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Comparative analysis between Convolutional Neural Network (CNN) and Starfish Optimized with CNN for citrus fruit disease detection and classification

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Abstract

Agriculture is a backbone of our country. Many farmers face different challenges in their crop cultivation due to limited water resources, plant diseases, climate change, improper fertilization. This study focuses on citrus fruits. Citrus crops play a vital role in the food production and contribute significantly to the agricultural sector. Early detection of citrus disease helps prevent the yield reduction and economical losses. This research presents a deep learning approach using Convolutional Neural Network (CNN) for the automatic detection and classification of citrus diseases such as black spot, canker, greening, scab. In this paper, primary dataset was used, containing labeled images of both diseased and healthy citrus fruits. In this proposed system, deep learning approached based on convolutional neural network (CNN) model is used for classification and detection of citrus disease. Starfish optimization algorithm (SFOA) is introduced to tune the hyperparameters in CNN. CNN model achieved a training accuracy of 92.44 % with loss of 0.2704, demonstrating high performance in distinguishing among multiple citrus disease classes. In comparison of CNN, CNN with SFOA achieved 96.55 % with loss0.0739, demonstrating high performance in distinguishing among multiple citrus disease classes. This paper provides an efficient, scalable and reliable tool for early citrus disease diagnosis, which can assist farmers and agricultural experts in real-time monitoring and management of citrus crops.

Keywords – Deep learning, Convolutional Neural Network, Disease diagnosis, Star fish optimization algorithm, Primary Dataset.

1. Introduction

Agriculture plays an important role in sustaining human life. However, it faces different challenges due to crop diseases and environmental changes. Traditional disease detection methods trust on human expertise, which can be subjective, labour-intensive and time-consuming. In recent years advanced technologies such as Artificial Intelligence, machine learning and deep learning have revolutionized image recognition tasks, making them highly suitable for fruit disease detection and classification.

This study aims to design, develop and train a Convolutional Neural Network (CNN) model and CNN with SFOA model for identifying different citrus diseases automatically and accurately. The proposed system provides a foundation for developing automated agricultural monitoring tools to support farmers and researchers.

2. Literature Review

In crops disease detection using machine learning and image processing technologies has seen significant advancements over the last decade. With the fast development of deep learning, especially convolutional neural networks(CNNs), researchers have attained high accuracy for identifying diseases in various crops. Citrus fruits are enrich in vitamin C, fiber and antioxidants. The most common diseases that affect the citrus fruits are canker, greening and scab. Early detection is crucial to prevent major yield losses. This review makes key contributions in plant and citrus fruit disease detection as well as recent improvements achieved through optimization algorithms and enhanced CNN architectures.

2.1 Image Processing and Feature Extraction

Initial stage of research focused on traditional image processing techniques for identifying the citrus diseases. Pydipati et al. (2006) showed one of the earliest studies on citrus disease detection based on extraction of color and texture features from citrus leaf image. This work established that handcrafted features could distinguish diseases like citrus canker with moderate accuracy. A1-Hiary et al. (2011) proposed a model using segmentation and feature extraction to detect the citrus diseases. This achieved good result for field use.

Barbedo (2013) extended the techniques using thresholding, clustering and segmentation to identify the citrus diseases. This study highlighting the need for more robust, automated feature extraction methods.

2.2 Deep Learning Techniques for Plant Disease Detection

Mohanty, Hughes and Salathe (2016) were to determine that CNNs could automatically learn discriminative features from plant leaf images without manual preprocessing. This process achieved high accuracy using 54000 images dataset across 14 different crops.

Ferentinos (2018) expanded with multiple deep learning architectures such as AlexNet, VGG and GoogleNet on plant disease datasets, producing high accuracy 99% in several cases. These findings established CNNs as a preferred method in disease detection research due to their superior generalization and solve complex problems.

Sladojevic et al. (2016) used deep neural networks to detect and classify plant leaf diseases and achieved high accuracy across multiple plant species.

Reddy et al. (2018) applied CNNs explicitly for plant leaf disease identification and strengthened the applicability of deep learning in real world scenarios.

2.3 Deep Learning for Citrus Disease Detection

Shrivastava and Singh (2020) developed a CNN based citrus disease detection and classification using a selected dataset of healthy and unhealthy leaves, indicating improved accuracy through deep learning architecture.

Studies concentrating on advanced techniques also achieved good results. For example, Fan et al. (2019) used hyperspectral imaging combined with Convolutional Neural Networks to detect Huanglongbing citrus diseases achieving early detection and produced high accuracy.

Sabzi et al. (2020) proposed a machine vision system utilizing CNNs to detect citrus fruit diseases in real time with strong classification performance.

More recent hard work explored transfer learning. Babu and Kumar(2021) used CNN models for pre trained on large datasets to classify leaf diseases and reducing training time while maintaining strong performance.

Yadav and Mishra (2021) further validated deep learning for citrus canker and greening diseases showing high performance in the detection.

Zhang et al. (2019) and Singh et al. (2019) improved CNN models for various citrus fruits diseases, indicating that deep learning significantly outperforms classical machine learning techniques in disease detection reliability and robustness.

2.4 Optimization Algorithms and Hyperparameter Tuning

Beyond the improvements of CNN architecture, recent researchers have focused on optimization techniques to enhance training efficiency and accuracy. Khan et al (2020) and Alzubaidi et al. (2021) offered comprehensive reviews of modern CNN architectures, their strengths and challenges such as underfitting, overfitting, computational cost, learning rate and limited dataset availability.

Several studies provided hyperparameter optimization techniques to enhance accuracy and efficiency. Li et al. (2021) reviewed different optimization algorithms including Bayesian optimization and evolutionary algorithms, highlighting the importance of optimal hyperparameter selection for high performance.

Fawagreh et al. (2022) and Albadr et al. (2022) studied the role of nature inspired algorithms in tuning deep learning models, indicating that bio-inspired methods often achieve better results than manual process.

Ibrahim et al. (2022) implement the Starfish Optimization algorithm which mimics starfish movement and regeneration strategies. This algorithm has demonstrated strong optimization capabilities and applied in deep learning model.

Wang and Liu (2023) observed the growing area of metaheuristic optimization algorithms for CNN training, validation. Some of the metaheuristic algorithms are PSO, Genetic Algorithm, Rabbit optimization Algorithm and newer bio-inspired methods can significantly improve convergence accuracy and speed.

Sethy and Barpanda (2021) further verified that improved training methodologies including learning rates, better augmentation and optimized architectures significantly enhance model reliability in plant disease detection.

2.5 Transfer Learning Methods

Too et al. (2021) compared several fine-tuning methods and answered that optimizing only the dense layers can lead to excellent accuracy even on small datasets. These methods are particularly beneficial for citrus fruit datasets which lack large volumes of labelled training data. Transfer learning reduces the essential for large datasets while still achieving high accuracy.

2.6 Summary

The reviewed literature shows clear result from basic image processing to advanced image processing in CNN for citrus disease detection. Deep learning techniques and their variants achieve high accuracy and scalability. Optimization algorithms further enhance the model performance and transfer learning has made CNN more accessible for agricultural applications.

2.7 Research Gaps

- Limited Real-Time Datasets

  Most secondary datasets are trained on laboratory, deployment performance is less studied.

- Early-stage disease detection

  While hyperspectral imaging helps, it is very expensive to farmers.

- Global model

Current models work only for specific types of citrus diseases.

Few studies provide understandable features or pictorial explanations for farmer friendly use.

Overall, the literature illustrates a strong and growing body of work focused on improving citrus disease detection using CNNs and optimization techniques, paving the way for more practical and scalable smart agriculture solutions.

3. Methodology

3.1 Dataset Preparation

A primary dataset was used, containing labeled images of both diseased and healthy citrus fruits. The dataset was split into training, validation, and testing categories. During preprocessing each image was resized, normalized, and augmented (rotation, zoom, and flipping) to improve the visibility and quality of an images. In this study different types of citrus disease such as canker, black spot, greening, scab was included. Total number of images are 1212.

Figure1: Primary Dataset

Figure 2: Canker

Figure 3: Greening

Figure 4: Scab

Figure 5: Black spot

Figure 6: Healthy

3.2 CNN Architecture

A convolutional neural network (CNN) architecture is designed the classify citrus fruit images into diseased and healthy categories. CNN consists of several types of layers such as input, convolution, pooling, flatten and activation functions that work together to extract relevant features and accurately classify the images.

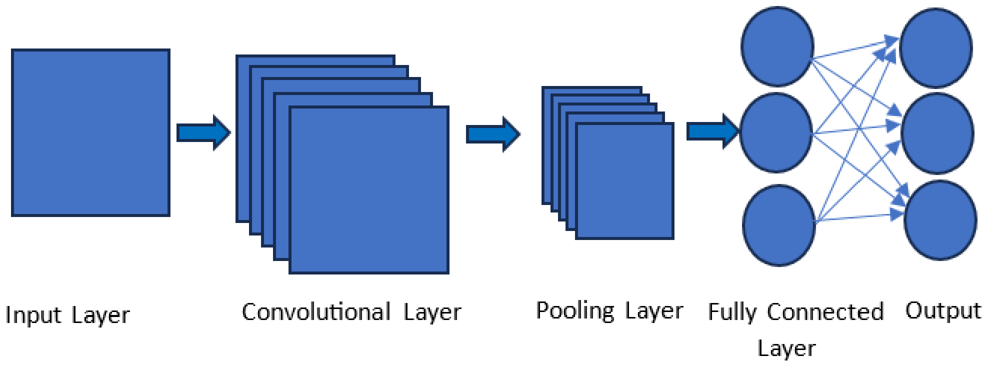

Figure 7: CNN ArchitectureProcess of CNN model

3.2.1 Input Layer

In a CNN, the first layer is the input layer. Here, we resize all images to a fixed size of 128 × 128×3, because CNN architectures require images to have the same width, height and number of channels.

3.2.2 Convolutional Layers

A convolutional layer contains a set of filters called kernel. Each filter contains 3X3 dimension than extends to the full depth of an input image with three RGB channels. During the training period, the network learns the weights in these filters that they help to extract the features such as edges, textures, colours and patterns. Each neuron in the convolutional layer looks only small patch of the input. As the filter slides over the entire input, each position produces one output, this builds up a feature map. Extract essential features using filters with ReLU Activation function.

3.2.3 Pooling Layers

Pooling layer uses a small window size that slides over the input feature map. The most common pooling layers are max pooling and average pooling. Max pooling selects the maximum value for its calculation. Average pooling selects the average of all values in the window. In this study, I applied max pooling on the input feature map and repeating this operation over the entire feature map in order to extract the most salient features.

3.2.4 Fully Connected Layers

In CNN, after completion of Convolution and max pooling, the next step is the fully connected layers (also known as a dense layers). Here before passing data into this layer, the multi-dimensional feature maps generated by previous layers are flattened into a one-dimensional vector. This transformation enables the dense layer to interpret the extracted features as a continuous set of numerical inputs.

In this layer, every neuron is connected to all neurons in the previous layer which allowing the network to learn complex relationships between features. These layers act as the decision-making component, combining and weighting the learned features to predict the final output in CNN. ReLU is a activation function commonly applied to introduce non-linearity and improve learning capabilities. Finally use softmax activation function in the fully connected layer to convert the output into citrus fruit classification and prediction.

3.3 Training Configuration

The model was compiled using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss function. Training was carried out for 10 epochs with a batch size of 32.

3.4 starfish Optimization algorithm

This study introduces the Starfish Optimization Algorithm, a metaheuristic algorithm used to solve the complex optimization problems by simulating the behaviour of starfish like exploration, preying and regeneration. This algorithm operates based on two primary phases namely exploration and exploitation.

In the exploration phase, the algorithm replicates the starfish's varied search behaviours by integrating both five dimensional and one-dimensional search patterns, resulting in enhanced the computational efficiency and a more extensive search range.In the exploitation phase, the algorithm extracts the starfish's preying and regeneration behaviours through two-dimensional search approach and specific movement patterns to ensure efficient and reliable convergence.

Algorithm

Initialize the population P, Candidate vectors N

Evaluate the fitness for each candidate

Best= best candidate (Highest fitness value of candidate)

For each iteration= 1 to max_iteration:

For each candidate i in p:

```
        x=p[i]
step 1. Five-dimensional search
        Candidate = generate_5D_variants(x)
    Evaluate each variant with low fidelity training
    Select best variant, v1(replace x)
step 2. One-dimensional search
        Candidate =generate_1D_variants(x)
        Evaluate each variant
        Select best variant, v2
Step 3. Two-dimensional preying
        Candidates=generate_2D_variants(x)
    Evaluate each variant
        Select best variant, v3
step 4. Regeneration
        If random< regeneration_prob:
            x-new=random-candidates ()
        evaluate x-new
    Update P[i] = best fitness of the starfish
    Update best if improved
    Optionally: apply successive halving every K iteration:
    keep top M candidates and give them larger training budget
end
Return best candidate result
```

3.5 Starfish Optimization Algorithm (SFOA) helps in image classification

SFOA is not used to train the CNN weights but it used to optimize the CNN's hyperparameter as follows

- Number of convolutional filters
- Kernal size
- Number of hidden layers
- Learning rate
- Batch size
- Dropout rate
- Dense layer size (fully connected layer)
- Activation functions

These hyperparameters shows a big impact on prediction and classification accuracy. so SFOA searches for best hyperparameter than can applied in CNN architecture to produce good accuracy.

4. Results and Discussion

4.1 The CNN model's training progress

Epoch	Accuracy	Loss
1	0.3511	1.6246
2	0.3258	1.7988
3	0.4788	1.3234
4	0.6194	0.9441
5	0.7168	0.8919
6	0.772	0.6716
7	0.8296	0.5125
8	0.9036	0.3905
9	0.8938	0.4535
10	0.9244	0.2704

Table 1

The CNN model was trained for 10 epochs and showing the result in both accuracy and loss. This model achieved a highest accuracy of 92.44% and lowest loss of 0.2704 shows strong convergence and learning capability on the training dataset. When tested on unseen data, the CNN model successfully predicted and classified the disease. The predicted and classified output of this model is as shown in figure 8.

Figure 8: This fruit affected by canker disease

4.2 The CNN with SFOA model's training progress

Epoch	Accuracy	Loss
1	0.8103	1.131
2	0.8103	1.1464
3	0.8621	1.1719
4	0.9483	1.1711
5	0.8966	1.1702
6	0.931	1.1867
7	0.9645	1.1845
8	0.9675	1.1834
9	0.9695	1.1976
10	0.9705	1.1914

Table 2

The Convolutional Neural Network optimized with the Starfish Optimization Algorithm completed 10 epoch and result produced 97% in training accuracy and corresponding decrease in training loss, showing that the model is performing well. The learning rate was initially 0.0023, gradually reduced over the 10 epochs to 0.0009, contributing to the stabilization of the training process. Validation accuracy showed moderate improvement, through validation loss fluctuated slightly. In overall, this model showed strong learning on the training set with gradual improvements in validation performance. When tested on unseen data, the CNN model successfully predicted and classified the disease. The predicted and classified output is as shown in figure 9.

Figure 9: This fruit is healthy

5. Comparison of CNN and Starfish Optimized with CNN

The basic CNN model was trained for 10 epochs and demonstrated steady improvements in performance. This achieving a highest training accuracy of 92.44% with a minimum loss of 0.2704, indicating strong convergence and effective feature learning. In comparison, the CNN enhanced with starfish Optimization Algorithm (SFOA) achieved even stronger training performance, produce 97% accuracy with a consistent reduction in training loss across epochs. Overall, the SFOA- optimized CNN outperformed the standard CNN in training efficiency and accuracy, while maintaining comparable validation performance. When evaluated on unseen data, the model was able to accurately predict and classify the disease, confirming its generalization ability. Difference can shown in the below table 3.

Epoch	Accuracy (CNN)	Accuracy(CNN with SFOA)
1	0.3511	0.8103
2	0.3258	0.8103
3	0.4788	0.8621
4	0.6194	0.9483
5	0.7168	0.8966
6	0.772	0.931
7	0.8296	0.9645
8	0.9036	0.9675
9	0.8938	0.9695
10	0.9244	0.9705

Table 3

6. Conclusion

The comparative analysis between the Convolutional Neural Network(CNN) and the CNN with Starfish Optimization Algorithm (SFOA) shows that optimization significantly enhances the performance of the model. The standard CNN showed strong learning capabilities, achieving a training accuracy of 92.44% with effective disease classification on unseen image. However, the SFOA-optimized CNN achieved even better results, reaching 97% training accuracy with a smoother reduction in training loss, supported by a tuned learning rate. Even though validation accuracy improved moderately and validation loss exhibited slight fluctuations, the optimized CNN model maintained stable and efficient learning throughout the training process. Overall study of this paper, integrating SFOA into the CNN training process proved beneficial, enabling more effective hyperparameter tuning and improving the over all performance and accuracy of the model.

References

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” *Frontiers in Plant Science*, vol. 7, p. 1419, 2016.

[2] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.

[3] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep neural networks based recognition of plant diseases by leaf image classification,” *Computational Intelligence and Neuroscience*, 2016.

[4] R. R. Reddy, M. P. Reddy, and P. Reddy, “Identification of plant leaf diseases using convolutional neural networks,” *International Journal of Engineering & Technology*, vol. 7, no. 2.7, pp. 899–902, 2018.

[5] P. Shrivastava and V. Singh, “Citrus disease detection and classification using convolutional neural networks,” *Procedia Computer Science*, vol. 167, pp. 2410–2418, 2020.

[6] X. Zhang, Y. Qiao, F. Meng, C. Fan, and M. Zhang, “Identification of maize leaf diseases using improved deep convolutional neural networks,” *IEEE Access*, vol. 6, pp. 30370–30377, 2018.

[7] Khan, A., Sohail, A., Zahoora, U., & Qureshi, A. S. (2020). A survey of the recent architectures of deep convolutional neural networks. *Artificial Intelligence Review, 53*(8), 5455–5516.

[8] Li, X., Li, Y., & Zhang, J. (2021). Hyperparameter optimization methods for deep learning models: A survey. *Neurocomputing, 461*, 597–615.

[9] Kaur, S., & Gandhi, T. K. (2021). Plant disease detection using deep learning: A review. *Sustainable Computing: Informatics and Systems, 30*, 100512.

[10] Ibrahim, R. A., Houssein, E. H., & Helmi, A. M. (2022). A novel bio-inspired Starfish Optimization Algorithm for solving engineering optimization problems. *Expert Systems with Applications, 201*, 117080.

[11] Albadr, M. A. A., Tiun, S., Ayob, M., & Mesleh, A. M. (2022). Bio-inspired optimization algorithms for deep learning: A survey. *Neural Computing and Applications, 34*, 12559–12579.

[12] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2021). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture, 186*, 106240.

[13] Wang, Y., & Liu, Z. (2023). Advances in metaheuristic optimization for deep neural network training. *Engineering Applications of Artificial Intelligence, 122*, 106082.

[14] Sethy, P. K., & Barpanda, N. K. (2021). Deep convolutional neural network for plant disease detection based on improved training methodology. *Journal of Plant Pathology, 103*, 1115–1126.

[15] Alzubaidi, L., Zhang, J., Humaidi, A. J., et al. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, and future directions. *Journal of Big Data, 8*, 53.

[16] Fawagreh, K., Al-Khateeb, B., & Almuhaideb, A. (2022). Hyperparameter tuning for deep learning models using nature-inspired algorithms: A comprehensive review. *Applied Soft Computing, 127*, 109399.

[17] Shrivastava, P., & Singh, V. (2020). *Citrus disease detection and classification using convolutional neural networks*. Procedia Computer Science, 167, 2410–2418.

[18] Pydipati, R., Burks, T. F., & Lee, W. S. (2006). *Identification of citrus disease using color texture features and discriminant analysis*. Computers and Electronics in Agriculture, 52(1–2), 49–59.

[19] Al-Hiary, H., et al. (2011). *Fast and accurate detection and classification of plant diseases*, including citrus. International Journal of Computer Applications, 17(1), 31–38.

[20] Barbedo, J. G. A. (2013). *Digital image processing techniques for detecting, quantifying, and classifying plant diseases*, including citrus. SpringerPlus, 2, 660.

[21] Sabzi, S., Abbaspour-Gilandeh, Y., & García-Mateos, G. (2020). *A machine vision system for detecting citrus fruit diseases using a novel deep learning approach*. Sustainability, 12(17), 7234.

[22] Singh, A., Misra, A. K., & Verma, A. K. (2019). *Detection of citrus greening disease using image processing techniques*. International Journal of Advanced Science and Technology, 28(15), 203–212.

[23] Yadav, A. K., & Mishra, A. (2021). *Deep CNN-based detection of citrus canker and other citrus leaf diseases*. Materials Today: Proceedings, 46(6), 10436–10440.

[24] Babu, V. R., & Kumar, G. K. (2021). *Citrus leaf disease identification using transfer learning-based CNN models*. International Journal of Innovative Technology and Exploring Engineering, 10(5), 34–40.

[25] Fan, J., et al. (2019). *Detection of citrus Huanglongbing (HLB) using deep CNN and hyperspectral imaging*. Sensors, 19(20), 4657.

[26] Zhang, M., Meng, F., Qiao, Y., & Fan, C. (2019). *Citrus disease recognition using improved deep convolutional neural networks*. Journal of Physics: Conference Series, 1176(4), 042017.

[27] Mwebaze, E., & Owomugisha, G. (2016). Machine learning for plant disease diagnosis: A review. *Proceedings of IEEE AFRICON*, 1–6.

[28] Amara, J., Bouaziz, B., & Algergawy, A. (2017). A deep learning-based approach for banana leaf disease classification. *Proceedings of BTW Workshops*, 79–88.

[29] Rahman, C. R., Arko, P. S., Ali, M. E., et al. (2020). Automated system for plant leaf disease detection using CNN. *International Journal of Computer Vision and Signal Processing*, *10*(1), 1–6.

[30] Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato plant disease detection. *Computers and Electronics in Agriculture*, *142*, 361–368.

[31] Hlaing, C. S., & Zayar, A. (2019). Mango leaf disease detection using CNN. *International Journal of Engineering and Advanced Technology*, *8*(6), 2311–2316.

[32] Ubbink, S., & Löffler, A. (2021). Deep learning for fruit disease detection: A survey. *Precision Agriculture*, *22*, 1–32.

[33] Hasan, M. M., et al. (2020). Citrus fruit grading and disease detection using deep learning. *Journal of Agricultural Engineering*, *51*(2), 89–98.

[34] Alfasly, S., et al. (2021). Detection of citrus canker using mobile-based CNN models. *Journal of Imaging*, *7*(11), 224.

[35] Islam, M. R., Dinh, A., Wahid, K. A., & Bhowmik, P. (2017). Citrus greening disease detection using image processing techniques. *IEEE International Symposium on Circuits and Systems*, 1–4.

[36] Liu, B., et al. (2018). Identification of citrus fruit diseases using deep residual networks. *International Journal of Agricultural and Biological Engineering*, *11*(4), 115–121.

[37] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Deep learning for fall tomato disease detection. *Cluster Computing*, *22*, 1–12.

[38] Chen, J., Liu, Q., & Gao, L. (2020). Citrus disease detection using ResNet and transfer learning. *Multimedia Tools and Applications*, *79*, 1–18.

[39] Saleem, M. H., et al. (2019). Automated plant disease detection using deep CNNs: A survey. *Information Processing in Agriculture*, *7*(4), 566–577.

[40] Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests. *Sensors*, *17*(9), 2022.