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Deep convolutional neural network for detecting plant disease in apple leaves

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ABSTRACT

Agricultural diseases stand as a significant threat to global food security, yet their accurate diagnosis remains challenging due to inadequate infrastructure in various regions worldwide. Notably, signs manifesting on plant leaves often provide crucial indicators of illness presence. Moreover, with technological advancements, the precision and effectiveness of diagnosing both animal and plant ailments have significantly improved. The identification stage sets the foundation for a series of concerted efforts to combat and curtail disease spread. Within this paper, the YOLOv3 model, hinging on advanced deep transfer learning object detection technology, is harnessed to develop a robust system for recognizing healthy and diseased apple leaves. The study's findings reveal an impressive detection approach with an mAP value of 96.38%. Given its superior efficiency compared to preceding methods for diagnosing apple plant diseases, the proposed model emerges as a suitable solution for both apple orchards and apple plant tree producers.

Keywords: apple leaf disease, object detection, deep learning, transfer learning

1. Introduction

In recent years, advances in artificial intelligence and machine learning have transformed several areas, including agriculture [1]. Early detection and diagnosis of plant diseases is one crucial area that has benefited from technological advances [2]. Plant diseases pose a significant threat to global food security by causing significant production losses and crop quality degradation. The quick and precise identification of these disorders is crucial for successful disease treatment and preventing their rapid spread [3].

Apple cultivation is not immune to the threat of plant diseases. Infections caused by fungi, bacteria, and viruses can severely impair the health of apple trees, resulting in lower fruit output and economic losses for producers [4]. Traditional disease detection methods need skilled specialists manually checking leaves, which is time-consuming, labor-intensive, and usually prone to human error [5].

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as a viable alternative for automating plant disease identification [6]. CNNs are specialized neural network architectures designed to manage and assess visual input, making them perfect for image classification, object identification, and segmentation applications. CNNs' ability to automatically learn hierarchical characteristics from raw visual input has proven crucial in enhancing the accuracy and efficiency of disease detection systems [7].

Furthermore, YOLOv3 (You Only Look Once version 3) has gained fame for its extraordinary speed and precision in recognizing and finding objects within images. YOLOv3 predicts many bounding boxes and class probabilities at the same time using a single neural network, making it perfect for real-time applications such as plant disease diagnostics [8].

In this context, the current study addresses a key issue by finding and addressing flaws in existing plant disease diagnosis approaches. While several studies have demonstrated the promise of YOLOv3 and deep learning for this purpose, the intricacies of apple leaves and the diseases associated with them demand tailored solutions. In [9], the incorporation of CycleGAN-based data augmentation and DenseNet into YOLOv3 showed increases in detection accuracy for apple surface defects. Similarly, [10]'s use of drone video and hardware for disease identification underlines the need for realistic data collection. Furthermore, the examination of anchor box optimization in [11] illustrates the requirement for precision in object detection. In this work, we significantly improved these techniques by strategically employing transfer learning and data augmentation. We maximized the use of pre-trained models using transfer learning, overcoming data limitations and expanding the capabilities of our Deep Convolutional Neural Network (DCNN). Furthermore, data augmentation broadens the variety of our training dataset, encouraging resilience and adaptability. This combined technique validates our YOLOv3

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-based DCNN as a practical option capable of diagnosing common plant pathology problems affecting apple leaves. Our innovation is found not only in the adoption of individual technologies, but also in their combined application, which supports accurate, and proactive disease management in agricultural situations.

This study aimed at improving disease diagnosis accuracy by merging domain-specific data with YOLOv3. Transfer learning techniques inside the YOLOv3 framework provide a distinct advantage, allowing pre-trained models on large datasets to capture broad attributes and fine-tune them for detecting apple leaf disease. This strategy would enhance the model's convergence and tackle data scarcity, which typically affects agricultural datasets.

The paper also discusses the development of a tool that can assist farmers in preventing diseases in their apple trees. The tool provides a practical and helpful means of quickly diagnosing diseased and healthy apple leaves. Proposed and thoroughly explained here is a YOLOv3-based DCNN architecture which include the dataset, preprocessing, evaluation metrics, and training approach. Lastly, highlighted are the contributions of the present work and the potential of using YOLOv3-based deep learning algorithms for automated detection of plant diseases.

2. Materials and methods

Figure 1 depicts the work that adopts a methodical approach that involves dataset collection and preprocessing, picture annotations, data augmentation, deep learning training and validation with YOLOv3, and deep learning inference. Curated diversified images provide domain-expert-based annotations, boost dataset diversity, and allow the model to discern between healthy and unhealthy apple leaves through this well-defined process.

2.1. Preparation and dataset collection

The dataset used in this study consisted of three hundred images of apple leaves from Kaggle [12] classed as healthy as shown in Figure 2 or diseased as shown in Figure 3. Each class comprises one hundred fifty images. To minimize overfitting and ensure generalization, the dataset has been divided into two parts: a training set containing 80% of the data and a validation set with the remaining 20%. This divide ensures that the model has been trained on a diverse variety of data and can make accurate predictions on previously unknown data.

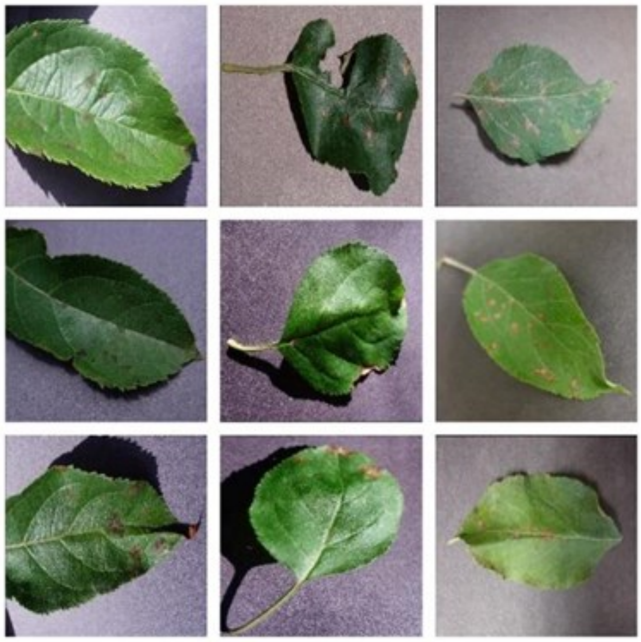

Figure 2. Sample datasets of diseased apple leaf.

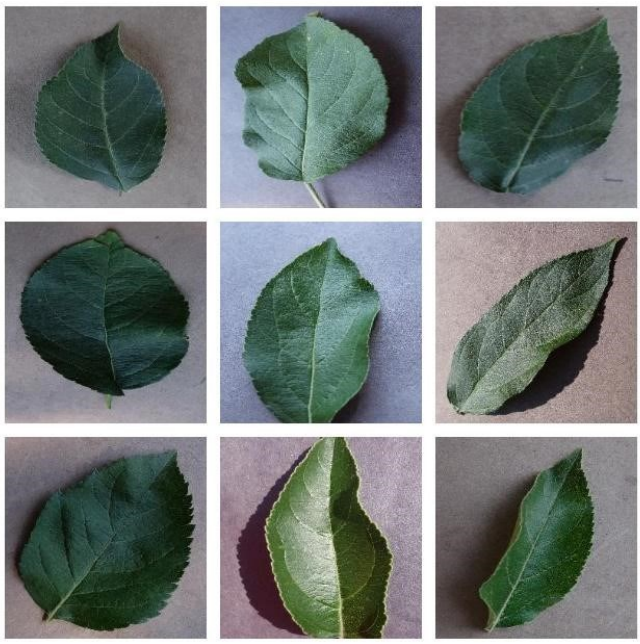

Figure 3. Sample datasets of healthy apple leaves.

2.2. Annotation and augmentation of the dataset

The LabelImg annotation tool [13] was utilized in the study as shown in Figure 4, and the annotated files were saved in the XML PascalVOC format. Using LabelImg's

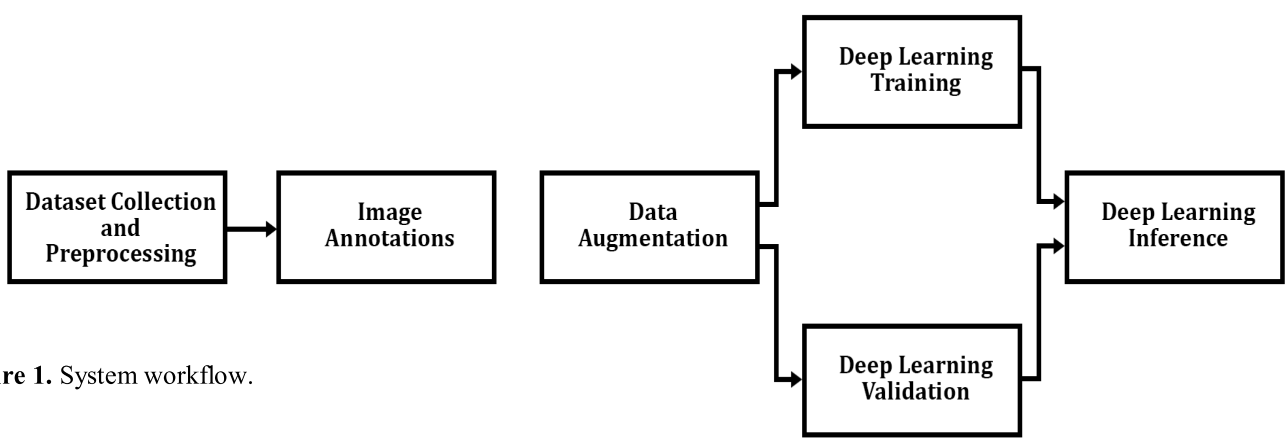

Figure 1. System workflow.

interactive annotation features enabled accurate labelling of the dataset, boosting its suitability for training the YOLOv3 model. The use of the XML PascalVOC format for annotations ensured interoperability with the YOLO framework and allowed for the easy insertion of labeled data into the model training process.

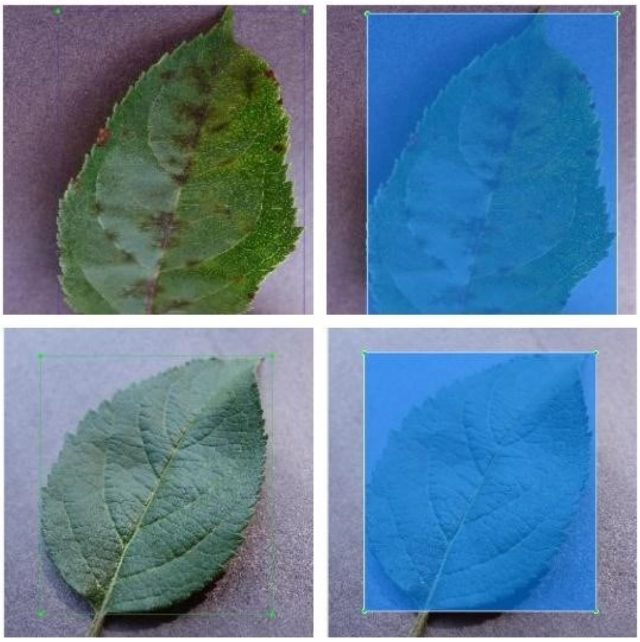

Figure 4. Image annotation of diseased and healthy apple leaf.

The study introduced four separate filtering methods into the pipeline—scaling, cropping, HSV distortion, and picture flipping—and demonstrated a systematic approach to improving the model's performance. The use of these strategies not only increased the variety of the dataset but also provided resilience against fluctuations in picture circumstances, angles, and color distributions. This thorough method demonstrated the importance of deliberate data preparation measures in improving the model's capacity to generalize successfully.

2.3. Deep learning algorithm

YOLOv3 is a visual recognition system that segments the entire image before forecasting border boxes using a single CNN. CNN's ability to produce numerous projections at the same time leads it to greater success. YOLOv3 splits up the image into numerous parts using a single CNN [14].

The classic sliding window strategy, which searches for items pixel by pixel throughout the full frame, was surpassed by this model. Certain object detection parameters may be unusually loud, crowded, or complex, resulting in an incorrect interpretation of the item. To overcome this issue, YOLOv3 employs a regional strategy, providing image qualities with the best approaches that are closest to the categorized item [15].

As shown in Figure 5, YOLOv3 was selected as the foundation for several lightweight networks due to its widespread adoption in business applications. This choice was driven by YOLOv3's prevalent use and user-friendly nature, attributed to its core architecture [17]. Prior to commencing training with YOLOv3, a recommendation was made to implement image and data augmentation techniques for the purpose of identifying diseased and healthy instances.

2.4. Model evaluation

The mean Average Precision (mAP) served as a crucial metric for evaluating the constructed models, ensuring the selection of the most optimal design for model inference. This metric played a pivotal role in processing data for the subsequent testing phase. As the mAP value improves, the detection effectiveness of the product also advances, with mAP being the average of the individual Average Precision (AP) scores and the approach for calculating the mAP for different classes is expressed as follows.

$$mAP = \frac{\sum_{i=1}^{o} AP_i}{o} \quad (1)$$

$$AP = \sum_{i=1}^{n-1} (r_{i+1} - r_i) p_{interp}(r_{i+1}) \quad (2)$$

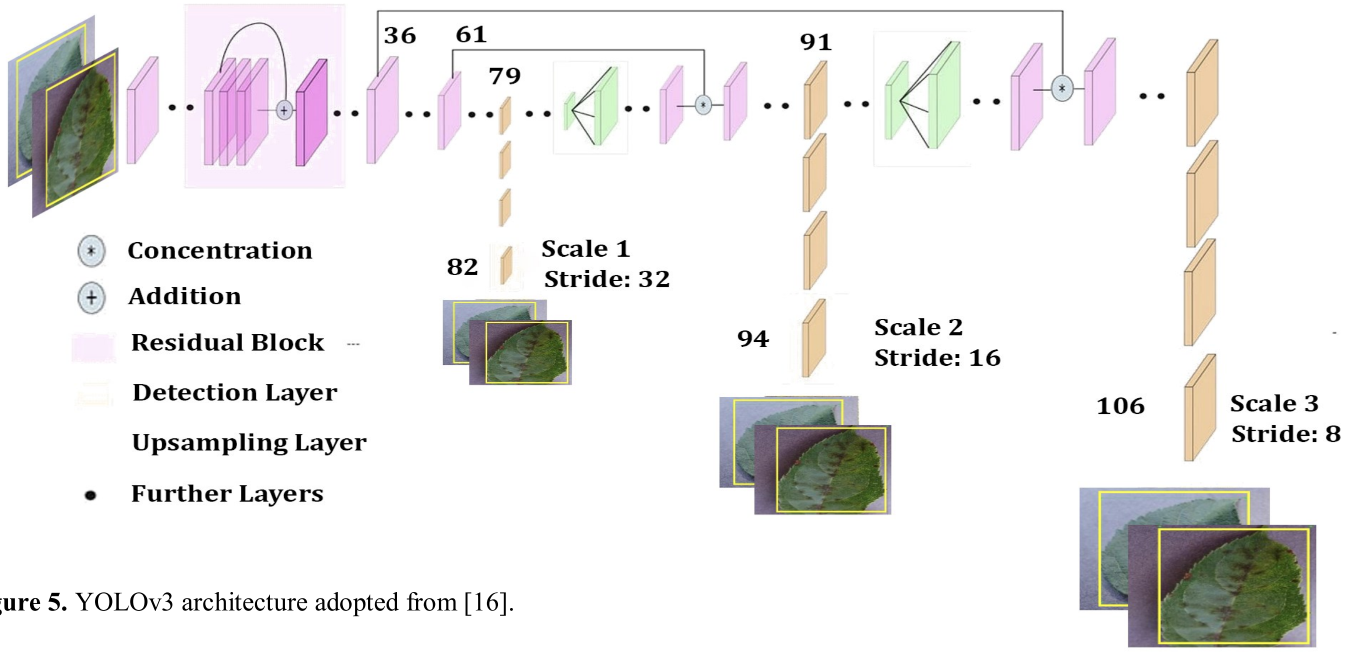

Figure 5. YOLOv3 architecture adopted from [16].

2.5. Model inference and testing

The interface design was realized through the utilization of the Anaconda IDE, PyQt5 framework, and ImageAI recognition software. The graphical user interface (GUI) encompasses three primary functions: picture recognition, video recognition, and live stream classification. The model itself was crafted using the provided learning algorithm h5 file, in conjunction with its associated JSON configuration file, collectively forming the foundational components of the model's architecture.

The evaluation methodology employed in this study involved collecting apple orchard images and video recordings from online sources. This approach was adopted to mitigate potential biases in the assessment of testing performance, as these additional images were distinct from the original set of three hundred photos utilized for training and validation purposes as express in the below equation.

$$Accuracy = \frac{\#\ of\ Detected\ Object}{Total\ \#\ of\ Objects} x\ 100 \quad (3)$$

3. Results and discussion

3.1. Result of training and validation

Figure 6 illustrates the testing and verification outcomes derived from the dataset. Within the graph, the training iteration level has been established at 26. As the training progresses, the model exhibits a decreasing loss trend. Upon initiation, the model exhibited a training loss of 34.03% and a validation loss of 10.61%. This trajectory is graphically represented.

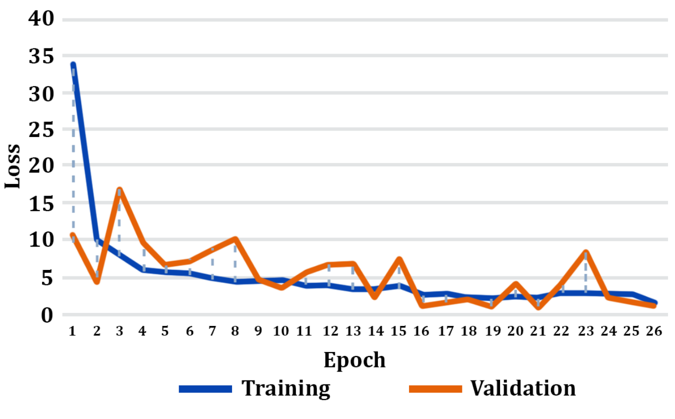

Figure 6. Model training and validation results.

By epoch 26, substantial progress was achieved, resulting in a training loss of 1.46% and a validation loss of 0.86%. Notably, the lowest testing and verification loss score of 5 was observed at training epoch 26, while the highest occurred during training epoch 1, as illustrated in Figure 7. This pattern indicates an enhanced loss performance as training duration extends, attributed to the model's learning from the provided training samples. Conversely, the validation loss tends to diminish over time. It is important to highlight that while a test dataset is primarily designed to evaluate a specific model, it can also be repurposed to assess multiple models.

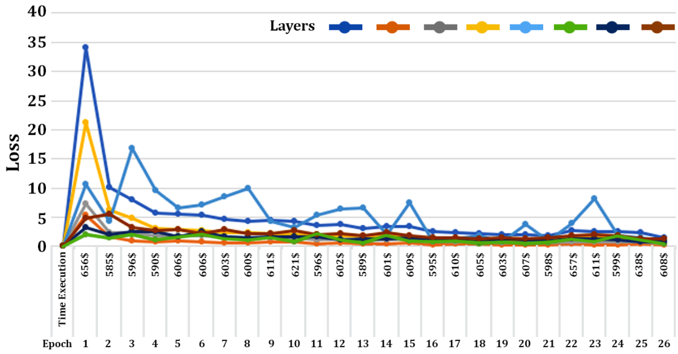

Figure 7. Training and validation layer's loss.

3.2. Model evaluation

The mAP result, presented as a percentage, serves as a measure of dataset validation accuracy. Notably, a higher mAP value indicates greater reliability, approaching the ideal value of 100%. As seen in Figure 8, the mAP resulting from model evaluation is graphically represented. Among the models, Model 1 exhibits the lowest mAP at 0.062. Interestingly, the performance trend shows a consistent improvement from Model 9 onwards. It is noteworthy that Models 12, 15, and 20 yielded indistinct results, while Models 14 and 26 demonstrated the most favorable outcomes, achieving impressive mAP values of 0.9638 (96.38%), as depicted in Figure 8. Due to its superior mAP performance, Model 14 was selected for testing and inference.

3.3. Inference and testing of model

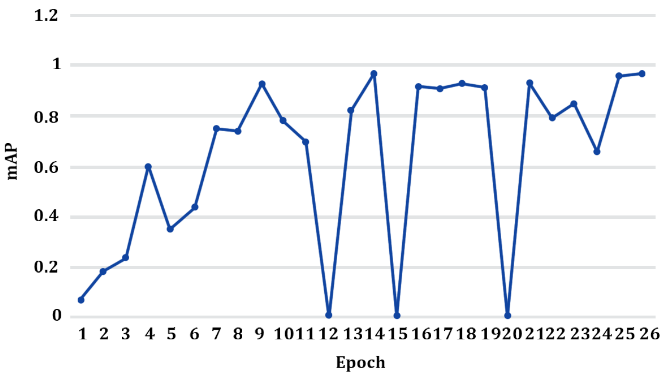

Figure 8. Model evaluation result.

Utilizing the developed Model 14, every frame captured by the detection equipment underwent thorough analysis. GUI was designed to assess the reliability of the inference results derived from Model 14. It offers three distinct execution options: importing photos, engaging in a live broadcast, and importing videos. The process of detection registers the recognized apple leaf objects and subsequently stores this information in the form of a CSV file.

The inference capabilities of Model 14 were assessed by employing a range of images depicting both healthy and damaged apple leaves. Additionally, a live stream dataset, compiled from camera footage, was generated for deployment and testing scenarios, showcasing the variation in detection accuracy across different contexts. The evaluation of per-frame video testing results indicated Model 14's commendable performance in accurately distinguishing between healthy and diseased apple leaves. Figure 9 represents this distinction, with a noteworthy accuracy of 97.56% for healthy leaf identification and 40.04% for diseased leaf identification.

Figure 9. Image and video frame testing result.

4. Conclusions

Plant diseases pose a significant global threat to food security and can have devastating effects on the livelihoods of small-scale farmers, whose sustenance relies on successful harvests. The apple industry is also affected by the recurrent occurrence of leaf diseases, which can impede consistent growth. Currently, the identification of diseases in large-scale apple orchards heavily relies on human visual assessment, making it necessary to depend on disease experts. In this context, the integration of the YOLOv3 algorithm, which leverages deep learning via CNNs, offers a promising approach to disease diagnosis. The system's robustness is underscored by achieving an mAP score of 0.9638 for Model 14. YOLOv3 is a potent strategy for detecting apple leaf diseases, especially within orchards, even when working with a limited dataset. The system's exceptional performance was confirmed through testing, revealing an accuracy of over 95%.

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