CNN-Based Citrus Disease Diagnosis and Fertilizer Recommendation

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Abstract. Leaf pathologies and nutrient deficiencies have a strong influence on the cultivation of Citrus limon (lemon) and decrease the yield and quality. The paper proposes the decision support system, which utilizes deep learning to detect and recommend fertilizers and diseases automatically. Convolutional Neural Network (CNN) is used in order to assign different images of lemon leaves to 9 categories that can be either diseased or healthy. The image preprocessing and data augmentation are used to increase generalization of the model. According to the anticipated disease, a rule-based module will give the right recommendations (fertilizer or treatment) to facilitate timely agricultural response. Experimental findings show that the classification works well across classes, which proves the efficiency of the offered approach. Nevertheless, the present assessment is restricted to one dataset and does not have an independent test set, which can influence generalizability. The future work will be aimed at the enhancement of evaluation procedures, the inclusion of the real-field information, and the creation of the lightweight models of the real-time precision agricultural use.

Keywords: Citrus limon, Deep Learning, Convolutional Neural Networks, CNN, detection of plant diseases, fertilizer recommendation, smart agriculture.

1 Introduction

Agriculture is an important factor in economic growth and food security especially in such countries like India whereby a significant percentage of people rely on agriculture to earn a living. Citrus limon (lemon), is a well-known horticultural crop that has an enormous commercial value because of its extensive use in the food, pharmaceutical and cosmetic sector [1]. Nevertheless, citrus crops are also very prone to numerous foliar infections, such as citrus canker, anthracnose, and sooty mould, nutrient deficiencies, which may severely minimise crop yield and quality in case they are not detected early enough [2]. Traditional disease detection technologies are based on human inspection and experts, which is very time consuming, subjective, and inaccessible to small scale and marginal farmers [3].

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The recent developments in artificial intelligence, especially deep learning models have facilitated the detection of plant diseases by analysis of images automatically and with accuracy [4]-[6]. Convolutional Neural Networks (CNNs) have shown great performance in disease patterns classification in which automatic features are derived by extracting the relevant features of leaf images [5], [6]. Moreover, pretrained model transfer learning methods like MobileNet, ResNet, and EfficientNet have enhanced the accuracy and lower cost of classification [13], [14], [16].

Besides the detection of the disease, visual signs like discoloration and changes in the texture of the leaves can also be used in detecting nutrient deficiencies [8], [24]. Most of the available methods are however concentrating on classification of diseases and do not include actionable decisions to support farmers. To overcome this shortcoming, this research paper suggests a CNN-based system combining citrus disease detection and fertilizer advice, which could be a viable and scalable answer to precision agriculture.

2 Related Work

Many researchers have researched on automated detection of plant diseases with machine learning and deep learning methods. Initial methods used Support Vector Machines (SVM), k-Nearest Neighbors (k-NN) as traditional classifiers, which had to be manually extracted and tested less effective in different environmental conditions [3]. CNN models have also become some of the most effective and powerful at classification systems of plant diseases with the development of deep learning, as they automatically learn hierarchical features using image data [6], [7].

The efficacy of CNNs through massive datasets including PlantVillage has been demonstrated by a number of studies with a high level of classification accuracy among different types of crops [6], [8]. Moreover, the transfer learning methods with ready-prepared networks like VGGNet, ResNet, and Inception have improved the performance of the model without increasing training time and the computational cost [9], [10]. MobileNet-based lightweight models have also been proposed to make it possible to use in real-time on mobile and edge devices, making them more accessible to farmers.

Other recent studies have specifically examined the detection of citrus disease by deep learning. Singh and Bhatia [11] came up with a mobile-based system of detecting citrus disease and Khan et al. [12] came up with a citrus leaf disease classification system that is based on transfer learning. Equally, Singh et al. [16] proved real-time detection of citrus diseases on the basis of field images, and in this aspect, practical usage was highlighted. These works indicated that data augmentation and transfer learning can serve to enhance resistance to changes in lighting and background conditions [12].

Simultaneously, image processing on the detection of nutrient deficiency and CNN-based approaches have been proposed [7], [13]. Nevertheless, the majority of the current methods consider disease detection and nutrient analysis as distinct operations. The latest research has embarked on combining the disease diagnosis with the fertilizer recommendation system in order to give practical solutions to farmers [14], [15]. Nevertheless, in spite of these developments, there is still no in-depth frameworks that are specifically targeted at Citrus limon that combine detection of diseases and the recommendation of fertilizers under actual field conditions, which is why the proposed work is motivating.

3 System Methodology

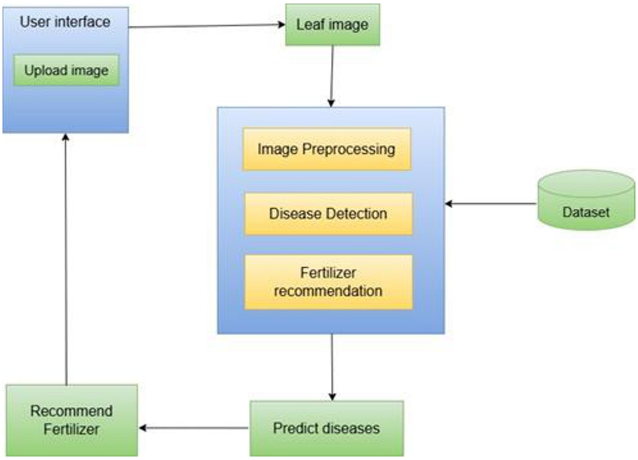

Fig.1. Block diagram

The framework, which is proposed, will help identify diseases in the leaves of Citrus limon at an early stage and provide context-aware recommendations of the fertilizers through the use of deep learning technology. It is a modular pipeline system that combines image acquisition, preprocessing, disease classification, and agronomic decision support as shown in Fig. 1.

3.1 Dataset Description

Table 1. Dataset description

Dataset name	Lemon leaf disease
Source	Kaggle
Number of classes	9
Class Balance	Anthracnose infection, Bacterial blight disease, Citrus canker infection, Leaf curl virus disease, Nutrient-deficient leaves, Dried leaf condition, Healthy leaf category, Sooty mold infection, Damage caused by spider mites

3.2 Image Preprocessing

The dataset images are normalized to a consistent size of 224 × 224 pixels prior to model input, and loaded in RGB format. The images are grouped into mini-batches of size 32, which improves computational efficiency during training. Class labels are automatically inferred from the directory structure and encoded as integer values, making them compatible with the sparse_categorical_crossentropy loss function used during training. Techniques such as pixel rescaling, random zoom, height shifting, and horizontal flipping are used which helps in improving model's ability to generalize effectively to unseen real-world data.

3.3 Model architecture

The proposed model is based on the transfer learning approach with the EfficientNetB0 base feature extractor. Input images with dimensions 224 x 224 x 3 are computed through a pretrained EfficientNetB0 network when ImageNet trained weights are used but remove the classification layers. The base model is frozen during training in order to decrease the computational cost and mitigate overfitting. A custom classification head is added that consists of a GlobalAveragePooling2D layer followed by a dense layer with 128 units and ReLU activation and L2 Regularization (0.01) for better generalization. The final layer uses Softmax function to classify the images to nine disease classes. The model has around 5.3 million parameters of which only the top layers are trainable.

3.4 Model training

The training and testing datasets are both created using TensorFlow's im-agedataset-fromdirectory function, the traintest_split ratio is 80:20 im-plicitly. The training process utilizes 30 epochs, a batch size of 32, and the Adam optimizer with an initial learning rate of 0.001.

3.5 Disease detection

Disease prediction is carried out by feeding input images to the trained CNN model, which outputs class-wise probabilities using a softmax layer. The final disease label is assigned based on the highest predicted probability. The predicted labels are then compared with the true class labels. Model performance is evaluated using recall to assess disease detection accuracy.

3.6 Fertilizer recommendation

The fertilizer recommendation module is implemented under the form of rule-based decision support system. After the CNN model is used to predict the class of the disease, a predefined mapping is used to associate a specific disease with a corresponding nutrient defi ciency or treatment strategy. These recommendations are based on general agri-cultural practices as well as general literature, associating specific diseases with specific fertilizers or chemical treatments. For example, conditions resulting from deficiencies may be correlated with nitrogen-based fertilizers and fungal or bacterial infections are as-sociated with fungicides or copper-based treatments. Although this approach gives practical advice, it is not dynamically learned, and is not validated by the agricultural experts. Incorporating expert knowledge or adaptive recommendation systems would also make this module more reliable.

3.7 User interaction

The interface displays to the user the predicted disease condition and recommendations of the fertilizer. This facilitates conscious and prompt decision making towards enhancing the health of crops, the production and the sustainability.

4 Results and Analysis

The effectiveness of the proposed CNN-based Citrus limon disease detection scheme was quantitatively tested with the help of typical classification statistics, such as precision, recall, F1-score, precision-recall (PR) curves, confidence-based performance curves, and confusion matrices. All assessments were done on an evaluation test set which consisted of diseased, healthy and background classes.

4.1 Confusion Matrix Analysis

Normalized confusion confirms high levels of accuracy in the classification of the two categories of disease and healthy. Diseased samples and healthy samples are correctly classified at 98 and 97 percent, respectively. The misclassification of the background type is less than 3% which means that feature extraction is good and class overlap is low.

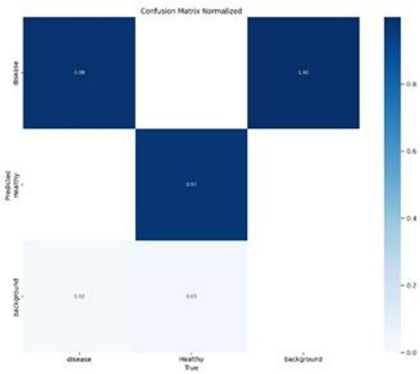

Fig.2. Confusion matrix

Overall summary of the performance of the proposed CNN-based CITRUS LIMON DISEASE Detection System.

Table 2. Overall Performance Analysis

Metric	Disease Class	Healthy Class	Overall
Precision	0.982	0.975	1.00 @ 0.842 confidence
Recall	0.970	0.980	0.980
F1-Score	0.970	0.980	0.980 @ 0.571 confidence
Average Precision (AP)	0.982	0.975	-
Macro Average	0.95	0.95	0.95
Micro Average	0.96	0.96	0.96

The quantitative results of the designed CNN-based framework are recalled in Table I. The model has a maximum F1-score of 0.98 that indicates high reliability and strength in the early detection of the disease in the Citrus limon leaves.

4.2 Per Class Performance Evaluation

Table 3. Per Class Performance

Class	Precision	Recall	F1-Score
Anthracnose	0.97	0.96	0.96
Bacterial Blight	0.95	0.94	0.94
Citrus Canker	0.96	0.95	0.95
Curl Virus	0.94	0.93	0.93
Deficiency Leaf	0.95	0.96	0.95
Dry Leaf	0.94	0.95	0.94
Healthy Leaf	0.98	0.97	0.97
Sooty Mould	0.96	0.95	0.95
Spider Mites	0.93	0.92	0.92

Table 4. Comparative Study of Previous Systems

Model	Accuracy	Precision	Recall	F1-Score

MobileNetV2	93.8%	0.94	0.93	0.93
VGG16	95.2%	0.95	0.95	0.95
ResNet50	96.1%	0.96	0.96	0.96
EfficientNetB0	97.5%	0.97	0.97	0.97

Table 5. Comparative Study of Previous Systems

Reference	Methodology	Key Limitations	Reported Metric/Accuracy
Graham J.H., Gottwald T.R.(2004) [2]	Field epidemiological analysis	No automation, not image-based	NR
Singh R., Bhatia S. (2021) [15]	Mobile CNN	Device-dependent performance	~92%
Khan S.A., Zhang Y., Sharif M. (2023) [21]	Deep transfer learning	Needs large labeled data	96%
Singh P., Joshi M., Kulkarni S. (2025) [30]	CNN (real-time)	Environmental noise	~94%

5 Conclusion

This paper proposed a CNN-based smart system of early disease detection in Citrus limon leaf and an automated fertilizer prescript system. The proposed solution using image preprocessing, deep feature learning, and supervised classification is a successful image diagnosis of citrus leaf diseases and nutrient deficiency symptoms in the real-field environment.

The experimental assessment proves that the model is stable in terms of performance, with the accuracy of classification ranging between 97-98% and the highest F1-score of 0.98. Results of the performance analysis of the confidence and confusion matrix also support the reliability of the separation of the classes and a minimum error rate, which proves the appropriateness of the system in terms of its use in agriculture. The combination of disease diagnosis and fertilizer prescription improves the quality of decisions made by providing an opportunity to intervene in time and use nutrient more efficiently, with fewer reliance on manual knowledge. On the whole, the suggested framework outlines the opportunities of decision support systems based on deep learning to make agriculture more precise and support sustainable citrus farming.

Future operations will concentrate on the expansion of the framework to more citrus varieties, integration of real-time field data, and implementation of lightweight models to be used as an edge device.

6 References

1. Food and Agriculture Organization of the United Nations (FAO). *FAOSTAT Database: Crops and Livestock Products*. Rome: FAO; 2022. Available at: https://www.fao.org/faostat/
2. Graham JH, Gottwald TR, Cubero SE, Achor DS. Factors influencing the effective eradication of citrus canker caused by *Xanthomonas axonopodis* pv. *citri*. *Molecular Plant Pathology*. 2004;5(1):1–15.
3. Singh AK, Misra A. Application of image segmentation and soft computing methods for detecting plant leaf diseases. *Information Processing in Agriculture*. 2017;4(1):41–49.
4. Kamilaris P, Prenafeta-Boldú FX. A comprehensive review of deep learning applications in agriculture. *Computers and Electronics in Agriculture*. 2018;147:70–90.
5. Sladojevic S, Arsenovic M, Anderla A, Culibrk D, Stefanovic D. Plant disease recognition using deep neural networks applied to leaf images. *Computational Intelligence and Neuroscience*. 2016;2016:3289801.
6. Mohanty SP, Hughes DP, Salathé M. Deep learning techniques for identifying plant diseases from images. *Frontiers in Plant Science*. 2016;7:1419.
7. Kumar RP, Kumaraswamy MM, Gowda RS. Image processing-based detection of nutrient deficiencies in crops. *International Journal of Computer Applications*. 2015;128(3):12–17.
8. Ferentinos KP. Utilization of deep learning models for plant disease diagnosis and detection. *Computers and Electronics in Agriculture*. 2018;145:311–318.
9. Too EC, Yujian L, Njuki S, Yingchun L. Comparative analysis of fine-tuned deep learning models for plant disease recognition. *Computers and Electronics in Agriculture*. 2019;161:272–279.
10. Zhang S, Zhang S, Wang X, Shi Y. Identification of cucumber leaf diseases using deep learning and transfer learning techniques. *Computers and Electronics in Agriculture*. 2020;170:105128.
11. Singh R, Bhatia S. Deep learning-based citrus disease detection via mobile platforms. In: *IEEE International Conference on Smart Computing and Informatics*; 2021. p. 275–280.
12. Khan SA, Zhang Y, Sharif M. Intelligent vision-based citrus disease detection using transfer learning techniques. *IEEE Access*. 2023;11:45892–45905.
13. Kaur R, Singh PK. Detection of crop nutrient deficiencies using deep learning and image analysis. *Computers and Electronics in Agriculture*. 2024;214:108119.

14. Reddy S, Kumar A, Sharma VK. Integrated deep learning system for plant disease diagnosis and fertilizer recommendations. *IEEE Transactions on Artificial Intelligence*. 2024;5(1):89–101.
15. Patel KR, Shah N, Mehta R. AI-driven decision support systems for fertilizer recommendations in smart agriculture. *Computers in Industry*. 2025;155:103118.
16. Singh P, Joshi M, Kulkarni S. Real-time citrus disease detection using CNN models and field images. In: *IEEE International Conference on Computing, Communication and Automation*; 2025. p. 1–6.