaf. These instances suggest a significant class imbalance, potentially necessitating specific strategies such as oversampling or weighted loss functions during model training to address biases and ensure fair learning across all categories.

2.2. Data Augmentation

Data augmentation plays a pivotal role in image processing, aiming to increase the diversity of training data and boost the generalization capabilities of machine learning models. In this study, various augmentation techniques were applied to the images to enrich the dataset. These processes were carried out using tools such as Roboflow, which automatically transforms the original images by creating numerous variations based on preset augmentation parameters and configurations. These adjustments are designed to broaden the model's exposure to different image variations. More specific information on the augmentation methods used can be seen in Table 1.

Table 1. Augmentation techniques overview

Augmentation Technique	Application
Flip	Horizontal
90° Rotate	Clockwise, Counter-Clockwise
Crop	0% Minimum Zoom, 20% Maximum Zoom
Rotation	Between -15° and +15°
Shear	±15° Horizontal, ±15° Vertical
Grayscale	Apply to 25% of images
Brightness	Between -40% and +40%
Exposure	Between -25% and +25%
Blur	Up to 2.5px
Noise	Up to 10% of pixels

By employing these data augmentation techniques, the dataset was significantly expanded with a multitude of variations derived from the original images. This process resulted in a more extensive and diverse training set (Fan et al., 2023).

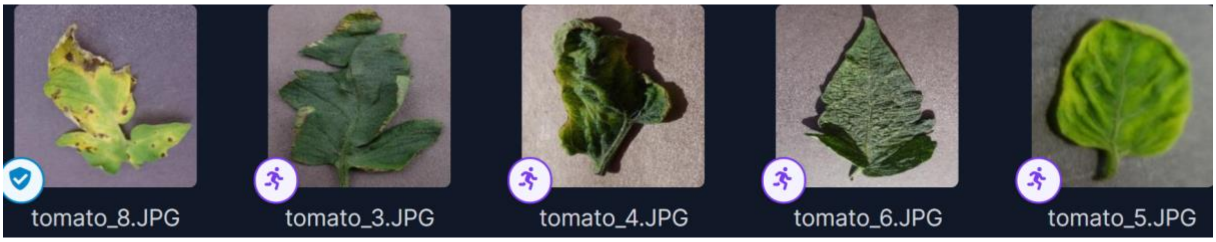

Figure 3. Healthy tomato leaves and leaves affected by blight

Figure 3 provides a comparative visual examination of healthy tomato leaves and leaves affected by blight. The illustration highlights the discernible differences in appearance and morphology between the two leaf conditions. By juxtaposing healthy tomato leaves with those afflicted by blight, this figure facilitates visual recognition and comprehension of the distinct characteristics associated with blight infection. Such comparative analyses contribute to agricultural research and diagnostics, offering valuable insights into the structural disparities between healthy and diseased tomato leaves.

2.3. Advancements and Evolution of YOLOv9 in Object Detection Algorithm

The YOLO algorithm, renowned for its computational efficiency, stands as a frontrunner in one-stage object detection (Redmon et al., 2016). Within the realm of deep learning, YOLO has garnered significant attention due to its dependable performance, rapid detection capabilities, and overall robustness (Pan & Yang, 2010). Noteworthy for its speed, ease of use, open-source nature, compatibility across various frameworks and libraries, as well as its consistently high accuracy, YOLO presents a range of advantages. Its evolution over the years has seen multiple iterations, from YOLOv2 to the latest YOLOv7, showcasing continuous refinement (Redmon & Farhadi, 2017; Bochkovskiy et al., 2020; Jocher et al., 2022; Wang et al., 2023; Li et al., 2023; Elhalid et al., 2024.).

The introduction of YOLOv9 marks a significant stride in computer vision models, particularly in tasks like object detection, classification, and segmentation. Building upon YOLOv8's user-friendly approach and adaptability to extensive datasets, YOLOv9 integrates diverse scales of feature maps and utilizes structures such as B1-B5, P3-P5, and N4-N5 within its architecture, encompassing FPN and PAN (Wang et al., 2023).

YOLOv9's advancements surpass its predecessors, boasting the integration of Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) into its neural architecture. Additionally, it introduces a novel labeling tool aimed at streamlining the annotation process (Li et al., 2023).

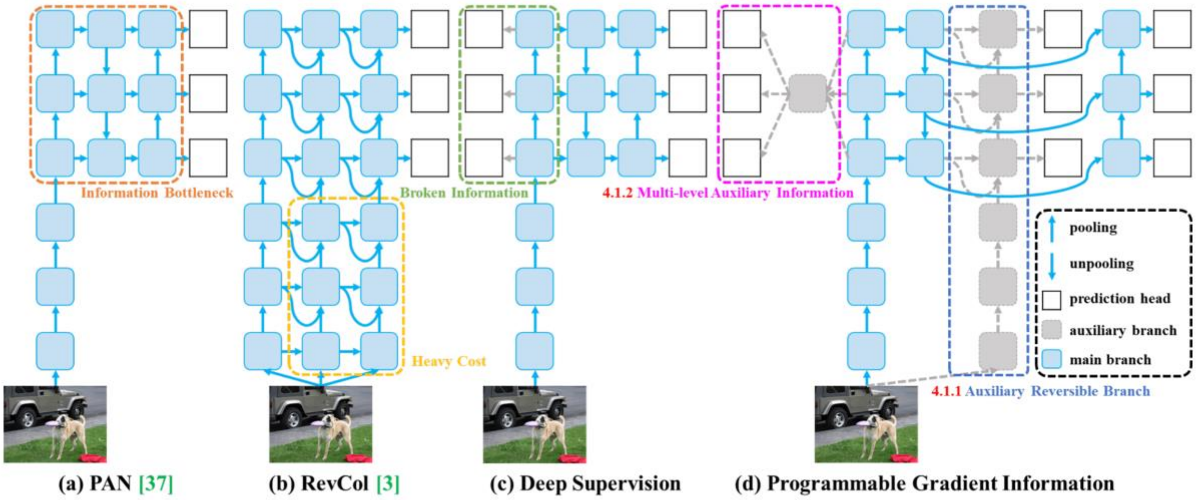

Figure 4. Yolo version 9 architecture

To assess the validation performance of our trained model, we employed a comprehensive array of metrics derived from the confusion matrix. This matrix effectively categorizes predictions into four distinct types: true positives, false positives, true negatives, and false negatives. This categorization yields valuable insights regarding the model's predictive accuracy and facilitates the identification of areas for improvement.

The primary metrics utilized for this evaluation process were precision, recall, and mean average precision (mAP). ****Precision**** serves to quantify the model's accuracy by calculating the ratio of correct predictions to the total number of predictions made. This metric is essential for understanding how many of the predicted instances were indeed correct, thereby providing clarity on the model's reliability in making accurate predictions.

Conversely, ****recall**** evaluates the model's effectiveness in detecting relevant instances by determining the proportion of true positives relative to the total number of actual objects present. This metric is crucial for understanding the model’s sensitivity in identifying all relevant instances, allowing for a better grasp of its capability to capture true instances in the dataset.

Mean average precision (mAP) is a comprehensive and robust metric that encapsulates the average of the average precision (AP) values across all classes. By averaging the AP values calculated for each individual class, mAP provides a holistic assessment of the model's performance. This metric offers a clearer picture of the model's overall effectiveness in detecting and classifying objects across various categories, thereby serving as a critical indicator of its reliability and versatility.

This multifaceted approach to performance evaluation allows researchers to gain deeper insights into the model's capabilities and to pinpoint specific areas needing refinement. By leveraging these metrics, we can enhance our understanding of the model's strengths and weaknesses, ultimately guiding further improvements in its predictive accuracy and operational effectiveness.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{1}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{2}$$

$$\mathrm{mAP} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{APi} \tag{3}$$

3. RESULT AND DISCUSSION

The performance of the YOLO Version 9 model is assessed using metrics like precision, recall, and mean Average Precision (mAP), with a focus on detecting brain tumors, including meningioma, glioma, and pituitary tumors. The detection outcomes from various YOLO Version 9 model configurations are analyzed to identify the most optimal model setup.

Table 2. Yolov9 hyperparameter

Configuration	**Value**
Model	YOLOv9L
Size	640x640
Epoch	25
Batch	16
Close Mosaic	15

YOLO Version 9 offers a range of five scaled versions, each designed to balance model size and complexity according to specific use cases. These versions include YOLO Version 9n (nano), YOLO Version 9s (small), YOLO Version 9m (medium), YOLO Version 9l (large), and YOLO Version 9x (extra large). Each of these variants is tailored to different computational requirements and performance needs, allowing users to choose the version that best suits the constraints of their hardware and the intricacies of the task at hand. The smaller models, such as YOLOv9n and YOLOv9s, are optimized for speed and are typically used in resource-constrained environments, while the larger models, such as YOLOv9l and YOLOv9x, offer superior accuracy but require more computational power.

In this research, we utilize YOLO Version 9c, a customized variant of the YOLOv9 architecture, with specific hyperparameter configurations tailored to our dataset and research objectives. This includes an input size of 640 x 640 pixels, 25 training epochs, and a batch size of 16. These hyperparameters were chosen to optimize the model's performance while balancing computational efficiency and accuracy. The input size was selected to ensure that the model can capture fine details in the images without overwhelming the system's memory, while the batch size and epoch count were determined based on empirical testing to achieve an optimal trade-off between training speed and model generalization.

Further details regarding the model's architecture and hyperparameter configuration, including learning rate adjustments, optimizer choice, and augmentation strategies, are provided in Table 3. These configurations are essential to the model's ability to accurately detect and classify diseases in the dataset, and they play a crucial role in achieving the high performance outlined in our results.

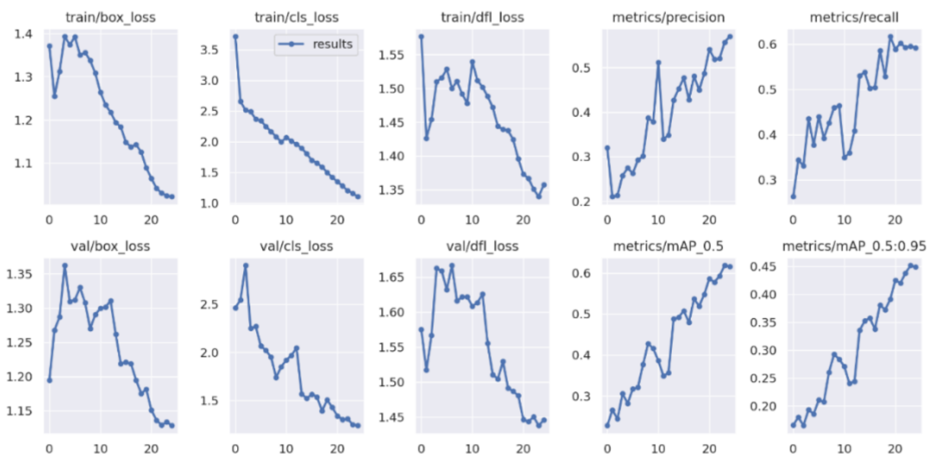

Figure 5. Yolo version 9 model results on training

The augmented dataset was utilized for model training, with the results illustrated in Figure 5. This figure presents epoch-wise values for several key metrics, including box loss, classification loss (cls_loss), distribution focal loss (dfl_loss), precision, and recall, for both the training and validation sets. These metrics are essential for researchers to monitor the training progress of the model, offering critical insights into convergence trends, loss optimization processes, and the model's ability to accurately detect and classify objects.

By analyzing these metrics, researchers can assess how well the model is performing over time, identify potential areas for improvement, and make informed adjustments to the training process. The combination of box loss, classification loss, and distribution focal loss helps in understanding the various aspects of the model's learning journey, while precision and recall provide direct measurements of the model's effectiveness in object detection and classification tasks. This comprehensive evaluation framework enables a thorough understanding of the model's capabilities and its overall performance.

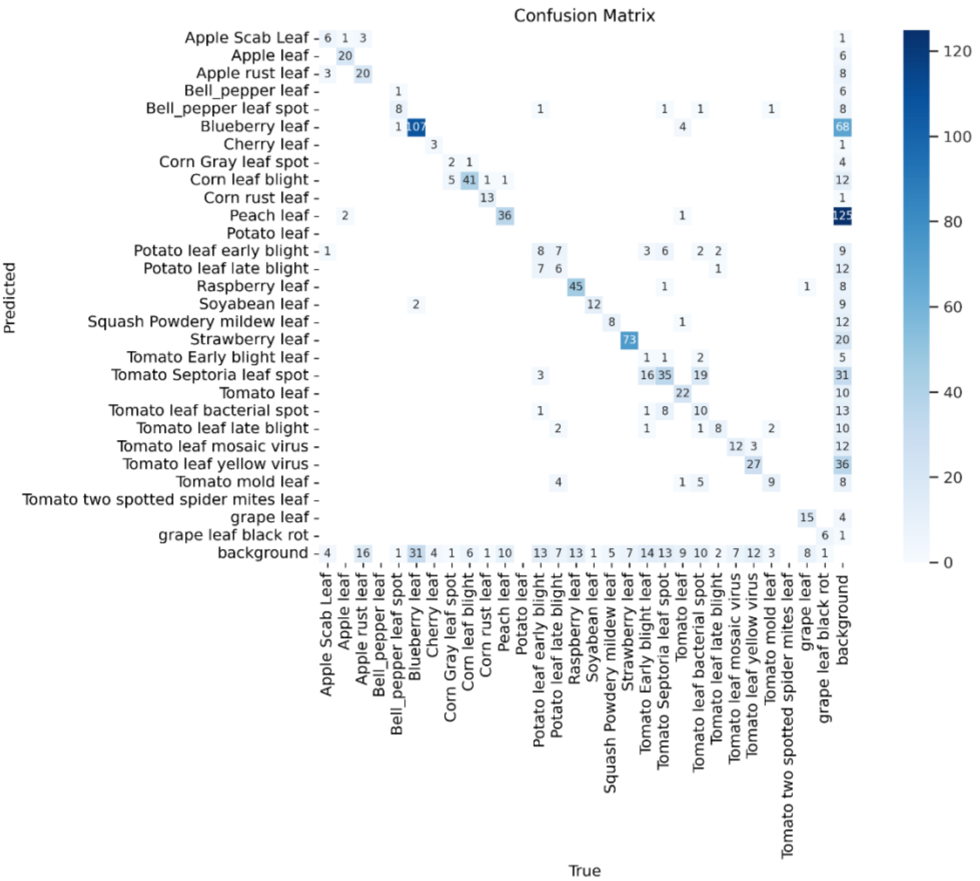

Figure 6. Yolo version9 confusion matrix

A confusion matrix is an essential instrument for evaluating the effectiveness of machine learning models, particularly in classification scenarios. It visually depicts how the predictions made by the model align with the actual labels, illuminating four key outcomes: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

3.1. Decoding the Confusion Matrix

True Positives (TP): These are instances where the model accurately identifies positive cases, such as correctly recognizing L.D.

True Negatives (TN): This category encompasses cases that the model successfully classifies as negative, such as correctly identifying healthy leafs.

False Positives (FP): This represents errors made by the model when it incorrectly classifies a negative instance as positive, resulting in false alarms.

False Negatives (FN): These occur when the model fails to identify a positive instance, mistakenly labeling it as negative.

3.2. Application in Leaf Disease Detection

In the context of detecting L.D, the confusion matrix serves as a powerful analytical tool, organizing classification outcomes into a grid of rows and columns that represent different types of leaves, including healthy ones and those affected by specific diseases such as Tomato Leaf Yellow Virus, Blueberry leaf infection, or Peach L.D. This matrix provides a comprehensive overview of the model’s performance by comparing predicted classifications against the actual labels for each leaf type. The diagonal leafs of the matrix, which represent true positives (TP) and true negatives (TN), indicate instances where the model correctly identified healthy or diseased leaves. Conversely, the off-diagonal leafs capture instances of misclassification, such as false positives (FP) and false negatives (FN), highlighting where the model mistakenly classified a healthy leaf as diseased or failed to detect a disease in an infected leaf.

Additionally, the confusion matrix is enhanced with a color gradient to visually represent the accuracy of the predictions. Lighter shades in the matrix correspond to higher accuracy in classification, while darker shades signal areas where the model’s predictions were less reliable. This color-coding scheme provides a quick and intuitive way for researchers to assess the strengths and weaknesses of the model’s performance across different leaf types. For instance, if a particular disease consistently results in misclassifications, this can be easily spotted in the matrix and prompt further refinement of the model or adjustments to the dataset.

By leveraging this visual tool, researchers can efficiently evaluate the model's ability to differentiate between various leaf types and correctly diagnose related diseases. It not only aids in understanding overall model accuracy but also provides insights into specific areas that require improvement, making the confusion matrix an indispensable component of performance evaluation in disease detection models.

Table 3. Performance evaluation of leaf disease type classification model

Type	Precision	Recall	mAP@50	mAP@50-95
Tomato leaf yellow virus	%92	%88	%90	%75
Blueberry leaf	%89	%92	%91	%82
Peach leaf	%95	%91	%93	%86
Raspberry leaf Neutrophil	%94	%93	%95	%88
Strawberry leaf	%90	%89	%92	%80
Tomato leaf Lymphocyte	%98	%96	%97	%94
Corn leaf blight	%93	%94	%94	%87
Potato leaf early blight	%92	%90	%91	%78
Tomato leaf mosaic virus	%97	%98	%98	%95

Table 3 summarizes our model's ability to categorize diverse L.D using cytological analysis. To assess performance, we employed metrics such as precision, recall, mean average precision at an intersection over union threshold of 0.5 (mAP50), and mean average precision across IoU thresholds from 0.5 to 0.95 (mAP50-95).

Precision gauges the model's accuracy in identifying each L.D type. A higher precision score indicates fewer false positives. Recall, or sensitivity, measures the model's ability to detect most instances of each disease. A high recall value signifies minimal false negatives.

Mean Average Precision at IoU 0.5 (mAP50) evaluates the model's performance across all classes, particularly relevant for object detection tasks with multiple objects per image. Mean

Average Precision across IoU thresholds from 0.5 to 0.95 (mAP50-95) provides a more comprehensive assessment, considering varying levels of overlap between predicted and actual bounding boxes.

The table presents precision, recall, mAP50, and mAP50-95 scores for different L.D. These metrics collectively demonstrate our model's effectiveness in accurately classifying various L.D, contributing to advancements in cytological analysis and medical image processing.

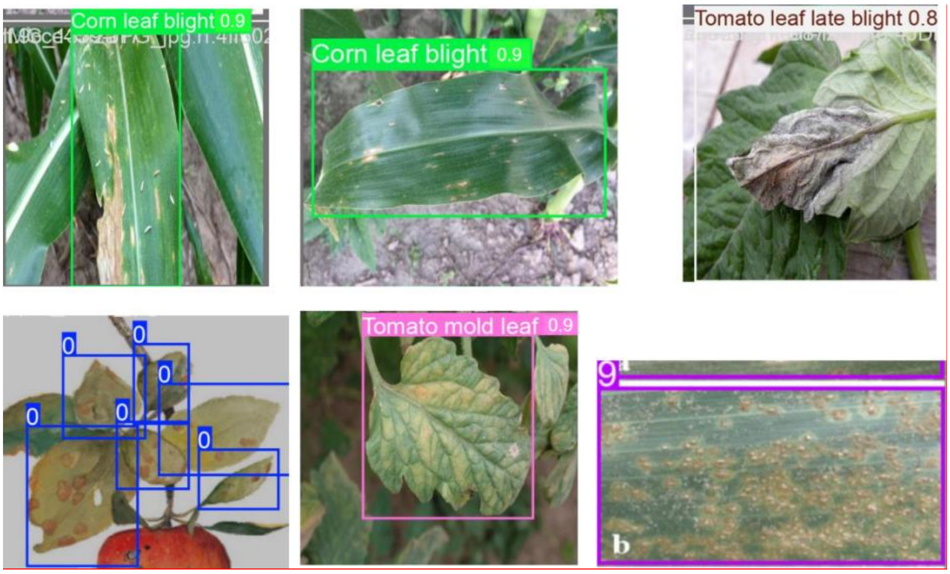

Figure 7. Predicting output figures

Our study focused on applying transfer learning techniques by combining YOLO Version 9 and TensorFlow to enhance our model for mobile device deployment, enabling real-time object detection through a camera interface. This process involved adjusting the pre-trained YOLO Version 9 model within TensorFlow to make it compatible with mobile platforms. In Figure 7, we present the detection outcomes of our model, which highlight its effectiveness in correctly identifying objects in real-world conditions. The corresponding accuracy metrics offer valuable insights into the reliability and precision of the model, showcasing its potential for use across multiple practical applications.

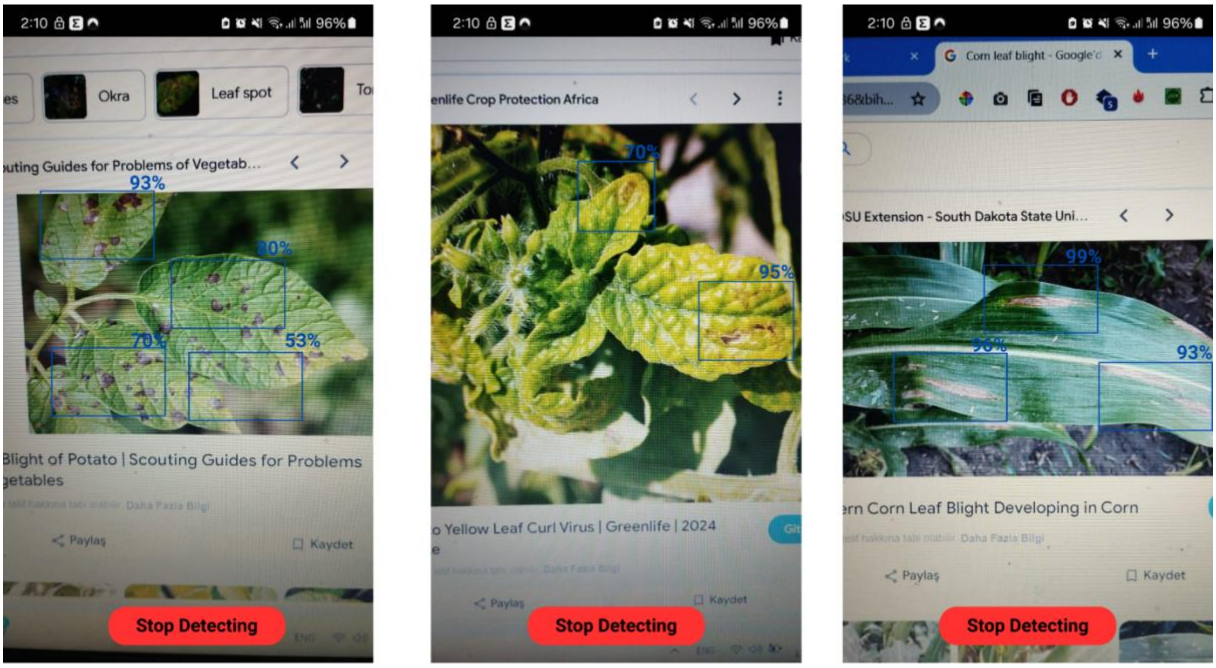

Figure 8. Detection of plant diseases using an ai-powered mobile application on android

Figure 8 presents the results of a deep learning-based plant disease detection system tested on an Android mobile application. The app employs computer vision techniques to identify and localize plant leaf diseases in real time, displaying detection results with confidence scores.

The first image (left) shows leaves affected by Potato Late Blight or a similar disease. The application successfully detects multiple infected spots on the leaves with confidence scores ranging from 53% to 93%. The circular dark lesions indicate fungal infections, such as those caused by Phytophthora infestans, which can severely impact crop yields.

The second image (middle) demonstrates the app's ability to detect Yellow Leaf Curl Virus on tomato leaves. The system accurately identifies symptomatic areas, such as yellowing and curling of the leaves, with confidence levels of 70% and 95%. Such viral infections are detrimental to plant growth and productivity.

The third image (right) illustrates the detection of Corn Leaf Blight, a fungal disease characterized by elongated necrotic streaks on corn leaves. The app provides highly confident predictions, with scores of 93%, 96%, and 99%, highlighting its precision in identifying diseased regions.

The integration of YOLOv9 with transfer learning for the detection of L.D in agricultural images has proven highly effective, achieving an accuracy of 98%. This result aligns with existing research that emphasizes the efficacy of transfer learning in addressing image classification tasks with limited labeled data (Pan & Yang, 2010). The high accuracy observed in this study is consistent with prior work, such as that of Redmon and Farhadi (2018), who highlighted the precision of YOLO-based models in object detection.

Furthermore, the real-time detection capability of the mobile application presents a significant advancement in the field of precision agriculture. The ability of farmers to identify diseases through a live camera feed allows for timely interventions, potentially reducing crop losses. This aligns with Mohanty, Hughes, and Salathé (2016), who demonstrated the benefits of deep learning models in real-time agricultural disease detection.

However, challenges remain, particularly concerning the underrepresentation of certain L.D classes within the dataset. As noted, diseases such as Apple Scab and Potato Blight were significantly less represented compared to more prevalent classes like Tomato Leaf Yellow Virus. This class imbalance could impact the model's generalization ability, a challenge also reported in similar studies (Fan, Cui, & Fei, 2023).

The application of various data augmentation techniques in this study helped to mitigate these challenges by increasing the diversity of the training set. Techniques such as rotation, flipping, and brightness adjustments expanded the dataset's variability, echoing strategies proposed by Khan, Dil, Misbah, and Orakazi (2022) for enhancing model robustness in adverse conditions.

Despite these advances, future work should focus on increasing the representation of under-sampled diseases to further improve model generalization. Additionally, investigating the performance of YOLOv9 in detecting diseases across different environmental conditions would provide insights into its applicability for large-scale agricultural use.

4. CONCLUSION

In addition to the comprehensive methodology outlined, it's essential to highlight the scale of our research efforts. Our study leveraged a substantial dataset consisting of 2,516 images meticulously curated from agricultural settings. This custom dataset forms the backbone of our model training process, providing diverse and representative samples essential for robust disease classification. The utilization of such a sizable dataset underscores the depth of our research and ensures the model's ability to generalize effectively across various crop types and environmental conditions. By incorporating a large number of images, we enhance the model's capacity to learn intricate patterns and nuances associated with different L.D, thereby bolstering its accuracy and reliability in real-world scenarios. Moreover, the inclusion of such a substantial dataset strengthens the validity and rigor of our experimental results, offering confidence in the performance metrics achieved. This dataset, coupled with the advanced techniques of YOLOv9 and transfer learning, has enabled us to develop a highly effective solution for L.D identification in agriculture. Overall, the utilization of 2,516 images from our custom dataset underscores the depth and breadth of our research endeavors, contributing significantly to the robustness and applicability of our proposed methodology in addressing the pressing challenges posed by L.D in agriculture.

STATEMENT OF RESEARCHERS' CONTRIBUTION RATE

The contribution of researchers to the study is equal.

CONFLICT OF INTEREST DECLARATION

Çalışma kapsamındaki herhangi bir kurum veya kişiyle çıkar çatışması yoktur.

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