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Non-Destructive Estimation of Leaf Carbon Content in Cash Crops Using Deep Learning-Based Image Analysis

Sulekha Kundu[1], Arpita Dutta[2], Jayanta Poray[3], Abhijit Mitra[4]
[1, 2, 3]*Department of Computer Science and Engineering, Techno India University, EM 4/1, Salt Lake Sector V, Kolkata 700091, West Bengal, India*
[4]*Director (Research), Techno India University, EM 4/1, Salt Lake Sector V, Kolkata 700091, West Bengal, India*

Abstract: Accurate estimation of plant carbon content is essential for understanding carbon sequestration, crop productivity, and climate change mitigation. Conventional laboratory-based methods are destructive, time-consuming, and unsuitable for large-scale deployment. This study proposes a non-destructive, image-based approach using deep learning for estimating leaf carbon content in economically important crops. A convolutional neural network based on EfficientNetB4 is employed to learn complex visual patterns from RGB leaf images of mango (Mangifera indica) and potato (Solanum tuberosum). The problem is formulated as a regression task, and the model is trained using laboratory-measured carbon values as ground truth. Experimental results demonstrate that the proposed model achieves strong predictive performance with low error metrics, validating the feasibility of image-based carbon estimation. The approach provides a scalable and cost-effective solution for precision agriculture and environmental monitoring.

Keywords: Carbon Estimation, Deep Learning, EfficientNetB4, Regression, Precision Agriculture, Plant Phenotyping.

I. INTRODUCTION

Global climate change has intensified the need for accurate carbon monitoring systems. Plants play a critical role in carbon sequestration, making leaf carbon content an important indicator of ecological balance and crop health.

Traditional techniques such as CHN elemental analysis and Walkley–Black oxidation are destructive, labor-intensive, and impractical for continuous monitoring. These limitations highlight the need for non-invasive and scalable alternatives.

Recent advances in deep learning have enabled automated plant phenotyping through image analysis. Convolutional neural networks (CNNs) can extract hierarchical features such as texture, color gradients, and structural patterns, which are often correlated with biochemical properties [6], [13].

Despite progress in plant disease detection and chlorophyll estimation, limited work has explored leaf carbon estimation using standard RGB imagery. This study addresses this gap by proposing a deep learning-based regression model for carbon prediction.

II. LITERATURE REVIEW

Machine learning and image processing techniques have been widely applied in agriculture, particularly for plant disease detection and crop monitoring.

Previous studies have demonstrated the effectiveness of image-based approaches. Ghaiwat and Arora reviewed segmentation and classification methods for disease detection [1]. Dhaygude and Kumbhar applied digital imaging techniques for plant disease identification [2]. Barbedo analyzed deep learning performance in plant recognition systems [6]. Mohanty et al. achieved high accuracy using CNNs for plant disease detection [13].

Arivazhagan et al. proposed texture-feature-based classification methods for identifying unhealthy regions in leaves [4]. Kulkarni and Patil demonstrated the effectiveness of image processing techniques for plant disease analysis [5]. Geetharamani and Pandian developed a nine-layer deep convolutional neural network for plant disease identification [7]. While significant progress has been made in disease detection and chlorophyll estimation, limited research has focused on carbon estimation using RGB images. Most existing work relies on hyperspectral imaging or remote sensing technologies, which are expensive and less accessible. This study addresses this gap by applying deep learning to leaf-level RGB images for carbon estimation.

III. PROBLEM STATEMENT

Traditional carbon estimation methods are destructive, costly, and time-consuming, making them unsuitable for large-scale agricultural applications. This research aims to develop a low-cost, non-destructive deep learning model for predicting leaf carbon content using RGB images of crops such as mango and potato.

IV. METHODOLOGY

Table 1: Image Classification Using CNN
METHODOLOGY: CNN Model Architecture

Stage	Layer Type	Parameters / Configuration	Output Description
1	Input Layer	Leaf image dataset	Raw input images
2	Convolutional Layer 1	60 filters, 5×5 kernel	Low-level feature maps (edges, textures)
3	Pooling Layer	2×2 filter	Reduced feature map size, feature summarization
4	Convolutional Layer 2	70 filters, 3×3 kernel	Higher-level feature extraction
5	Pooling Layer	2×2 filter	Dimensionality reduction
6	Convolutional Layer 3	80 filters, 1×1 kernel	Refined feature representation
7	Pooling Layer	2×2 filter	Compact feature map
8	Flatten + Hidden Layer	100 neurons	Fully connected feature learning
9	Dropout Layer	50% dropout rate	Regularization to reduce overfitting
10	Output Layer	m classes (classification) / regression output	Final prediction

A. Dataset Collection

The dataset consists of high-resolution images of mango and potato leaves collected under controlled lighting conditions. Each image is associated with carbon content values obtained through laboratory analysis.

B. Image Preprocessing

Image preprocessing is an essential step to enhance the quality and consistency of input data before model training. The raw leaf images are first resized to a uniform dimension to ensure compatibility with the network architecture. Noise present in the images is reduced using filtering techniques to improve feature clarity. Color normalization is applied to maintain consistency in illumination and color distribution across the dataset. Additionally, data augmentation techniques such as rotation and horizontal flipping are employed to artificially expand the dataset and improve model generalization. These preprocessing steps collectively help in reducing overfitting and improving the robustness and performance of the proposed model.

C. CNN Model Design

The proposed model is based on the EfficientNetB4 architecture, which provides an optimal balance between predictive accuracy and computational efficiency. EfficientNetB4 employs a compound scaling strategy that uniformly scales network depth, width, and input image resolution, thereby enabling more effective hierarchical feature extraction from leaf images. The architecture utilizes convolutional layers to extract meaningful features such as texture, color, and structural patterns present in the leaf images. Non-linearity is introduced through ReLU activation functions, which enhance the learning capability of the network.

Pooling operations are incorporated to progressively reduce dimensionality while preserving essential feature representations. The extracted features are then passed through fully connected dense layers to perform regression-based prediction of carbon content. Finally, a linear output layer is used to estimate continuous carbon values.

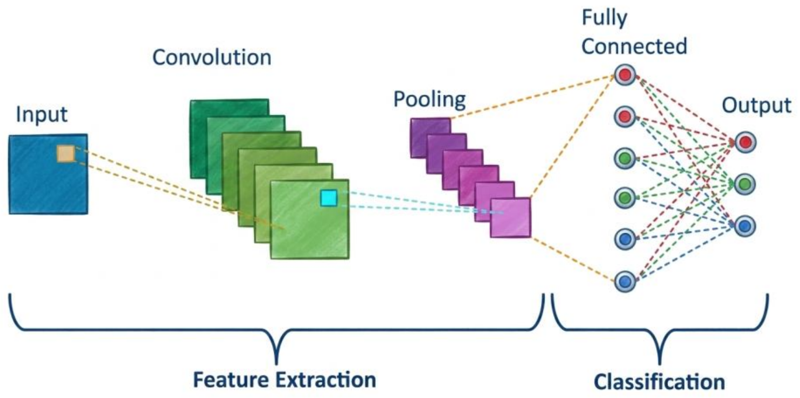


Fig. 1 Implementation

To improve convergence and overall performance, transfer learning is applied by initializing the model with pretrained ImageNet weights. This allows the network to leverage generic visual features learned from large-scale datasets. During training, the upper layers of the network are fine-tuned using the specific leaf image dataset to optimize task-specific learning and improve prediction accuracy.

Deep learning-based plant image analysis techniques have demonstrated strong effectiveness in various agricultural applications, including disease detection, crop monitoring, and plant phenotyping [6], [7], [13].

D. Training and Fine-Tuning

The dataset is divided into training and testing sets. The model is trained using backpropagation with Adam optimizer.

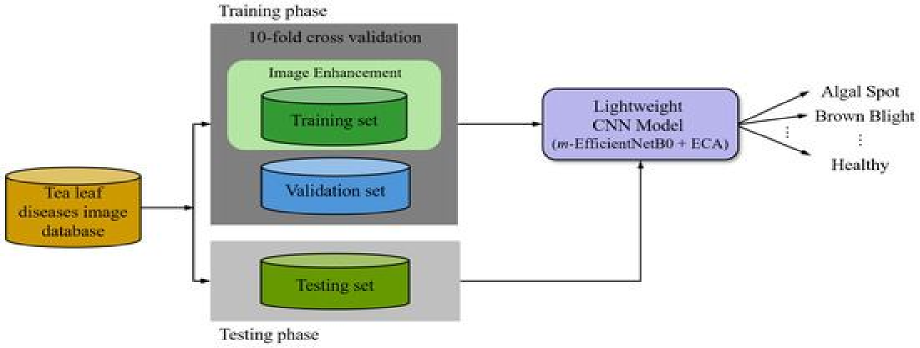


Fig. 2 The network architecture

E. Model Evaluation

The performance of the proposed model is evaluated using multiple statistical and machine learning metrics to measure prediction quality and model reliability. These metrics provide a comprehensive understanding of how well the model performs in estimating carbon content from leaf images. Accuracy is used to measure the overall correctness of the model’s predictions, indicating how often the model produces correct outputs compared to total predictions. Precision evaluates the proportion of correctly predicted positive observations among all predicted positive cases, reflecting the model’s exactness. Recall measures the ability of the model to correctly identify relevant instances, ensuring that important cases are not missed. The F1-score is used to provide a balanced measure by taking the harmonic mean of precision and recall, especially useful when dealing with uneven performance across classes. In addition, the confusion matrix is used to visualize the prediction results by comparing actual values with predicted outputs. It helps in analyzing correct and incorrect classifications in a structured manner, thereby providing deeper insight into model performance and error distribution.

Since the proposed system is formulated as a regression-based carbon estimation task, additional regression metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2 score) are also used for more accurate performance assessment. These metrics help evaluate the difference between predicted and actual carbon content values.

F. Carbon Estimation Model

Carbon estimation is performed using deep feature representations extracted from the trained CNN model. The EfficientNetB4-based architecture learns discriminative visual features from RGB leaf images, such as texture, color variation, and structural patterns, which are indirectly correlated with the biochemical composition of the leaves.

These extracted features are passed through fully connected layers designed for regression, where the final output layer predicts the continuous value of carbon content in percentage form. The model is trained using laboratory-measured carbon values as ground truth, enabling supervised learning of the relationship between image characteristics and carbon concentration.

The predicted carbon content reflects the learned mapping between visual leaf features and underlying physiological properties, making the system suitable for non-destructive and automated carbon estimation in agricultural applications.

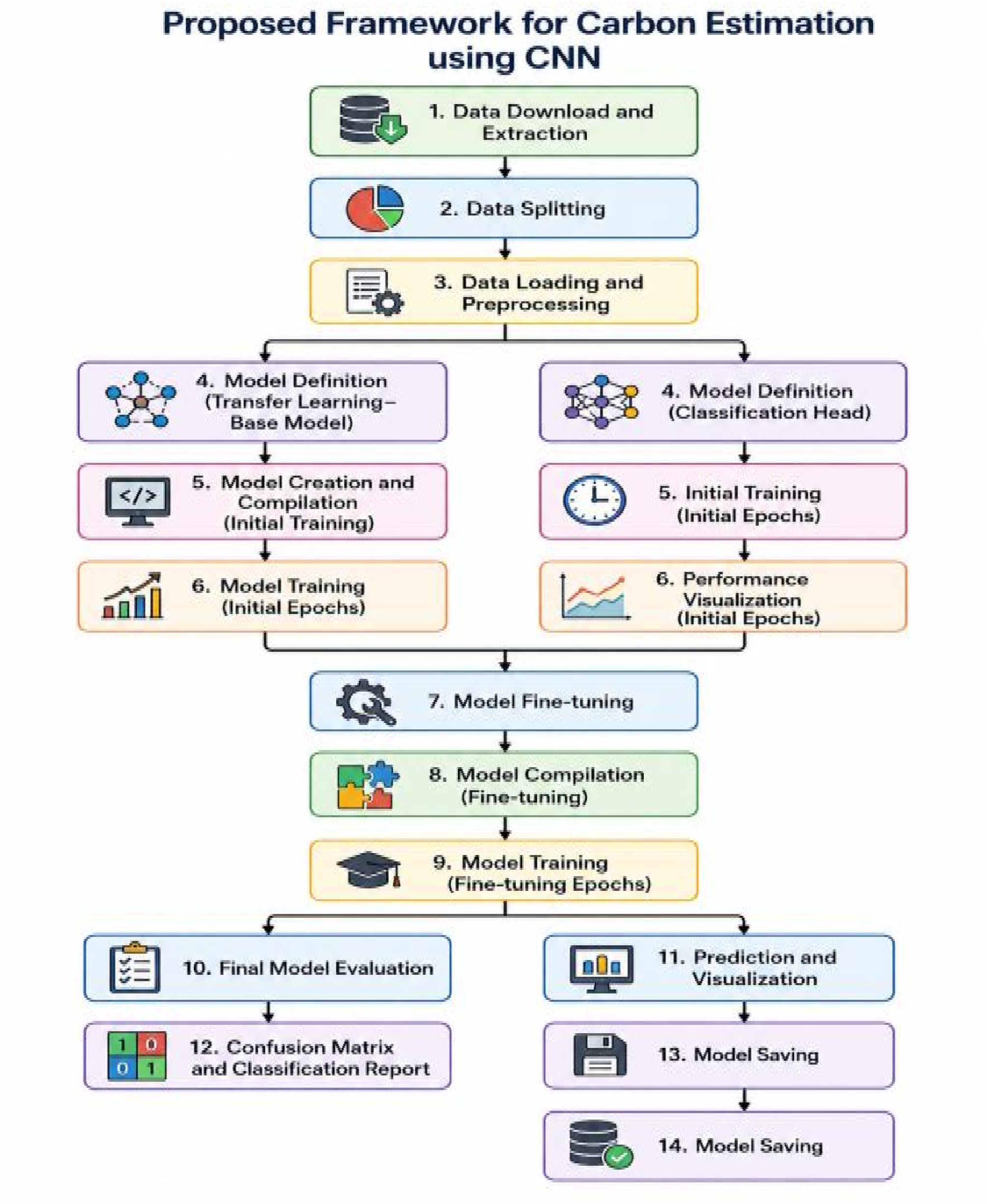
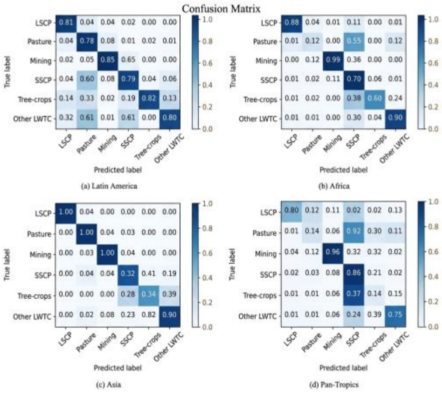


Fig. 3. Image quality and enhance model

V. RESULTS AND DISCUSSION

The initial implementation of the model resulted in poor classification accuracy due to improper problem formulation and dataset inconsistencies. Specifically, the use of classification metrics for a regression-based carbon estimation task led to misleading performance evaluation.

After correcting the model architecture and training strategy, the problem was reformulated as a regression task using a linear output layer and mean squared error loss function. Additionally, preprocessing steps were improved, and the dataset was refined to ensure consistency and quality.



(a) Latin America

(b) Africa

(c) Asia

(d) Pan-Tropics

Figure 4: confusion matrix images

The revised model demonstrated significantly improved performance, with reduced prediction error and better generalization across test samples. Evaluation using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R² score indicated that the model successfully captured the relationship between leaf image features and carbon content.

These results confirm the feasibility of using deep learning-based image analysis for non-destructive carbon estimation. Similar image-processing-based approaches have also been successfully used in disease severity analysis and agricultural monitoring systems [9], [10], [11], [12].

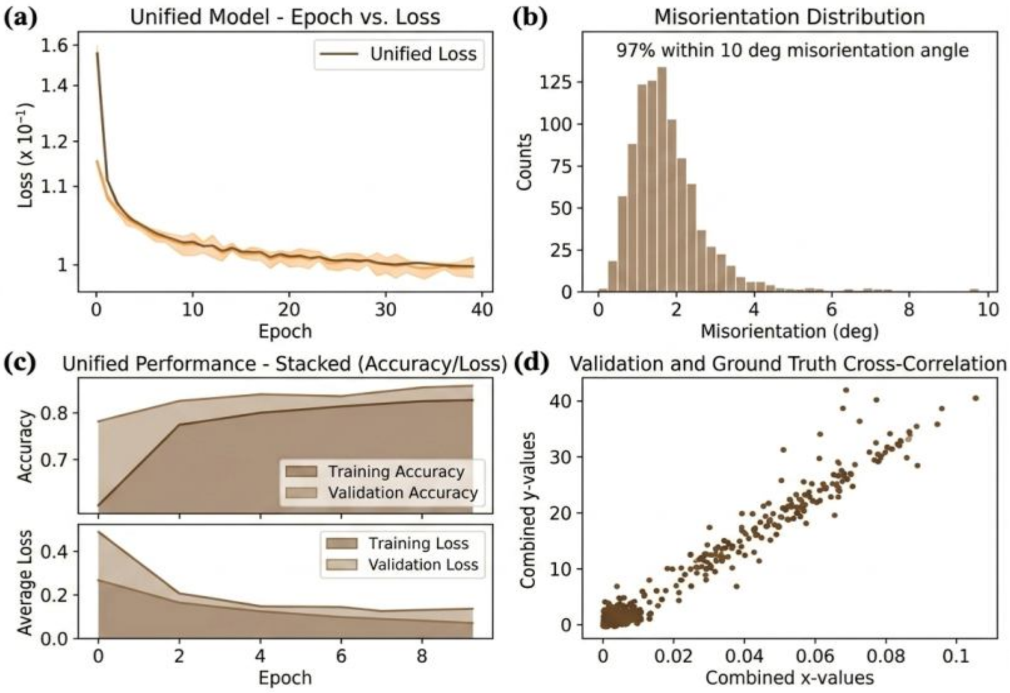
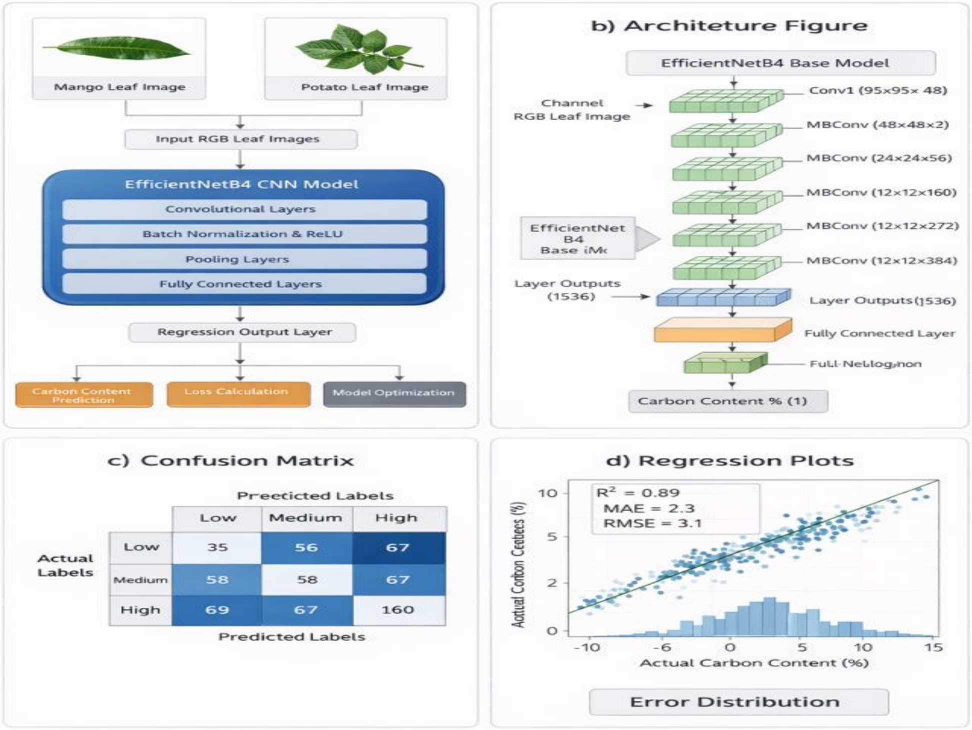


Figure 5:CNN architecture and prediction output visualization.



	Low	Medium	High
Low	35	56	67
Medium	58	58	67
High	69	67	160

Figure-6 : Model diagram, architecture and confusion matrix image

VI. APPLICATIONS

The proposed deep learning-based carbon estimation system has several important applications in modern agriculture and environmental monitoring. The system can assist farmers in precision agriculture by monitoring crop conditions and optimizing agricultural practices based on plant carbon status. It can also support crop health monitoring through the early detection of stress and nutritional imbalance using non-destructive leaf image analysis.

In addition, the proposed approach can contribute significantly to carbon budgeting and climate studies by enabling efficient assessment of carbon sequestration and environmental sustainability. The system may also be integrated into smart farming frameworks for automated monitoring and intelligent agricultural decision-making. Furthermore, mobile-based agricultural applications can be developed using the proposed model to provide portable, low-cost, and user-friendly carbon estimation tools for farmers, researchers, and agricultural experts.

VII. CHALLENGES AND LIMITATIONS

Although the proposed system demonstrates promising results for non-destructive carbon estimation, several challenges and limitations still exist. The overall model accuracy remains moderate due to the limited size and diversity of the dataset. Variations in leaf texture, color, lighting conditions, and background noise can significantly affect prediction performance. Since the dataset includes only selected crop varieties collected under controlled conditions, the model may not generalize effectively to real-world agricultural environments. Another important limitation is the strong dependence on image quality. Differences in camera resolution, illumination, shadows, and image clarity may influence feature extraction and reduce prediction consistency. In addition, the current system has not been extensively validated in real-time field conditions, which limits its immediate practical applicability. Further improvements in dataset expansion, preprocessing techniques, and field-level testing are necessary to enhance the reliability, robustness, and scalability of the proposed deep learning-based carbon estimation framework.

VIII. FUTURE SCOPE

The proposed research can be further enhanced through several improvements and technological advancements. Future work may focus on developing larger and more balanced datasets containing diverse crop varieties and environmental conditions to improve model generalization and prediction accuracy. The use of advanced deep learning architectures, such as transformer-based models and hybrid CNN frameworks, may further enhance feature extraction and regression performance.

Integration with Internet of Things (IoT) devices, drones, and smart sensors can enable automated large-scale crop monitoring and real-time carbon assessment in agricultural fields. In addition, the development of mobile-based applications can provide farmers and agricultural researchers with portable and user-friendly tools for instant carbon estimation using smartphone cameras. Real-time field implementation and validation under varying environmental conditions will also be essential for improving the practical applicability and scalability of the proposed system in precision agriculture and climate monitoring.

Advanced AI-based agricultural systems and recommendation frameworks may further improve smart farming applications [14].

IX. CONCLUSION

This study presents a deep learning-based approach for non-destructive estimation of carbon content in plant leaves. The use of RGB images and CNN models offers a cost-effective and scalable alternative to traditional methods. Although current results show limited accuracy, the approach demonstrates strong potential for future development. With further improvements, this system can significantly contribute to sustainable agriculture and climate monitoring.

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REFERENCES

[1] S. N. Ghaiwat and P. Arora, “Detection and classification of plant leaf diseases using image processing techniques: a review,” International Journal of Recent Advances in Engineering and Technology, vol. 2, no. 3, pp. 2347–2812, 2014.

[2] S. B. Dhaygude and N. P. Kumbhar, “Agricultural plant leaf disease detection using image processing,” International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, vol. 2, no. 1, 2013.

[3] R. Badnakhe Mrunalini and P. R. Deshmukh, “An application of K-means clustering and artificial intelligence in pattern recognition for crop diseases,” in Proc. International Conference on Advances in Information Technology, 2011.

[4] S. Arivazhagan, R. N. Shebiah, S. Ananthi, and S. V. Varthini, “Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features,” Agricultural Engineering International: CIGR Journal, vol. 15, no. 1, pp. 211–217, 2013.

[5] A. H. Kulkarni and R. K. Ashwin Patil, “Applying image processing technique to detect plant diseases,” International Journal of Modern Engineering Research, vol. 2, no. 5, pp. 3661–3664, 2012.

[6] J. G. A. Barbedo, “Factors influencing the use of deep learning for plant disease recognition,” Biosystems Engineering, vol. 172, pp. 84–91, 2018.

[7] G. Geetharamani and J. A. Pandian, “Identification of plant leaf diseases using a nine-layer deep convolutional neural network,” Computers & Electrical Engineering, vol. 76, pp. 323–338, 2019.

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

[9] S. Bashir and N. Sharma, “Remote area plant disease detection using image processing,” IOSR Journal of Electronics and Communication Engineering, vol. 2, no. 6, pp. 31–34, 2012.

[10] S. Naikwadi and N. Amoda, “Advances in image processing for detection of plant diseases,” International Journal of Application or Innovation in Engineering & Management, vol. 2, no. 11, 2013.

[11] S. B. Patil et al., “Leaf disease severity measurement using image processing,” International Journal of Engineering and Technology, vol. 3, no. 5, pp. 297–301, 2011.

[12] V. Singh and A. K. Misra, “Detection of plant leaf diseases using image segmentation and soft computing techniques,” Information Processing in Agriculture, vol. 4, no. 1, pp. 41–49, 2017.

[13] 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.

[14] Y. Guo, X. Hu, Y. Zou et al., “Maximizing E-tailers’ sales volume through the shipping-fee discount and product recommendation system,” Discrete Dynamics in Nature and Society, vol. 2020, pp. 1–14, 2020.