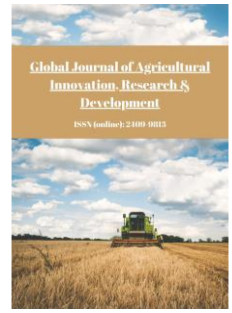
Published by Avanti Publishers

Global Journal of Agricultural Innovation, Research & Development

ISSN (online): 2409-9813



Chlorophyll based Downy Mildew Analysis in Cucumber using Deep Learning

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ARTICLE INFO

Article Type: Research Article
Academic Editor: A.K.M. Adham
Keywords:
Mildew
Deep learning
Computer vision
Disease prediction
Decision support system

Timeline:
Received: July 02, 2025
Accepted: September 30, 2025
Published: October 23, 2025

Citation: Das S, Mustafi S, Dan S, Mandal SN, Sinha P. Chlorophyll based downy mildew analysis in Cucumber using deep learning. Glob J Agric Innov Res Dev. 2025; 12: 27-38.

DOI: https://doi.org/10.15377/2409-9813.2025.12.3

ABSTRACT

Cucumber is one of the major crops in Indian agrarian society, and it is affected by various diseases such as Downy Mildew. Monitoring the crop field's condition might help evade the disease, which is costly and time-consuming. Therefore, an economically intelligent farming system requires for disease monitoring. The grading of the disease can be recognized depending on the distribution of chlorophyll content in a leaf. However, previous grading techniques lead to an erroneous framework due to the inequitable statistics of real-time images' healthy and unhealthy pixel ordination. Hence, an optimized Deep Learning (DL) model is proposed according to the grading of the disease. The proposed DL model provides a training accuracy of 94.82% and a validation accuracy of 84.15%. The model also tested over 300 leaves with different grades of diseases captured randomly in an uncontrolled environment, and was found to be 90% accurate, compared to over 69% by visual identification of experts. A decision support system built on the proposed technology's instantaneous image capture and prediction capabilities is a huge help to farmers and agriculturists in understanding the state of the field and responding to such circumstances.

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1. Introduction

Plant diseases in agro ecosystems occur due to the interaction between the host, the pathogen, and the environmental factors. Downy mildew is a harmful pathogen that lowers cucumber production and quality [1]. For disease management, preliminary information about the disease is required, as the infection process is influenced by multiple factors, where weather and plant growth play a significant role. Forecasting models to predict disease epidemics are available for decision-making, but require many interpretations before making strategic and management decisions. Disease monitoring to predict the stage of infection is essential for rational management. Nevertheless, disease assessment in the field is a cumbersome process and suffers from inaccuracy as grading is done on an arbitrary scale [2]. Wide variation in symptom expression, the difference in leaf age and structure, and variation in interaction lead to assessing a challenging task. All interactions cannot be addressed together; some information must be obtained before being used for disease assessment. Colour image statistical analysis is viable for identifying plant disease [3]. Chlorophyll fluorescence imaging can detect abiotic stresses in plants [4]. Pixel-wise analysis of greenness in a leaf would identify the chlorophyll composition of a leaf [5, 6]. Prediction of such processes requires representation, processing, and information communication in agro ecosystems. Artificial intelligence-based technology is one of the effective and accurate solutions for this situation in a fast way. Transfer learning-based DL tools are helpful for quick and accurate representation from such complex systems. Real-time technology for recognizing the disease could help everyone avoid a considerable agricultural loss [7].

DL models are helpful for disease assessment, and more accurate disease grading could be a possibility for more precise treatment. A method was proposed where the diseased part of the leaf is segmented and the disease is recognized using a machine learning algorithm [8]. DL techniques are widely used to detect the infestation stage of plant leaves, analyzing a single leaf at a time [9]. DL systems are very effective in distinguishing between a healthy and diseased portion of a leaf [2, 10, 11]. Proper disease grading is needed for sustainable agricultural management. Thus, the computational disease grading process could be impactful for detecting disease states. Disease samples can be analyzed by segmentation of colour features and texture analysis and then classified by a classification algorithm [6]. Image processing based neural network was used to analyze maize seed quality assessment for automatic seed grading in real time [12].

Previous literatures had given least momentous on non-linear weather parameters. Therefore, an intelligence-based automated system might be a cost-efficient technology for sustainable farming. Jeong *et al*. proposed a deep neural network model to identify tomato leaf miner using tomato leaves captured from a real-world environment [13]. A deep learning algorithm proposed to identify, categorize, and forecast nutritional deficiencies based on symptoms seen in tomato plant leaves and fruits [14]. Features in cotton leaf images can be extracted using segmentation techniques and help to distinguish different groups according to the features by the machine learning algorithm [15]. A modified YOLOv5 deep learning model can localize and classify pests for better agricultural productivity [16]. A deep learning model was introduced to identify the disease in the banana plants and provide a decision for the farmers [17]. A CNN model was proposed, which could help identify the disease and support guiding disease control [18]. Nevertheless, accurate automatic disease recognition faces issues with real-time images for analysis. It is hard to distinguish disease components from the soil surface background due to pixel interdependency. A model depending on artificial intelligence could suggest a natural environment [19]. The CNN-based system could be preferred as it has a lot of potential in innovative farming systems [20].

It was very challenging to classify the disease stage according to the chlorophyll. Various image processing techniques were applied to the affected or healthy leaves to develop a grading scale for downy mildew disease. However, only grading will not be guided toward a non-linear relationship of the pixel distribution. An intelligence-based image analysis simulation tool is required to predict the state of the disease using its respective leaf image. So a deep learning tool can help to overcome the challenging task. However, only deep learning based techniques may not achieve accurate and precise results in the agricultural industry. A fine-tuned deep learning-based transfer learning model had a greater impact on agricultural pest recognition. The model could make a real-time disease management system. The deep learning model-based automated diagnosis online system is a valuable tool in detecting and identifying citrus diseases [21, 22]. Downy mildew in vineyards was quantified using an image-based approach [23]. A CNN-based computational or deep learning model could be beneficial in making a real-time disease management system [24, 25]. Artificial Intelligence-based analysis of thermal images can improve the disease control system to determine downy mildew disease in grapevine [21].

An automatic intelligent system is required to be one step toward developing an automated disease management system. This research proposed an analysis of downy mildew disease of cucumber using chlorophyll content availability on the leaf. However, it was observed that only a deep learning model could provide misleading issues for identifying downy mildew disease. So the operation of extracted features is also necessary to design such a tool. A modified deep learning model is proposed to detect cucumbers' disease stage, address the limitations, and provide precise and accurate results. A decision support system was also developed to diagnose the affected plant according to the forecasting of the disease stage.

2. Materials and Methods

2.1. Dataset Discussion and Preparation

Our proposed technology could omit all the obstacles and provide a decision very quickly. A large number of datasets is required to develop the technology. We have collected more than 1500 leaf images from the Chasarhati farmer's field in Kalyani-741235, India. The 600 images were also collected from the rooftop garden at Kalyani Government Engineering College, Kalyani-741235, India. All disease severity contains 300 images per stage to develop the framework. It is very challenging to develop a large and rich dataset for analysis of the disease, as the disease depends on environmental factors. So it was tough to collect a dataset of various grades of the disease in one season. There were different factors for the disease activity and variable levels of this disease intensity [26]. The downy Mildew could be observed by keeping track of the temperature, which could help discriminate between a healthy leaf and an infected leaf [27]. In order to capture images, the digital camera's optical axis was positioned perpendicular to the leaf plane. The dataset collection was done using images collected on a white backdrop for leaf segmentation to discriminate between the afflicted and healthy sections [2]. We have also collected some random images where no white background is used. Those images are used for only testing purposes. Fig. (**1**) demonstrates different grades of cucumber leaves in a generalized way.

Figure 1: Dataset of various grades of affected cucumber leaves.

2.2. Symptoms of Downy Mildew

Downy mildew, caused by Pseudoperonospora cubensis, is a severe disease of cucumbers. The disease can spread quickly, resulting in a severe loss of fruit quality and output. After defoliation, a reduced photosynthetic area due to infection results in stunted plants, poorer yields, and sunburnt fruit. Small chlorotic patches on the upper leaf surface are the first symptoms that usually appear on the older crown leaves. The pathogen is an obligatory parasite that requires living cucurbit plants to develop and thrive. Windblown sporangia can move up to 600 kilometres in 48 hours on air currents.

2.3. Image Acquisition

All leaf images were collected from various farmers' fields in a controlled and uncontrolled environment. The images are captured by mobile phones, DSLRs, and any image-capturing device that supports RGB format images. A white background was used to fix behind the leaf image of the cucumber for a controlled environment. The distance between the image-capturing device and the interesting leaf could be an acceptable, arbitrary range where the disease section of a leaf could be visible, ideally.

2.4. Deep Learning Approach

A deep learning approach is used to gather the information from an image and classify the image as supervised learning according to the collected data. In this paper, a deep learning algorithm is used to recognize the grade of the downy mildew, which could prepare an automated disease recognition system. However, a large dataset is required for training a deep learning model [28]. However, a large dataset is not available or hard to collect to recognize the downy mildew disease in cucumbers. Nowadays, a CNN-based transfer learning classifier can train well in smaller datasets [29]. Transfer learning is a pre-trained model that can be reused after omitting its previous weights. Various transfer learning-based models were applied in this paper to recognize the downy mildew disease, such as Inception V3 [30], Resnet152V2 [31], VGG 16 [32], and VGG 19 [32]. The results achieved by those models were unacceptable due to overfitting issues for our dataset. When a large gap between a model's training accuracy and validation accuracy is achieved after training the model, then the model will be defined as overfitting. Due to this issue, we could not receive the actual result of the model. This paper introduces a novel network model, which is the extended version of transfer learning models, to recognize the grade of the downy mildew disease in cucumbers. Our proposed model could avoid the overfitting issue of identifying the grade of the downy mildew in cucumber. The architecture of our proposed model is depicted in Fig. (**2**).

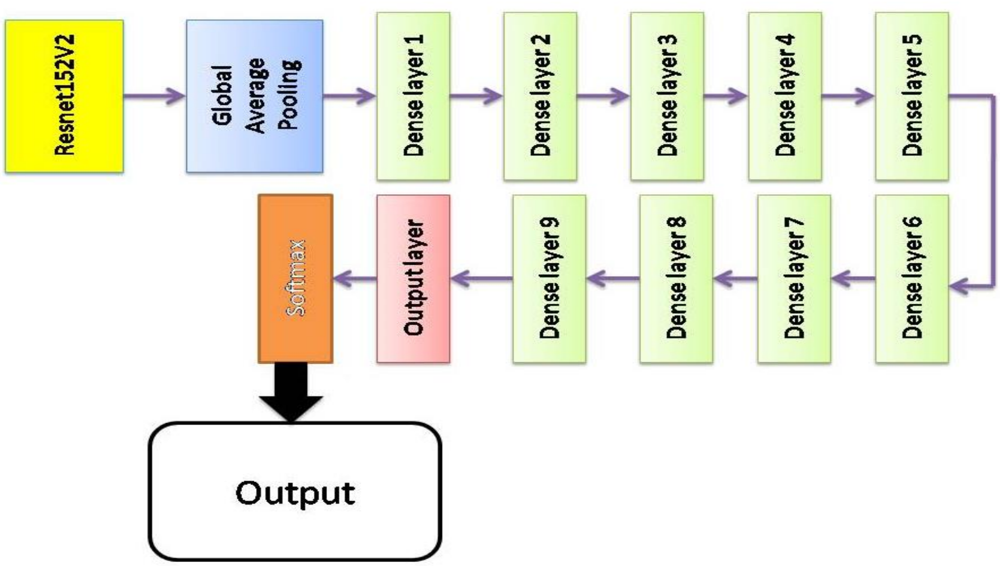

Figure 2: The architecture of our proposed model.

Resnet152V2 consists of various convolution layers, max pooling, and batch normalization parameters to learn from the input images. Convolution layers extract features, and max pooling focuses on the maximum attractive region of extracted features. Many extracted information can create problems for models in the learning phase. So, the batch normalization technique has been used to normalize the network's learning process. Batch normalization is used to stabilize the learning process of the model. Our extension model consisted of a global average pooling layer and various dense layers with rectified linear unit activation functions. Global average pooling converts the model into a fully connected model or one-dimensional matrix. Moreover, Softmax activation was used on the output layer to find the maximum output probability from every production possibility. If the production of the global average pooling layer will be a1, then the model can be mathematically expressed as:

z1 = $\sum_{i=1}^{1024} \mathbf{w}_i \, \boldsymbol{x}_i + \boldsymbol{b}_i$ [x = a1, w = weights, b= bias] (7)

a2 = max (0, z1) (8)

z2 = $\sum_{j=1}^{512} \mathbf{w}_j \, \boldsymbol{x}_j + \boldsymbol{b}_j$ [x = a2, w = weights, b = bias] (9)

a3 = max (0, z2) (10)

z3 = $\sum_{k=1}^{1024} \mathbf{w}_\mathrm{k} \, \boldsymbol{x}_k + \boldsymbol{b}_k$ [x = a3, w = weights, b = bias] (11)

a4 = max (0, z3).......... (12)

z4 = $\sum_{l=1}^{2048} \mathbf{w}_\mathrm{l} \, \boldsymbol{x}_l + \boldsymbol{b}_l$ [x = a4, w = weights, b = bias] (12)

a5 = max (0, z4) (13)

z5 = $\sum_{m=1}^{1024} \mathbf{w}_m \, \boldsymbol{x}_m + \boldsymbol{b}_m$ [x = a5, w = weights, b = bias] (14)

a6 = max (0, z5) (15)

z6= $\sum_{n=1}^{2048} \mathbf{w}_\mathrm{n} \, \boldsymbol{x}_n + \boldsymbol{b}_n$ [x = a6, w = weights, b = bias] (16)

a7 = max (0, z6) (17)

z7 = $\sum_{p=1}^{1024} \mathbf{w}_\mathrm{p} \, \boldsymbol{x}_p + \boldsymbol{b}_p$ [x = a7, w = weights, b = bias] (18)

a8 = max (0, z7) (19)

z8 = $\sum_{q=1}^{256} \mathbf{w}_q \, \boldsymbol{x}_q + \boldsymbol{b}_q$ [x = a8, w = weights, b = bias] (20)

a9 = max (0, z8) (21)

z9 = $\sum_{r=1}^{128} \mathbf{w}_\mathrm{r} \, \boldsymbol{x}_r + \boldsymbol{b}_r$ [x = a9, w = weights, b = bias] (22)

a10 = max (0, z9) (23)

z10 = $\sum_{t=1}^{7} \mathbf{w}_\mathrm{t} \, \boldsymbol{x}_t + \boldsymbol{b}_t$ [x = a10, w = weights, b = bias] (24)

Output = $\frac{e^{z10}}{sum\,(e^{z10})}$ (25)

From equation (25), we will receive seven different values in the range between 0 and 1. The maximum value of probability will be the output of the model. Our proposed net-work-based model is recognized as a more precise and stable model than traditional transfer learning models.

2.5. Downy Mildew Management

In this paper, we have proposed a downy mildew management advisory system for cucumbers. The management system is developed with the knowledge of plant pathologists. So, with the help of the automated digital system for detecting the grade of an affected leaf, a solution will be generated to manage the disease. In this way, we could avoid a considerable vegetable loss in India. Pesticide spray can control the disease, but the amount of spray and mixture of various chemicals should be determined. Downy mildew is often controlled using kresoxim-methyl and azoxy-strobin in cucumber-growing regions [33]. However, the mixture of water with Mancozeb (2 gm per litre) or Zineb (2 gm per litre) or Sulfex (2 gm per litre) or Bavistin (1 gm per litre) or Calixin (1 ml per litre) or Karathane (1/5-1 ml per litre) or Ridomil (2 gm per litre) will be the best for controlling the disease in cucumber. The amounts of fungicide depend on the quantity of water for spraying on the field. The lower side of the leaf should be more focused during the spray. It will be best if a sticker (wetting agent) is added to the spraying solution so that spray droplets remain attached to the leaves. The management of the disease leads to develop an automated system for downy mildew identification and management. The proposed architecture of the automated system is depicted on Fig. (**3**).

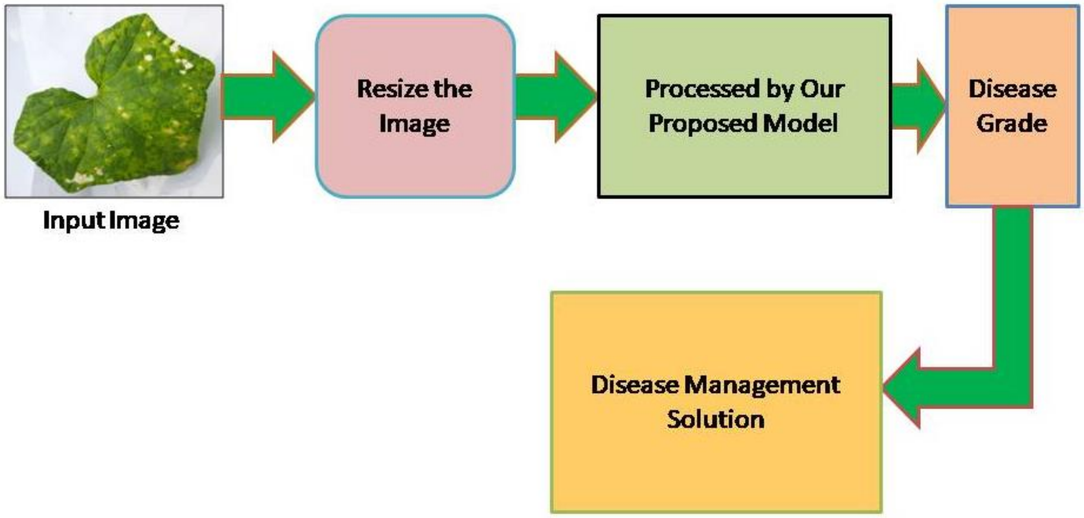

Figure 3: Architecture of our proposed automated system for downy mildew management.

3. Experimental Results

3.1. Transfer Learning Analysis

The transfer learning algorithm is a deep learning algorithm previously trained on a large dataset of various classes. We can use the architecture of transfer learning that may provide a good result for any dataset. In this scenario, all RGB images had been divided into 80% training and 20% validation for the analysis. It is analysed by four transfer learning models such as inception v3, resnet152v2, vgg 16, vgg19. It is observed that the obtained result is not satisfactory due to its overfitting issue. Overfitting is a complication for deep learning models that may predict the wrong classification. So, overfitting issue should be omitted from the model. The obtained result from various transfer learning models is demonstrated in Table **1**. Generally, the more significant difference between training and validation accuracy reveals the overfitting problem.

Table 1: Transfer learning result.

Transfer Learning Model	Training Accuracy (%)	Validation Accuracy (%)
Inception V3	77.50	65.00
Resnet152V2	82.77	68.33
VGG 16	60.48	50.83
VGG 19	56.89	49.17

3.2. Proposed Model Analysis

In our research, the transfer learning model causes an overfitting issue. We should propose a model that does not consist of overfitting and under fitting problems. So, we offered a novel neural network applied to every transfer learning model as an extended version of transfer learning to overcome the issue. The achieved result of our proposed model is depicted in Table **2**. It is noticed that the achieved result is quite different compared with Table **1**. It can be said our proposed network-based transfer learning model is more efficient in recognizing the gradation of the disease.

Table 2: The performance analysis of our proposed model.

Model Name	Training Accuracy (%)	Validation Accuracy (%)
Inception V3 + Our Model	87.12	77.83
Resnet152V2 + Our Model	94.82	84.15
Vgg 16 + Our Model	76.89	66.33
Vgg 19 + Our Model	70.05	62.50

The resent 152v2 model with our novel network can provide the best accuracy for disease management grading analysis. The performance of our approach model is demonstrated in Fig. (**4**).

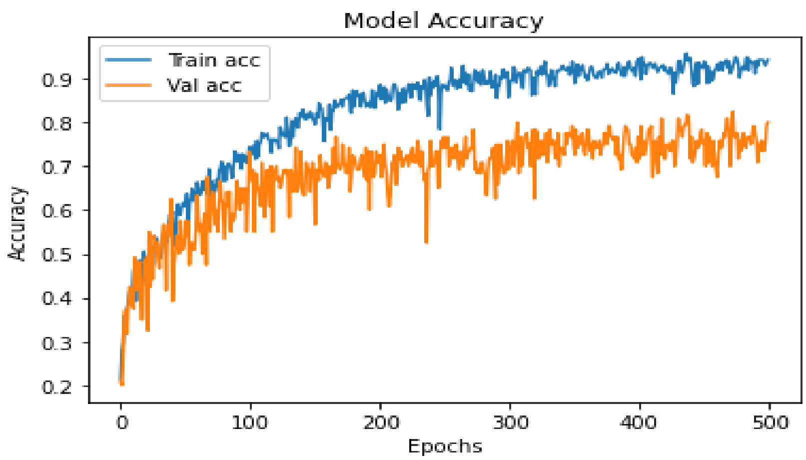

Figure 4: Performance of our approached model.

We have also analyzed our model with the confusion matrix observation. A confusion matrix is generally used to measure the percentage of total observations obtained by a model. It confused the model at the time of prediction, where the matrix row focused on the actual class, and the matrix column denoted the predicted class of the dataset. There are two types of confusion matrix: a normalized confusion matrix and another without a normalized confusion matrix. The normalized confusion matrix defined each class as 100%, representing 1.00. It helps us find the percentage of predicted class compared to the actual class. We can see the actual classification accuracy regarding each class using the technique. A normalized confusion matrix is depicted in Fig. (**5**).

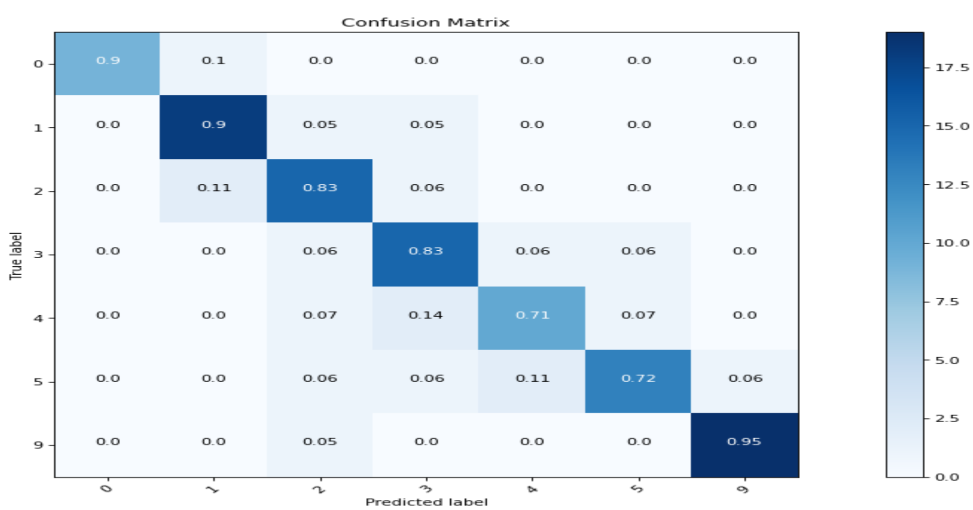

Figure 5: Confusion matrix with normalization.

Without normalizing the confusion matrix helps us to find the actual number of predictions of the class label concerning the true label of each class. It helps to find the number of observations present for each class and the proper prediction of each class. This technique can help observe the actual number of errors in each class. The figure of the without normalize confusion matrix is depicted in Fig. (**6**).

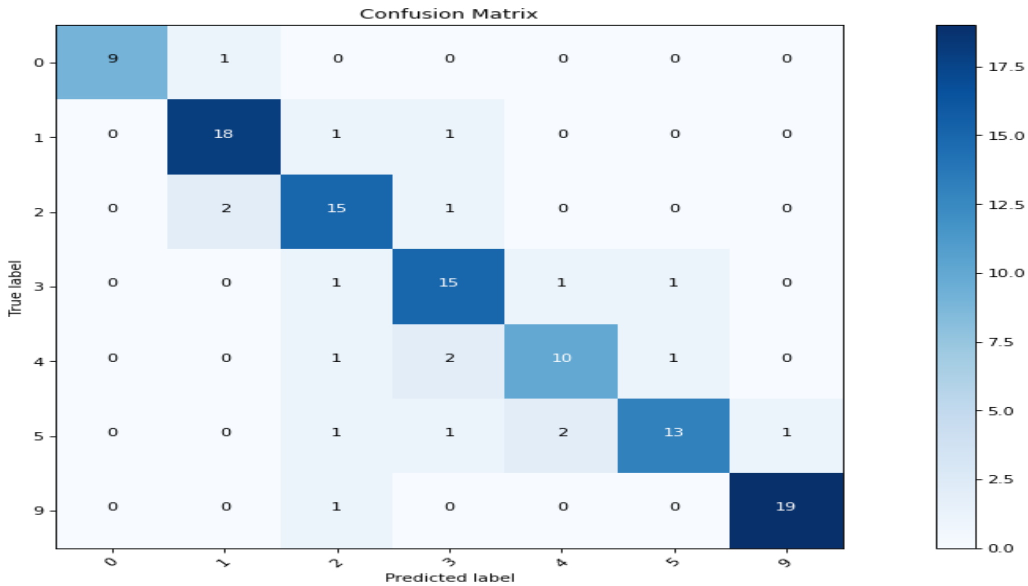

Figure 6: Confusion matrix without normalization.

This model also evaluated various performance analyses such as precision, Recall, and F1 score. Precision can be defined as the ratio of accurate images concerning the total images. Precision can be mathematically derived as TP/ (TP+FP). Recall is derived as the ratio of the total number of images classified by the model for one class to the total number of images of that class. The mathematical expression of Recall is TP/ (TP+FN). The F1 score defines the harmonic mean of precision and Recall. The mathematical expression of the F1 score is 2* ((precision * recall) / (precision + recall)), where TP, FP, TN and FN denote true positive, false positive, true negative, and false negative, respectively. The performance analysis of precision, recall, and F1 scores is demonstrated in Table **3**.

Table 3: Performance analysis of our proposed model.

Grade	Precision	Recall	F1-Score
0	1.00	0.90	0.95
1	0.86	0.90	0.88
2	0.75	0.83	0.79
3	0.75	0.83	0.79
4	0.77	0.71	0.74
5	0.87	0.72	0.79
9	0.95	0.95	0.95

Table **3** can able to express the accuracy of the model and performances of each class by the model.

Table **4** presents an evaluation of the ANOVA test, which assesses the efficacy of the Resnet152V2 + Our Model framework in comparison to alternative approaches in the study. The table summarizes variance components for Treatment and Residual, including sum of squares (SS), degrees of freedom (DF), mean squares (MS), F-statistic, and p-values.

Table 4: The analysis of ANOVA test for evaluating the proposed framework.

Source	SS	DF	MS	F	p-Value
Treatment (Between)	0.03622	3	0.012073	26.104505	2E-6
Residual (Within)	0.00740	16	0.000463		
Total	0.04362	19			

The Treatment component represents the variance of the techniques, with a sum of squares (SS) of 0.03622 in 3 degrees of freedom (DF). This determines the mean square (MS) of 0.012073. For this margin, the appropriate F-statistic is 26.104505. The p-value for the Treatment element is 2E-6, indicating that it is statistically significant and emphasizing the differences between competing techniques and the proposed framework. The Residual portion, which is regarded as residual variance within the data, has an SS of 0.00740 with 16 DF, resulting in an MS of 0.000463.

4. Discussion

People can use the proposed system to reduce the time and cost of agricultural disease management. The disease management system can also develop an automation system to maintain a huge field. There will be less chance of detecting the wrong gradation of the disease. Various plant pathologists also analyzed the results provided by our system to generalize the system. The analyzed images are captured in an uncontrolled environment, which can be defined as a leaf image without a white background. The analysis result is demonstrated in Table **5**.

Table 5: Comparative analysis of plant pathologist and proposed model.

Image Id	Plant Pathologist 1	Plant Pathologist 2	Plant Pathologist 3	Plant Pathologist 4	Plant Pathologist 5	Proposed Model Prediction
4689.jpg	1	2	1	2	2	2
7890.jpg	0	0	0	1	0	0
3049.jpg	3	4	2	3	3	3
8900.jpg	*4*	*4*	*4*	*5*	*4*	*4*
5789.jpg	3	2	2	3	2	3
3410.jpg	9	9	9	9	9	9
6549.jpg	4	3	4	4	5	4

It is observed from Table **7** that the proposed system can able to provide more accurate and precise results than the decision regarding plant pathologists. We tested on 300 images that were captured in an uncontrolled environment. It was observed that our model predicts accurate grades in 270 appearances, whereas no plant pathologist can expect more than 207 samples. The maximum number of voting by plant pathologists' gradation selected as an accurate status for each in-stance. A decision-making system is also introduced after recognizing the grade of the disease. The advisory management system is demonstrated in Table **6**.

Sampling should start to predict the disease between grades 0 and 1. At least 10 -20 leaves will be picked randomly from the field to get a solution. Sampling can be defined as the leaf's RGB image to be used to predict disease grade. Follow the advisories of the above Table **6** after the grade is predicted. Spray under the normal condition at 7-10 days intervals from the beginning of crop development till flowering and fruiting without any prediction.

Table 6: Solutions after gradation by the system.

Grade	Sampling by the Growers	Solution based on Prediction System
0	After system evaluation, if grade 0	No diseaseand check for next sampling (say after 4-7 days)
1	After system evaluation if grade 1	Immediate spray and second spray after 5-7 days
2	After system evaluation if grade 2	Immediate spray and continue for 3 days
3	After system evaluation if grade 3	Immediate spray and continue for 5-7 days
4	After system evaluation if grade 4	Immediate spray and continue till flowering every 5-7 days
5	After system evaluation if grade 5	Collect all crops from the plants
9	After system evaluation if grade 9	Out of shape for vegetation

4.1. Performance Comparison

Our proposed technology is compared with other published technologies in terms of accuracy and method of different technologies. Table **7** describes the comparison result.

Table 7: Performance comparison table.

Object	Methodology	Result
Fruits [34]	K-means Clustering	Normal 84.65% and affected 76.6%
Vegetables [34]	ANN	84.11%
Maize Leaf [35]	Fuzzy Logic	Healthy: 45.21% Diseased: 54.79%
Cucumber Leaf [36]	Image Processing and ANN	80.46%
Cucumber Leaf (This Paper)	Our Proposed Model using Deep Learning	84.15%

5. Conclusions

This paper introduces a deep learning based downy mildew disease assessment framework to detect the disease. The pixel distribution of downy mildew disease is complex due to its non-linear relationship. To deal with this issue, a fine-tuned optimized DL model is evaluated to extract spatial features from field-level images. It is observed that transfer learning models cannot extract features, avoiding overfitting problems. Since the optimized DL model is proposed that achieves a training accuracy of 94.82% and a success rate of 84.15% on previously unseen data by the model. This high performance makes it clear that deep learning models are well-suited for automated downy mildew disease identification and diagnosis using simple image analysis. The model enables its incorporation into mobile applications for usage on portable electronics. Farmers, agronomists, drones, and other autonomous agricultural vehicles may utilize these tools to monitor and identify disease in huge open-field cropping systems. The automated disease detection system would have to validate the creation of an automated pesticide prescription system before the farmer could buy the right pesticides. It could be a future possibility in the former case in particular, aside from the fact that a farmer in a remote location could have an incoming warning about a potential threat during cultivation, and an agronomist could have a useful advisory tool. The system is valuable due to its favourable results in various uncontrolled environments.

Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript.

Funding

The study received no financial support.

Acknowledgments

The authors would like to thank Dr. Sourabh Kumar Das, Principal, Kalyani Government Engineering College, for helping us to implement this research work. The necessary help and cooperation extended by Mr. Kaushik Mukherjee and Mr. Kunal Roy, Department of In-formation Technology, Kalyani Government Engineering College, Kalyani, Nadia- 741235, West Bengal, India are duly acknowledged.

References

[1] Yang X, Li M, Zhao C, Zhang Z, Hou Y. Early warning model for cucumber downy mildew in unheated greenhouses. N Z J Agric Res. 2007; 50(5): 1261-8. https://doi.org/10.1080/00288230709510411

[2] Weizheng S, Yachun W, Zhanliang C, Hongda W. Grading method of leaf spot disease based on image processing. In: 2008 Int Conf Comput Sci Softw Eng. 2008; 6: 491-4. https://doi.org/10.1109/CSSE.2008.1649

[3] Cen ZX, Li BJ, Shi YX, Huang HY, Liu J, Liao NF, *et al*. Discrimination of cucumber anthracnose and cucumber brown speck based on color image statistical characteristics. Acta Hortic Sin. 2007; 34(6): 1425-30.

[4] Arief MA, Kim H, Kurniawan H, Nugroho AP, Kim T, Cho BK. Chlorophyll fluorescence imaging for early detection of drought and heat stress in strawberry plants. Plants. 2023; 12(6): 1387. https://doi.org/10.3390/plants12061387

[5] Faqeerzada MA, Park E, Kim T, Kim MS, Baek I, Joshi R, *et al*. Fluorescence hyperspectral imaging for early diagnosis of heat-stressed ginseng plants. Appl Sci. 2022; 13(1): 31. https://doi.org/10.3390/app13010031

[6] Mukherjee K, Das S, Mustafi S, Dan S, Mandal SN. IGDM: Image-based grading system of downy mildew in cucumber using digital image processing and unsupervised learning. J Inst Eng (India) Ser B. 2024; 105(4): 825-39. https://doi.org/10.1007/s40031-024-01005-2

[7] Mandal SN, Mukherjee K, Dan S, Ghosh P, Das S, Mustafi S, *et al*. Image-based potato phoma blight severity analysis through deep learning. J Inst Eng (India) Ser B. 2023; 104(1): 181-92. https://doi.org/10.1007/s40031-022-00820-9

[8] Masood R, Khan SA, Khan MN. Plants disease segmentation using image processing. Int J Mod Educ Comput Sci. 2016; 8(1): 24-8. https://doi.org/10.5815/ijmecs.2016.01.04

[9] Ramanjot, Mittal U, Wadhawan A, Singla J, Jhanjhi NZ, Ghoniem RM, *et al*. Plant disease detection and classification: a systematic literature review. Sensors. 2023; 23(10): 4769. https://doi.org/10.3390/s23104769

[10] Sladojevic S, Arsenovic M, Anderla A, Culibrk D, Stefanovic D. Deep neural networks based recognition of plant diseases by leaf image classification. Comput Intell Neurosci. 2016; 2016: 3289801. https://doi.org/10.1155/2016/3289801

[11] Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Front Plant Sci. 2016; 7: 215232. https://doi.org/10.3389/fpls.2016.01419

[12] Putra BT, Amirudin R, Marhaenanto B. Evaluation of deep learning using convolutional neural network approach for identifying Arabica and Robusta coffee plants. J Biosyst Eng. 2022; 47(2): 118–29. https://doi.org/10.1007/s42853-022-00136-y

[13] Jeong S, Jeong S, Bong J. Detection of tomato leaf miner using deep neural network. Sensors. 2022; 22(24): 9959. https://doi.org/10.3390/s22249959

[14] Tran TT, Choi JW, Le TT, Kim JW. Comparative study of deep CNN in forecasting and classifying the macronutrient deficiencies on development of tomato plant. Appl Sci. 2019; 9(8): 1601. https://doi.org/10.3390/app9081601

[15] Camargo A, Smith JS. Image pattern classification for identification of disease-causing agents in plants. Comput Electron Agric. 2009; 66(2): 121-5. https://doi.org/10.1016/j.compag.2009.01.003

[16] Aladhadh S, Habib S, Islam M, Aloraini M, Aladhadh M, Al-Rawashdeh HS. Efficient pest detection framework with a medium-scale benchmark to increase agricultural productivity. Sensors. 2022; 22(24): 9749. https://doi.org/10.3390/s22249749

[17] Amara J, Bouaziz B, Algergawy A. Deep learning-based approach for banana leaf diseases classification. In: Datenbanksysteme für Business, Technologie und Web (BTW 2017) Workshopband. Gesellschaft für Informatik eV; 2017. p. 79-88.

[18] Das S, Bikram P, Biswas A, Sinha P. Multilayer optimized deep learning model to analyze spectral indices for predicting condition of rice blast disease. Remote Sens Appl Soc Environ. 2025; 37: 101394. https://doi.org/10.1016/j.rsase.2024.101394

[19] Zhou B, Xu J, Zhao J, Li A, Xia Q. Research on cucumber downy mildew detection system based on SVM classification algorithm. In: 3rd Int Conf Mater Mech Manuf Eng (IC3ME). 2015; pp. 1681-4. https://doi.org/10.2991/ic3me-15.2015.324

[20] Gikunda PK, Jouandeau N. State-of-the-art convolutional neural networks for smart farms: a review. In: Intelligent Comput Proc Comput Conf. 2019; pp. 763-75. https://doi.org/10.1007/978-3-030-22871-2_53

[21] Kalaivani S, Tharini C, Viswa TS, Sara KF, Abinaya ST. ResNet-based classification for leaf disease detection. J Inst Eng (India) Ser B. 2025; 106(1): 1-4. https://doi.org/10.1007/s40031-024-01062-7

[22] Cohen B, Edan Y, Levi A, Alchanatis V. Early detection of grapevine (Vitis vinifera) downy mildew (Peronospora) and diurnal variations using thermal imaging. Sensors. 2022; 22(9): 3585. https://doi.org/10.3390/s22093585

[23] Liu E, Gold KM, Combs D, Cadle-Davidson L, Jiang Y. Deep learning-based autonomous downy mildew detection and severity estimation in vineyards. In: ASABE Annu Int Virtual Meet. 2021; pp. 1-8. https://doi.org/10.13031/aim.202100486

[24] Lin K, Gong L, Huang Y, Liu C, Pan J. Deep learning-based segmentation and quantification of cucumber powdery mildew using convolutional neural network. Front Plant Sci. 2019; 10: 155. https://doi.org/10.3389/fpls.2019.00155

[25] Chen M, Brun F, Raynal M, Makowski D. Forecasting severe grape downy mildew attacks using machine learning. PLoS One. 2020; 15(3): e0230254. https://doi.org/10.1371/journal.pone.0230254

[26] Ojiambo PS, Paul PA, Holmes GJ. Quantitative review of fungicide efficacy for managing downy mildew in cucurbits. Phytopathology. 2010; 100(10): 1066-76. https://doi.org/10.1094/PHYTO-12-09-0348

[27] Mebrate SA, Dehne HW, Pillen K, Oerke EC. Molecular diversity in Puccinia triticina isolates from Ethiopia and Germany. J Phytopathol. 2006; 154(11-12): 701-10. https://doi.org/10.1111/j.1439-0434.2006.01177.x

[28] Ngugi LC, Abelwahab M, Abo-Zahhad M. Recent advances in image processing techniques for automated leaf pest and disease recognition: a review. Inf Process Agric. 2021; 8(1): 27-51. https://doi.org/10.1016/j.inpa.2020.04.004

[29] Cruz AC, Luvisi A, De Bellis L, Ampatzidis Y. X-FIDO: an effective application for detecting olive quick decline syndrome with deep learning and data fusion. Front Plant Sci. 2017; 8: 1741. https://doi.org/10.3389/fpls.2017.01741

[30] Nikhitha M, Sri SR, Maheswari BU. Fruit recognition and grade of disease detection using inception v3 model. In: 3rd Int Conf Electron Commun Aerosp Technol (ICECA). 2019; pp. 1040-3. https://doi.org/10.1109/ICECA.2019.8822095

[31] Chandra NM, Reddy KA, Sushanth G, Sujatha S. Versatile approach based on convolutional neural networks for early identification of diseases in tomato plants. Int J Wavelets Multiresol Inf Process. 2022; 20(1): 2150043. https://doi.org/10.1142/S0219691321500430

[32] Kumar A, Razi R, Singh A, Das H. Res-VGG: a novel model for plant disease detection by fusing VGG16 and ResNet models. In: Int Conf Mach Learn Image Process Netw Secur Data Sci. 2020; pp. 383-400. https://doi.org/10.1007/978-981-15-6318-8_32

[33] Ishii H, Fraaije BA, Sugiyama T, Noguchi K, Nishimura K, Takeda T, *et al*. Occurrence and molecular characterization of strobilurin resistance in cucumber powdery mildew and downy mildew. Phytopathology. 2001; 91(12): 1166-71. https://doi.org/10.1094/PHYTO.2001.91.12.1166

[34] Pujari JD, Yakkundimath R, Byadgi AS. Image processing-based detection of fungal diseases in plants. Procedia Comput Sci. 2015; 46: 1802-8. https://doi.org/10.1016/j.procs.2015.02.137

[35] Sibiya M, Sumbwanyambe M. Algorithm for severity estimation of plant leaf diseases using colour threshold image segmentation and fuzzy logic inference. AgriEngineering. 2019; 1(2): 15. https://doi.org/10.3390/agriengineering1020015

[36] Pawar P, Turkar V, Patil P. Cucumber disease detection using artificial neural network. In: Int Conf Invent Comput Technol (ICICT). 2016; 3: pp. 1-5. https://doi.org/10.1109/INVENTIVE.2016.7830151