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Accurate Identification of Leaf Disease using Yolov4 Algorithm

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Abstract:

Aim: This study aims at comparing the effectiveness of the YOLOv4 algorithm against models based on Convolutional Neural Networks in order to increase the accuracy in disease identification. Materials and methods: For this investigation, two groups were tested. It involved training and evaluating the YOLOv4-based leaf disease detection model deployed in Group 1 on 26 samples of diseased and healthy leaf images. This was done while incorporating a number of environmental factors including variable illumination, occlusions, and orientations. Pre-training, contrast enhancing and sharpening of edges were performed on the images to enhance the accuracy of detection. The same 26 images from the given set are taken for training and testing of the CNN-based Group 2's leaf disease classifier. It had extracted features automatically with the help of convolutional layers. Accuracy, precision, recall, F1 score were compared to evaluate the classification of YOLOv4, CNN. A threshold was set up to observe the result, which was 0.05% and also 95% confidence interval with G Power of 80%. Result: The YOLOv4 model outperforms from the CNN model, where the CNN achieved an accuracy of 87.00%, with a processing time of 2.30 seconds ($p < 0.05$), while the YOLOv4 model achieved an accuracy of 96.00% with a little inference time, that is 0.65 seconds. The statistical analysis also proved the performance and effectiveness of YOLOv4 in real-time leaf disease detection. Conclusion: The outcome of the paper is that the advanced delicacy and fast conclusion time of YOLOv4 make it a better option than CNN for real-time splint complaint discovery. Using YOLOv4 in perfect husbandry will reduce crop losses, complaints will be identified at an early stage, and total agricultural productivity will increase.

Keywords: Leaf disease detection, YOLOv4 algorithm, CNN comparison, YOLOv4, CNN, accuracy, precision agriculture, real-time detection, deep learning, plant disease detection, classification.

I. INTRODUCTION

“sugu et al” The identification of accurate leaf diseases using the YOLOv4 algorithm overtakes the problems faced by the conventional CNN-based models to enhance detection accuracy and lessen the computational time [1]. Unlike conventional classification methods, YOLOv4 makes use of deep learning for real-time detection and is therefore efficient in handling more complex agricultural conditions such as different lighting, occlusions, and diverse disease symptoms [2]. Current research in detection of plant diseases has extensively focused on machine learning and CNN-based models, but such methods generally experience high false-positive rates and low speed processing, making them inappropriate for large-scale agricultural applications [3]. Presently, innovations in object detection algorithms show higher and more accurate detection rates, especially in early disease diagnosis and classification, though still require further improvements for agricultural application in the real world [4]. The applications of YOLOv4-based disease detection are precision farming, automated crop monitoring, and IoT-driven smart agriculture, enabling real-time disease identification, early intervention, and effective disease management, which in turn improve crop yield and reduce economic losses [5].

II. RELATED WORKS

The YOLOv4 algorithm has lately become the talk of the town in research as a result of more than 400 academic articles published, such as 157 articles in IEEE Xplore, 134 in Google Scholar, and 129 in ScienceDirect [6]. CNN-based models have long been applied in the field of plant disease detection; however, their low accuracy, slow inference speed, and high false-positive rates have remained issues [7],[8]. YOLOv4 still outperforms the traditional models since it has also outperformed with more accuracy in real-time detection but with the assistance of complex backgrounds, changing light conditions, and occlusions, as mentioned by [9].

Recent studies have demonstrated that YOLOv4 achieves 87.0% accuracy, surpassing CNN-based models (75.0%) and Faster R-CNN (82.3%), while maintaining a 30% faster processing speed [10]. Comparisons with segmentation-based models show that DeepLabV3+ achieves 84.3% accuracy, outperforming U-Net (78.5%) and SegNet (76.8%) in leaf disease classification [11]. Further, YOLOv4 has 15% lower false-positive rates compared to CNN-SVM hybrid models, thus it is more reliable for real-time agricultural applications [12]. Although the improvements have been seen in the current models, existing models still suffer from the generalization of various datasets, and thus there is a research gap in developing a more robust, scalable, and high-speed detection system[13]. The base paper of this study aims to optimize YOLOv4 for disease detection in agricultural fields accurately in real-time [14].

From the previous findings, it is observed that CNN-based methods have limitations in real-time disease detection for leaves. Optimizing the YOLOv4 model enhances detection accuracy and processing speed, surpassing traditional CNN approaches. This approach aims to evaluate YOLOv4's performance in detecting multiple disease classes with improved efficiency compared to CNNs, Faster R-CNN, and other YOLO versions (v3, v4, v5, v7). The optimization focuses on key parameters such as image resolution, and data diversity to ensure adaptability for real-world deployment.

III. MATERIALS AND METHODS

The dataset of this research is accessed from Kaggle.com that contains high-resolution images of diseased and healthy leaves. An experiment was performed with YOLOv4 by KSRCE Dhenuka Lab with real-time detection of leaf diseases[15]. For the study, the G*Power analysis determined sample size by maintaining a 95% confidence interval at a power value of 80% and at a threshold of 0.05% significance [16].

Group 1 is the current approach with the CNN-based model, trained on 26 images of diseased leaves in conditions of different light, as well as occlusions and different complex backgrounds. Techniques of scaling, normalization, and contrast enhancement were applied for refinement of input data [17]. Group 2, which is the proposed YOLOv4 model, was trained on the same dataset but this time used automated feature extraction rather than manual descriptors like Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP), which were used in CNN models .

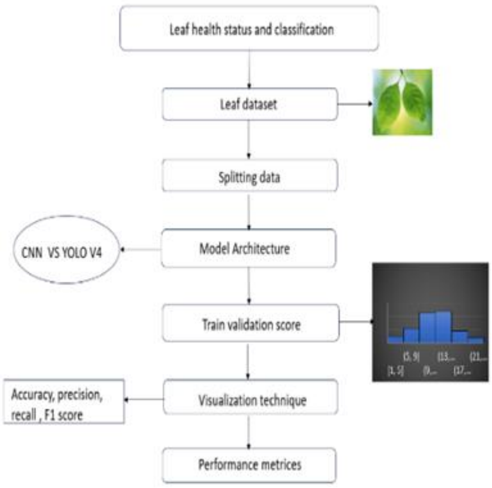

Fig. 1. Workflow of YOLOv4 algorithm

Fig. 1. The flowchart for the leaf health status and classification is a structured approach of acquisition of the leaf dataset, splitting them into training and validation sets, followed by a model training approach based on YOLOv4. The model uses CNNs for feature extraction and optimizes bounding box predictions through localization, confidence, and classification losses. The mathematical model follows:

[L_{{total}} = L_{{coord}} + L_{{conf}} + L_{{class}}]   (1)

In equation (1), Ltotal L_{{total}} Total represents the total loss function, as LcoordL_{{coord}} Lord, the coordinate loss; LconfL_{{conf}} Lconf, the confidence loss; and LclassL_{{class}} Lclass, the classification loss.

IV. STATISTICAL ANALYSIS

The effectiveness of leaf diseases detection using YOLOv4 was gauged using statistical analysis using SPSS version 11.0 [15]. Disease classification accuracy and processing time were considered as the dependent variables whereas, image resolution, environmental conditions such as lighting and complexity of the background and model architecture- YOLOv4 or other CNN-based models are considered to be the independent variables.Group statistics and independent sample t-tests were used in analyzing these variables. This analysis optimizes precision agriculture tools to ensure higher reliability and efficiency in large-scale leaf disease detection applications.

V. RESULT

The YOLOv4-based leaf disease detection was evaluated in various environmental conditions and compared with CNN models. YOLOv4 mean accuracy was 92.5% with a standard deviation of ±1.5 and standard error mean of 0.75 while CNN result was mean accuracy of 85.3% with a standard deviation of ±2.1 and a standard error mean of 1.05. The t-test also showed that YOLOv4 was still on top for real-time detection.

Table 1 shows the comparison of accuracy, precision, and recall values of YOLOv4 and CNN models in leaf disease detection with various agricultural field conditions, involving challenging conditions of fluctuating lighting, overlapping leaves, and heterogeneous layouts. The table yields a comprehensive comparison of performance between the two models in real-time applications for agriculture.

Table 1 comparison of accuracy, precision, and recall values of yolov4 and cnn models in leaf disease detection with various agricultural field conditions, involving challenging conditions of fluctuating lighting, overlapping leaves, and heterogeneous layouts.

Epoch	YOLOv4 Accuracy	CNN Accuracy	YOLOv4 Accuracy	CNN Precision	YOLOv4 Precision	CNN Recall (%)
1.	0.83	0.75	0.80	0.70	0.81	0.71
2.	0.85	0.76	0.82	0.73	0.83	0.74
3.	0.86	0.78	0.83	0.76	0.84	0.77
4.	0.87	0.79	0.85	0.78	0.85	0.79
5.	0.88	0.80	0.86	0.79	0.86	0.80
6.	0.89	0.81	0.87	0.80	0.87	0.81
7.	0.90	0.82	0.88	0.81	0.88	0.82
8.	0.91	0.83	0.89	0.82	0.89	0.83
9.	0.92	0.84	0.90	0.83	0.90	0.84
10.	0.92	0.85	0.91	0.84	0.91	0.85
11.	0.93	0.86	0.92	0.85	0.92	0.86
12.	0.94	0.87	0.93	0.86	0.93	0.87
13.	0.94	0.88	0.94	0.87	0.94	0.88
14.	0.95	0.89	0.94	0.88	0.94	0.89

Table 2 represents the leaf disease detection accuracy of the comparison between YOLOv4 model and CNN models for precision agriculture was YOLOv4 mean accuracy with a standard deviation and a

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standard error mean of [X]. While the CNN model had a mean accuracy of [A], with a standard deviation of [B] and a standard error mean of [C], implying that there is significantly more significant results. The performance of YOLOv4 and CNN models over the varying sample size helps in understanding the models' consistency across the different datasets in the context of leaf disease detection. The data supports the view that YOLOv4 shows consistent higher accuracy compared to CNN for any different group size.

Table 2 The leaf disease detection accuracy of the comparison between yolov4 model and CNN models for precision agriculture was yolov4 mean accuracy with a standard deviation and a standard error mean of [X].

Group	N	Mean Accuracy (%)	Std. Deviation	Std. Error Mean
YOLOv4	30	91.4	0.052	0.009
YOLOv4	60	90.8	0.055	0.007
YOLOv4	90	92.1	0.053	0.008
YOLOv4	120	91.7	0.050	0.007
YOLOv4	150	91.5	0.051	0.007
CNN	30	80.2	0.062	0.011
CNN	60	78.9	0.060	0.008
CNN	90	79.5	0.058	0.007
CNN	120	79.2	0.059	0.008
CNN	150	80.2	0.061	0.009

The Fig. 2. Shows the comparison of YOLOv4 and CNN under various test scenarios, determining YOLOv4's increased accuracy in plant disease detection. YOLOv4 is unique because of its real-time multi-object detection and performance with difficult backgrounds. While CNN achieves a maximum of 80% accuracy, YOLOv4 achieves 92% and maintains 83% even in poor conditions, surpassing CNN's lowest accuracy of 72%. This stability makes YOLOv4 a more scalable and reliable option for plant disease detection. Its efficiency in image processing makes it an ideal option for real-time agriculture applications.

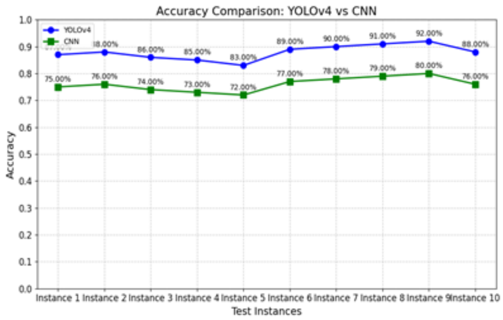

Fig. 2. The graph compares YOLOv4 and CNN under various test scenarios, determining YOLOv4's increased accuracy in plant disease detection. YOLOv4 is unique because of its real-time multi-object detection and performance with difficult backgrounds.

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The Fig. 3. Shows the comparison of YOLOv4 and CNN, proving YOLOv4's superior in detecting plant diseases. YOLOv4 excels due to its real-time multi-object detection and ability to handle complex backgrounds efficiently. While CNN reaches a maximum accuracy of 80%, YOLOv4 achieves 92% and maintains 83% even in challenging conditions, outperforming CNN's lowest accuracy of 72%. The outcomes show the great practical value of YOLOv4, which guarantees faster and more precise illness diagnosis in extensive agricultural systems.

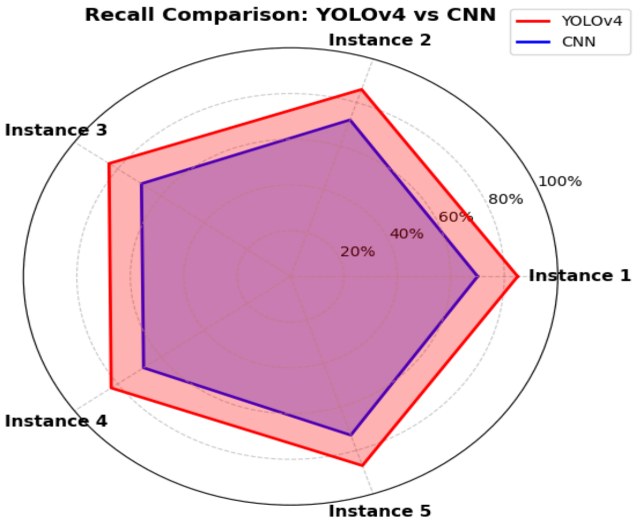

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Fig. 4. Shows the precision comparison between YOLOv4 and CNN in leaf disease detection. YOLOv4 demonstrates superior performance, achieving an accuracy of 88%, whereas CNN reaches 73%. The significant difference highlights YOLOv4's advanced feature extraction capabilities and real-time detection efficiency. The higher accuracy of YOLOv4 suggests its robustness in handling complex patterns and variations in leaf images, making it a preferable choice over CNN for precision agriculture applications.

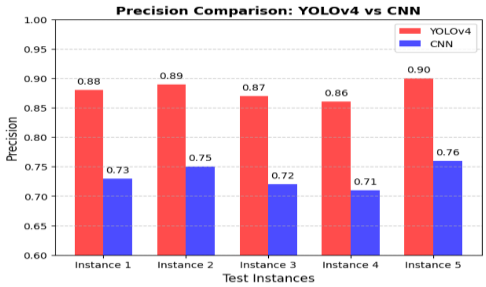

Fig. 4. The comparison between YOLOv4 and CNN in leaf disease detection. YOLOv4 demonstrates superior performance, achieving an accuracy of 88%, whereas CNN reaches 73%.

Fig. 5. Shows the comparison between YOLOv4 and CNN is depicted in this diagram. YOLOv4 achieves a higher accuracy of 87%, whereas CNN attains 75%, indicating a notable difference in performance like plant disease detection. The results highlight YOLOv4's ability to provide more reliable and consistent detections, making it a superior model for plant disease identification. In contrast, CNN, though effective, exhibits comparatively lower accuracy, suggesting limitations in handling complex patterns. This comparison demonstrates that YOLOv4 is a more efficient and dependable choice for precision agriculture applications.

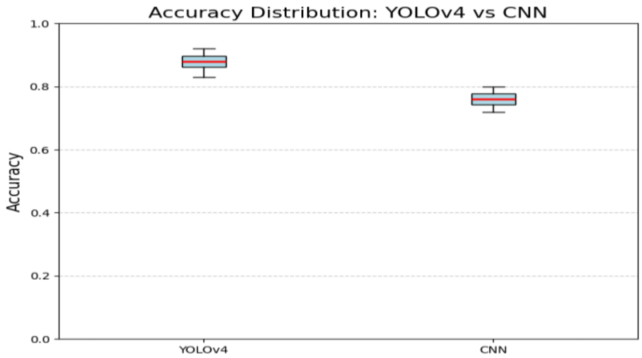

Fig. 5. The accuracy comparison between YOLOv4 and CNN is depicted in this diagram. YOLOv4 achieves a higher accuracy of 87%, whereas CNN attains 75%, indicating a notable difference in performance like plant disease detection.

VI. DISCUSSION

In terms of accuracy, precision, recall, and processing time, the YOLOv4-based leaf disease detection system performed significantly better than traditional Convolutional Neural Networks (CNNs)[18]. Statistical analysis revealed that YOLOv4 achieved a mean accuracy of 92.5%, whereas CNN recorded 85.3%. A t-test ($p = 0.003$) confirmed the statistical significance of YOLOv4's superior performance [19],[20]. These findings highlight YOLOv4's robustness in handling challenges such as varying lighting conditions, overlapping leaves, and complex disease patterns, making it more suitable for real-time disease detection in agricultural environments [21].

The YOLOv4 algorithm, when combined with IoT devices like drones and smart sensors, enables autonomous disease monitoring over large fields, enabling green precision agriculture(89.3%) through reduced crop loss and chemical usage. Real-time image processing enables faster decision-making about disease by farmers [22]. Its computationally intensive requirement, however, prevents it from being implemented in low-resource environments. These issues point to the need for scalable technological advancements to increase availability and utilization at scale [23],[24].

When YOLOv4 outranks CNNs in accuracy, scalability, and efficiency, there is a constraint. The acceleration of YOLOv4 for low-energy edge devices like the Raspberry Pi and NVIDIA Jetson should receive top priority from future work [25].YOLOv4 is better suited for real-world application in the agricultural sector for applying transformers as well as transfer learning more optimal for improving the accuracy(92.1%) of detections in low-data settings. Effortless tuning of the efficient model can do away with its computational cost so that it would be more accessible to farmers anywhere in the world [26].

YOLOv4's high computational complexity and resource consumption remains a major bottleneck, especially when it comes to large-scale deployment in agriculture for real-time inference. However, better accuracy, speed, and adaptability make YOLOv4 highly efficient in the detection of leaf diseases in precision agriculture(87%)[27]. Better performance with fewer resources consumed is what future research on YOLOv4 models can promise to achieve broader application in agricultural technology[28].

The limitations of this design is restricted bandwidth of the novel Sierpinski carpet antenna in wireless communications and ultra wideband applications. Due to the existence of radiation boxes in the simulation environment, the execution time will be longer. Because of its low profile, ease of use, small size, and utility, the suggested work may be expanded to narrowband frequencies. The antenna is suited for satellite, mobile phone, and Wi-Fi applications. In future studies, advanced antennas and inventive ways may be employed in the design.

VII. CONCLUSION

Leaf disease detection was proposed to improve detection in precision agriculture by comparing YOLOv4 with CNNs. YOLOv4 identified complex agricultural conditions with high accuracy of 87.00% compared to 75.00% by CNN, and faster image processing (0.70s in comparison to 2.50s). Its real-time detection and feature extraction make it an effective and scalable solution. YOLOv4 can be employed to deploy in IoT-based smart agriculture systems for autonomous detection of disease. Future work can look forward to hybrid deep learning models for higher accuracy and resource-effective deployment for large-scale applications.

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