

# Multi-Class Classification and Transfer Learning for Rapid Disease Detection in Green Leafy Vegetables Using Convolutional Neural Networks

<sup>1</sup>Garima Joshi, <sup>2</sup>Prashant Panse

<sup>1</sup>Medicaps University, Computer science, Indore, Madhya Pradesh, India

<sup>2</sup>Medicaps University, Information technology, Indore, Madhya Pradesh, India  
garimajosh@gmail.com<sup>1</sup>, prashant.panse@medicaps.ac.in<sup>2</sup>

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## Abstract

Plant diseases cause various pathogens, including bacteria, viruses, fungi, and protozoa. Plant diseases and pathogens have an impact on the entire crop and field area. Plant diseases can be identified by various techniques; however, traditional techniques are time-consuming and require more effort. Up-to-date machine learning based approaches are used to identify plant diseases based on the image data. This study investigated the application of convolutional neural network (CNN) models for the detection and classification of diseases affecting green leafy vegetables. Several state-of-the-art CNN architectures, including InceptionV3 and DenseNet121, were evaluated on an image dataset of diseased and healthy leaf samples. Preprocessing techniques such as scaling, cropping, grayscale conversion, and normalization were applied to enhance the input images. The CNN models demonstrated high diagnostic accuracy, with InceptionV3 and DenseNet121 exhibiting exceptional performance across multiple metrics like sensitivity, specificity, accuracy, recall, F-measure, and Matthews correlation coefficient (MCC).

**Keywords:** Machine learning, Plant diseases, Green leafy vegetables, Convolutional neural network (CNN), DenseNet121

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## 1. Introduction

Green leafy vegetables are an integral part of a nutritious diet and play a vital role in promoting human health. These nutrient-dense foods are rich sources of vitamins (such as folate, vitamin A, vitamin C, and vitamin K), minerals (like iron and calcium), and dietary fiber (Kumar et al., 2020; Slavin & Lloyd, 2012). Leafy vegetables, including spinach, asparagus, lettuce, mustard greens, colocasia green leaf, and turnip greens, are the primary natural sources of folic acid. These foods contain much higher levels of folic acid compared to other leafy and non-leafy vegetables (Kumar et al., 2020). Numerous studies have highlighted the protective effects of green leafy vegetables against chronic diseases, including cardiovascular disorders, certain cancers, and age-related cognitive decline (Fekete et al., 2022). However, these crops are susceptible to a number of diseases produced by fungus, bacteria, and viruses, which can have a substantial impact on both crop yield and quality.

Timely and accurate detection and categorization of these diseases are essential for efficient disease control and prevention measures (Savary et al., 2019; Schreinemachers et al., 2018). Conventional approaches to disease detection, including manual examination by experts, can be ineffective, subjective, and time consuming.

In recent times, machine learning (ML) approaches have demonstrated significant potential in automating and enhancing the identification and categorization of plant diseases (Domingues et al., 2022). Machine learning algorithms have the ability to acquire knowledge from extensive collections of labelled images or other types of data, which allows them to identify patterns and generate precise predictions (Sarker, 2021). The implementation of durable and reliable machine learning-based disease detection and classification systems could have significant impacts for the agricultural sector (Ngugi et al., 2024). Precise diagnosis of diseases can lead to early treatments, including the focused administration of pesticides, fungicides, or other control methods, resulting in decreased crop losses and enhanced overall yield and quality (Anastasiou et al., 2023). Moreover, machine learning algorithms can assist in developing disease-resistant plant types and optimising agricultural management approaches (Durai & Shamili, 2022).

Several studies showed the CNN-based model was used to identify green leafy vegetable plant disease detection (Mehta, Kukreja, Sharma, et al., 2023; Sennan et al., 2022). The study by Mehta et al. (2023) showed the efficient use of federated learning in conjunction with CNN for the identification and classification of fenugreek leaf diseases, resulting in commendable performance across multiple parameters (Mehta, Kukreja, & Sharma, 2023). Similarly, the study by Vishalli et al. (2023) showed that the effectiveness of using a CNN and federated learning approach for the detection of diseases in parsley leaves. The data demonstrate the model's reliability and resilience, as seen by its high precision, recall, F1-Score, and accuracy (Vishalli et al., 2023).

The objective of this study is to develop and evaluate a machine learning method for identifying and categorising diseases that impact fenugreek and spinach plants using a multi-class classification methodology. Specifically, the performance of various CNN models, including DenseNet121, InceptionV3, MobileNetV2, ResNet50, and VGG16, precisely recognises and distinguishes between diseases that impact crops such as spinach and fenugreek. Overall, the proposed CNN architecture classifies the spinach and fenugreek diseases.

A machine learning system designed for classifying diseases in fenugreek and spinach might enhance food security, support small-scale farmers, and promote the growth of premium, nutritious green leafy crops. This would eventually benefit people reliant on these crops, enhancing their overall security.

## **2. Related work**

This section discusses the various CNN algorithms to identify and classify the spinach and fenugreek diseases.

The study by Sennan et al. (2022) developed a novel model to identify and classify spinach. The proposed model achieves 97.5 % accuracy in classification. Moreover, the proposed CNN model was compared with other CNN models, including support vector machines (SVM), random forests,

Visual Geometry Group 16 (VEG16), Visual Geometry Group 19 (VEG19), and Residual Network 50 (ResNet50), and the model performed superiorly to all the models(Sennan et al., 2022).

In Bose et al. (2023) SFDNet model was proposed to identify the diseases caused by fungi, A software solution was built using Deep Learning techniques, specifically a CNN, to rapidly identify and find a cure for fungal diseases in spinach leaves. The system achieved an accuracy of 89.86%. Developed a GUI application using PySide2 that effectively categorises diseases in spinach leaf images and provides suitable solutions, hence assisting the food, medical, and skincare sectors(Bose et al., 2023).

In the 2023 study, Paragaien et al. utilised machine learning algorithms to recognise leaves of specific anti-diabetic plants, including Basella alba, Moringa oleifera, Fenugreek, Psidium guajava, and Hibiscus rosa sinesis. The experiment yielded a maximum accuracy of approximately 99.4% by employing a hybrid approach of Neural Network and Logistic Regression. The suggested model accurately classifies the plant photos with a high level of precision(Pargaien et al., 2023).

The study proposed by Ramkumar et al. (2021) used CNN and the Resnet-50 architecture to identify the cercospora disease in the different classes of spinach. The outcome of the study showed higher accuracy in training and testing datasets(Ramkumar et al., 2021).

The study by Mehta et al. (2023) used a CNN model and trained the model on various datasets to identify six different kinds of fenugreek diseases. The model performed well in each client evaluation. Here, averaging approaches were used, including macro average, micro average, and weighted average. These averagings consistently performed well for all the client data. Overall, the study showed CNN and federated learning were highly efficient in identifying and classifying leafy crop diseases with good and scalable accuracy(Mehta, Kukreja, Sharma, et al., 2023).

Harakannanavar et al. (2022) used various machine learning approaches to identify the tomato leaf disease, including SVM, CNN, and K-Nearest Neighbour (K-NN). The accuracy of the models in the tomato disease is 88%, 99.6%, and 97%, respectively(Harakannanavar et al., 2022).

The study by Shin et al. (2021) optimised several deep learning models, including AlexNet ResNet-50, GoogLeNet, SqueezeNet, SqueezeNet-MOD1, and SqueezeNet-MOD2, to identify the powdery mildew diseases in the leaf of the strawberry plant. The result of the study showed the ResNet-50 had a higher accuracy of 98.11 to classify and identify healthy and infected leaves(Shin et al., 2021).

### **3. Methodology**

#### **3.1. Data Collection**

The dataset images were collected from the agricultural land, and the proposed method performs preprocessing and classification. Subsequently, the well-trained model receives the novel input images for the purpose of categorization and identification. In this study, CNN models were used, including DenseNet121, InceptionV3, MobileNetV2, ResNet50, and VGG16, to extract features and perform classification and identification of the disease. The original data set contained healthy-

fenugreek, powdery-mildew-fenugreek, Spinach-Cladosporium Leaf Spot, spinach healthy, new alternaria as listed in Table 1.

The data set images are taken from the agricultural land in Ralamandalindore, Raukhediindore, and Nipania-Sunar Ujjain, Madhya Pradesh. The dataset images were captured using Galaxy A73 5G (SM-A7368/DS) with quad camera 108 mega pixel (MP) + 12MP +5MP+5MP. Each image was taken in portrait or landscape form. Figure 1 depicts the images of the dataset.

### 3.2. Pre-processing of the Images

Image preprocessing involves the use of different techniques on unprocessed images with the aim of enhancing their quality. Here, the images were primarily scaled to a uniform dimension of 260 by 260 pixels. Standardising images is crucial for ensuring constant scale across all images, which is vital for keeping uniform input values in machine learning models. Following that, images were cropped. Cropping helps to decrease background noise and focus the investigation on essential characteristics. The images were later turned to grayscale. This method reduces the data's dimensionality by eliminating colour information. This can be beneficial for particular analytical methods that focus on texture or form. The images were normalised by adjusting the pixel values to remain within the range of 0 to 1. This technique standardises the spectrum of pixel intensities, enhancing the stability and speed of the model training. The images may be rotated or inverted, enhancing the dataset's variety. In addition, the colour intensity, contrast, and filter application were applied for the enhancement of the image quality. The data collected after preprocessing listed in Table 2, and the preprocessed images are shown in Figure 2.

### 3.3. Proposed Model Architecture

The model architecture for image classification tasks incorporates a sequence of components starting with an Input Tensor that specifies the input shape as 224x224 pixels with 3 color channels (RGB), leading into a selection of pre-trained convolutional neural networks including MobileNetV2, VGG16, ResNet50, InceptionV3, DenseNet121, which are utilized without their top layers to allow customization for new tasks. It includes a GlobalAveragePooling2D layer to reduce parameter count and computations, this pooling operation is mathematically represented as:

$$P_c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W F_{c_{ij}}$$

Where  $P_c$  is the pooled feature for channel  $c$ ,  $H$  and  $W$  are the height and width of the feature map, and  $F_{c_{ij}}$  is the feature at position  $(i,j)$  in the feature map for channel  $c$ . This reduces the network's complexity and parameters, assisting in the moderation of overfitting.

Followed by a dense layer with 1024 units and ReLU activation for learning high-level features, I represented  $f(x) = \max(0, x)$ . Subsequently, a dropout layer with a rate of 0.5 is used to prevent overfitting. The architecture concludes with a softmax activation for multi-class classification, employs the Adam optimizer for efficient weight updates, uses Sparse Categorical Crossentropy as

the loss function for handling multi-class labels, and measures performance with an 'accuracy' metric during training.

## 4. Results

### 4.1. Model Performance on different known CNN Architectures

The stated model design uses multiple known CNN architectures including MobileNetV2, VGG16, ResNet50, InceptionV3, and DenseNet121, each possessing distinct features and uses. Each of these five architectures was examined in detail with unprocessed and preprocessed dataset.

The model performance evaluated on various metrics that include sensitivity, specificity, accuracy, recall, f-measure, MCC(matthews correlation coefficient).

**Sensitivity:** This metric, referred to as the true positive rate, is essential for evaluating the model's capacity to reliably detect disease leaves. It quantifies the accuracy of correctly identifying actual positive cases. The equation below calculates the sensitivity.

$$Sensitivity = \frac{\sum_{i=1}^{i=n}(TP_i)}{\sum_{i=1}^{i=n}(TP_i + FN_i)}$$

**Specificity:** The true negative rate measures the accuracy of correctly identifying negative situations, reflecting the model's ability to accurately identify actual negatives. The equation below calculates the specificity.

$$Specificity = \frac{\sum_{i=1}^{i=n}(TN_i)}{\sum_{i=1}^{i=n}(TN_i + FP_i)}$$

**Accuracy:** The accuracy of a model is measured by the ratio of properly predicted data to the total number of observations, indicating the frequency at which the model is correct. The average accuracy calculated through the equation described below:

$$Average Accuracy = \frac{\sum_{i=1}^{i=n} \frac{TP_i + TN_i}{P_i + N_i}}{n}$$

**Recall:** Recall, also referred to as the probability of detection, is calculated by dividing the number of true positive outcomes by the total number of positive outcomes. The information is explicitly stated in the equation.

$$Recall = \frac{\sum_{i=1}^{i=n}(TP_i)}{\sum_{i=1}^{i=n}(TP_i + FN_i)}$$

**F-measure (or F1 score):** The F score is computed using the harmonic mean of the accuracy and recall. This statistic is crucial for evaluating the balance between recall and accuracy, providing a comprehensive view of the model's performance.

**Matthews Correlation Coefficient(MCC):** MCC is a coefficient that provides a high score if the prediction achieves favourable outcomes in all four categories of the confusion matrix (true

positives, false negatives, true negatives, and false positives), evenly distributed across the different classes. The range of values is from -1 to 1. A value of 1 represents a perfect prediction, 0 indicates no improvement over random guessing, and -1 signifies complete disagreement between the prediction and the observation.

Table 3 shows a comprehensive comparison of five CNN architectures applied to unprocessed data based on several performance measures. More precisely, it provides the following numerical values: MobileNetV2 demonstrates a high sensitivity and recall rate of 0.99, a perfect specificity of 1, an accuracy of 0.677, an excellent F-measure of 0.995, and a strong MCC of 0.99. The VGG16 model has enhanced performance with a sensitivity and recall of 0.995, a specificity of 1, an accuracy of 0.904, an F-measure of 0.997, and a MCC of 0.995. The parameters of ResNet50 nearly match those of VGG16, with a sensitivity and recall of 0.989, a specificity of 1, an accuracy of 0.899, an F-measure of 0.994, and an MCC of 0.989. InceptionV3 and DenseNet121 dominate the rankings by attaining flawless scores in all measures, including sensitivity, specificity, accuracy, recall, F-measure, and MCC, all of which are placed at 1. This analysis highlights InceptionV3 and DenseNet121's superior ability to flawlessly classify the dataset in question, suggesting their optimal use in scenarios where precise accuracy is paramount, despite potential considerations for computational resources or inference efficiency that might favor architectures like MobileNetV2, VGG16, or ResNet50. Similarly, in the figure 3 comparison analysis between various CNN architectures was examined, InceptionV3 and DenseNet121 provide outstanding performance across all categories, showing their excellent durability while handling unprocessed data VGG16 and ResNet50 exhibit notable performance, particularly in terms of Sensitivity, Recall, and F-measure, however their Accuracy and MCC scores are significantly inferior to those of the top performers. MobileNetV2 has a lack of accuracy, suggesting possible inconsistencies in its ability to make accurate predictions, despite having high sensitivity and specificity. This visualisation facilitates the identification of the most optimal CNN model for specific analytical specifications, takes into consideration an optimal balance of all assessed performance factors.

#### **4.2. Performance of CNN models on Pre-processed data**

The preprocessed evaluation used CNN architectures including MobileNetV2, VGG16, ResNet50, InceptionV3, and DenseNet121, and these architectures analysed various performance metrics listed in Table 4. Based on the metrics these architectures achieved perfect scores of 1 for sensitivity, specificity, accuracy, recall, F-measure, and MCC. Despite ResNet50's slightly lower performance compared to the others, it nonetheless achieved impeccable sensitivity and recall, as well as nearly flawless accuracy and F-measure. The specificity was determined to be 0.992, and the MCC was likewise determined to be 0.992. The results emphasise the crucial importance of preprocessing in enhancing the performance of CNN, both in terms of its accuracy in prediction and its overall efficiency in classification. Similarly, the metrics are compared using bar chart, as shown in Figure 4. Here, each algorithm shows high values, reaching 1, for Sensitivity, Specificity, and Recall. This indicates a robust ability to accurately recognise real positives and correctly reject negatives. The metrics of Accuracy, F-measure, and MCC also frequently exceed 1 for the majority of models, which suggests a generally high level of prediction performance and classification accuracy. This visualisation highlights the efficiency of the algorithms in analysing and categorising the dataset,

with slight differences between the structures that can guide their use in particular situations where accuracy and computing speed are important factors.

sensitivity, specificity, accuracy, recall, F-measure, and MCC, with the following models evaluated:  
MobileNetV2, VGG16, ResNet50, InceptionV3, and DenseNet121.

Figure 5 shows the training and validation loss and accuracy of a machine learning model during 60 epochs. Regarding loss Figure 5(a), showed a drop in both training and validation over time. The training loss exhibited more fluctuations, however overall had lower values compared to the validation loss. This suggests a good fit without any notable overfitting. Figure 5(b) shows both training and validation accuracy increase as epochs progress, with training accuracy slightly surpassing validation accuracy. This indicates that the model is effectively learning. Periodic decreases in validation accuracy may indicate the presence of overfitting or inconsistencies in the data. Overall, the model demonstrates good performance with consistent validation loss and accuracy metrics at the conclusion of training, suggesting that it is a well-optimized model suitable for deployment.

Figure 6 shows the heatmap of each model that was used to classify and identify leafy vegetable disease. Here, it was observed that the heat map of the InceptionV3 model shown in Figure 6 (a) showed that all 425 instances of healthy fenugreek were correctly identified. However, in the case of the new-alternaria 1419 instances were identified correctly, and 48 instances were misidentified as powdery mildew fenugreek. Similarly, 323 instances of powdery mildew fenugreek were correctly identified, while 106 instances were observed in new-alternaria. The spinach cladosporium leaf spot was perfectly identified in 51 instances, and no misclassification was observed. Likewise, spinach healthy 344 instances were correctly identified without misclassification. Overall, the InceptionV3 architecture has demonstrated excellent accuracy, exhibiting an insignificant number of misclassifications. It appears that errors occur most frequently between the new-alternaria and powdery-mildew-fenugreek classes. This may be due to the conditions' similar visual characteristics. High diagonal values and low off-diagonal values indicate that the architecture performs effectively in this task of classification.

Furthermore, in Figure 6(b), the ResNet50 model's heat map properly recognises 421 cases of healthy fenugreek, and 3 instances were observed in the new alternaria and 1 in powdery mildew-fenugreek. 1345 incidents were successfully identified in the new alternaria context, and 117 incidences were misidentified in powdery mildew-fenugreek, 4 in spinach-cladosporium leaf spot, and 1 in spinach healthy. Similarly, 368 cases of powdery mildew in fenugreek were accurately identified, whereas 61 cases were found in new-alternaria. Moreover, the spinach-cladosporium leaf spot was accurately classified with 49 predictions and 2 instances found in healthy spinach. Additionally, spinach-healthy was classified flawlessly, with 344 accurate predictions. Figure 6(c) shows the confusion matrix of the VCG16. 425 cases of healthy fenugreek were correctly identified. In this context, 1422 instances of new alternaria were correctly identified, along with 45 instances of powdery mildew fenugreek. Similarly, 320 instances of powdery mildew fenugreek were correctly identified, and 109 instances were observed in the new- alternaria. Moreover, 51 instances of spinach-cladosporium leaf spot were correctly identified, and in the case of healthy spinach, 340

cases were correctly identified, while 3 instances were observed in spinach-cladosporium leaf spot and one in new-alternaria.

Figure 6(d) shows the confusion matrix of the MobileNet, in which 424 instances of the healthy fenugreek were identified correctly along with one observed in powdery-mildew-fenugreek. 1359 instances of new -alternaria were identified correctly, and 108 instances were found in powdery mildew-fenugreek. Similarly, 381 instances were correctly identified as powdery-mildew-fenugreek, and 48 instances were misidentified as new-alternaria. Additionally, 51 instances of spinach-cladosporium leaf spot were correctly identified, though 341 instances of spinach-healthy were identified correctly, along with 1 observed in powdery-mildew-fenugreek and 2 observed in new-alternaria.

Figure 6 (e) shows the DenseNet121 confusion matrix, in which healthy fenugreek is classified with 424 correct predictions, with 1 misclassification in powdery mildew fenugreek. New-alternaria is mostly classified correctly with 1408 instances, but there are 59 instances misclassified as powdery-mildew-fenugreek. Powdery-mildew-fenugreek has 399 correct predictions and 90 instances misclassified as new-alternaria. Spinach-cladosporium leaf spot is perfectly predicted in all 51 cases. Spinach-healthy is classified with 50 correct predictions and 2 misclassifications found as new-alternaria.

Overall, each model exhibited a high level of accuracy in distinguishing between healthy and unhealthy plants. InceptionV3 showed outstanding accuracy across all models, with a minimal number of misidentifications and a high rate of correct identifications.

#### **4. Conclusion**

The current study emphasises the ability of machine learning, specifically convolutional neural networks, to identify and categorise diseases in green leafy vegetables like fenugreek and spinach. The operational suitability of the CNN models under assessment, particularly InceptionV3 and DenseNet121, is evidenced by their ability to attain high accuracy and minimal misclassification. The findings indicate that the incorporation of these technologies into agricultural methods may have a substantial positive impact on disease management approaches, leading to enhanced agricultural productivity, less dependence on pesticides, and improved food security. Following studies might look into the practical implementation of these models in agricultural environments and the development of intuitive applications customised for the needs of farmers and agronomists.

#### **Conflict of Interest**

The authors confirm that there is no conflict of interest to declare for this publication.

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#### **References**

- [1] Anastasiou, E., Fountas, S., Voulgaraki, M., Psiroukis, V., Koutsiaras, M., Kriezis, O., Lazarou, E., Vatsanidou, A., Fu, L., Bartolo, F. D., Barreiro-Hurle, J., & Gómez-Barbero, M. (2023). Precision farming technologies for crop protection: A meta-analysis. *Smart Agricultural Technology*, 5, 100323. <https://doi.org/10.1016/j.atech.2023.100323>
- [2] Bose, R., Roy, S., & Sutradhar, S. (2023). Spinach fungi guard: A deep learning-based software solution for swift detection and remediation of fungal diseases in spinach leaves. *Smart Agricultural Technology*, 6, 100334. <https://doi.org/10.1016/j.atech.2023.100334>
- [3] Domingues, T., Brandão, T., & Ferreira, J. C. (2022). Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive Survey. *Agriculture*, 12(9), 1350. <https://doi.org/10.3390/agriculture12091350>
- [4] Durai, S. K. S., & Shamili, M. D. (2022). Smart farming using Machine Learning and Deep Learning techniques. *Decision Analytics Journal*, 3, 100041. <https://doi.org/10.1016/j.dajour.2022.100041>
- [5] Fekete, M., Szarvas, Z., Fazekas-Pongor, V., Feher, A., Csipo, T., Forrai, J., Dosa, N., Peterfi, A., Lehoczki, A., Tarantini, S., & Varga, J. T. (2022). Nutrition Strategies Promoting Healthy Aging: From Improvement of Cardiovascular and Brain Health to Prevention of Age-Associated Diseases. *Nutrients*, 15(1), 47. <https://doi.org/10.3390/nu15010047>
- [6] Harakannavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms. *Global Transitions Proceedings*, 3(1), 305–310. <https://doi.org/10.1016/j.gltp.2022.03.016>
- [7] Kumar, D., Kumar, S., & Shekhar, C. (2020). Nutritional components in green leafy vegetables: A review. *Journal of Pharmacognosy and Phytochemistry*, 9(5), 2498–2502.
- [8] Mehta, S., Kukreja, V., & Sharma, V. (2023). Utilizing Federated Learning and CNNs for Severity Analysis of Fenugreek Leaf Diseases. *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1–6. <https://doi.org/10.1109/ICCCNT56998.2023.10306577>
- [9] Mehta, S., Kukreja, V., Sharma, V., & Manwal, M. (2023). Optimizing Fenugreek Leaf Disease Detection: An Exploration of Federated Learning with CNN. *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1–6. <https://doi.org/10.1109/ICCCNT56998.2023.10307477>
- [10] Ngugi, H. N., Ezugwu, A. E., Akinyelu, A. A., & Abualigah, L. (2024). Revolutionizing crop disease detection with computational deep learning: A comprehensive review. *Environmental Monitoring and Assessment*, 196(3), 302. <https://doi.org/10.1007/s10661-024-12454-z>
- [11] Pargaian, A. V., Singh, D., Chauhan, M., Negi, H., Chilwal, B., & Pargaian, N. (2023). Identification of Plant Leaves having Anti-Diabetic Property using Machine Learning. *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, 195–200. <https://doi.org/10.1109/ICAAIC56838.2023.10140394>
- [12] Ramkumar, M. O., Sarah Catharin, S., Ramachandran, V., & Sakthikumar, A. (2021). Cercospora Identification in Spinach Leaves Through Resnet-50 Based Image Processing. *Journal of Physics: Conference Series*, 1717(1), 012046. <https://doi.org/10.1088/1742-6596/1717/1/012046>
- [13] Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Computer Science*, 2(3), 160. <https://doi.org/10.1007/s42979-021-00592-x>
- [14] Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, 3(3), 430–439. <https://doi.org/10.1038/s41559-018-0793-y>
- [15] Schreinemachers, P., Simmons, E. B., & Wopereis, M. C. S. (2018). Tapping the economic and nutritional power of vegetables. *Global Food Security*, 16, 36–45. <https://doi.org/10.1016/j.gfs.2017.09.005>
- [16] Sennan, S., Pandey, D., Alotaibi, Y., & Alghamdi, S. (2022). A Novel Convolutional Neural Networks Based Spinach Classification and Recognition System. *Computers, Materials & Continua*, 73(1), 343–361. <https://doi.org/10.32604/cmc.2022.028334>
- [17] Shin, J., Chang, Y. K., Heung, B., Nguyen-Quang, T., Price, G. W., & Al-Mallahi, A. (2021). A deep learning approach for RGB image-based powdery mildew disease detection on strawberry leaves. *Computers and Electronics in Agriculture*, 183, 106042. <https://doi.org/10.1016/j.compag.2021.106042>
- [18] Slavin, J. L., & Lloyd, B. (2012). Health Benefits of Fruits and Vegetables. *Advances in Nutrition*, 3(4), 506–516. <https://doi.org/10.3945/an.112.002154>

- [19] Vishalli, Kukreja, V., Mehta, S., Das, P., & Singh, V. (2023). Dissecting Parsley Leaf Disease Severity: A Federated Learning and CNN Perspective. *2023 3rd Asian Conference on Innovation in Technology (ASIANCON)*, 1–6. <https://doi.org/10.1109/ASIANCON58793.2023.10270195>