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RESEARCH ARTICLE

Cucumber Leaf Diseases Recognition Based on Deep Convolutional Neural Networks

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Abstract

Cucumber cultivation is a vital component of Pakistan's agricultural economy and is a key vegetable in the national diet. However, crop yield and quality are severely threatened by diseases like powdery mildew and downy mildew. Early and accurate disease detection is critical for implementing targeted treatment and preventing widespread infection. This study proposes a deep learning-based framework for the automated recognition of cucumber leaf diseases. We designed and trained a custom Convolutional Neural Network (CNN) from scratch and compared its performance against powerful pre-trained transfer learning models, including VGG16 and InceptionV3. The models were evaluated on a dataset of cucumber leaf images. Our experimental results demonstrate that the transfer learning approach significantly outperforms the custom CNN. Specifically, the VGG16 model achieved the highest accuracy of 98.76% in classifying the diseases. The findings confirm that advanced deep learning models can serve as effective tools for rapid and precise plant disease diagnosis, offering a valuable application for sustainable agricultural practices.

Keywords: cucumber diseases, deep learning, convolutional neural network (CNN), transfer learning, VGG16, InceptionV3, image classification, plant disease recognition.

1 Introduction and Related Work

The agriculture sector greatly benefits Pakistan's entire economic growth. A significant 18.9 percent of Pakistan's Gross Domestic Product (GDP) is contributed by this sector, which also provides employment for almost 43 percent of the labor force [1]. Plant disease, which hinders plant development and results in huge financial losses, has a major influence on agricultural output. To stop the illness from spreading to unaffected plants and to facilitate a correct diagnosis, it is crucial to quickly recognize the apparent symptoms of plant disease.

The cucumber, also known as Cucumis sativus and belonging to the Cucurbitaceae family, is an economically significant crop in Pakistan. It is the fourth most grown vegetable crop worldwide.

Freshly picked cucumbers are a major source of critical vitamins like vitamin C and vitamin K, as well as essential minerals like calcium and iron. This product

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also includes dietary fiber and key nutrients like the B vitamins niacin and thiamine. Cucumbers are also valued for their refreshing taste. Diseases that affect cucumber plants can prevent them from growing properly, which eventually reduces the crop's quality and output [2]. These disorders are often caused by pathogenic bacteria, fungi, or viruses. Most plant diseases are contagious, may spread to unaffected plants, and result in significant harm, including lower yield and inferior quality. Rapid illness identification is essential for halting its spread. Conventional approaches for diagnosing cucumber diseases in large-scale agricultural operations are notoriously labor-intensive, costly, time-consuming, and difficult. It is also important to keep in mind that farmers in rural Pakistan and other developing countries regularly face the challenge of having to travel great distances to get professional advice [3]. Professionals could find it challenging to reach the specified site in the allocated time.

Several constraints imposed by the environment may now be overcome thanks to advances in agricultural research, the elevation of computer vision technology, and the incorporation of pattern recognition. Computer vision applications have shown their usefulness in the agriculture industry. The goal of imitating human visual perception to give machines artificial intelligence led to the development of computer vision in the early 1970s [4]. Computer vision is used in the agriculture sector to accurately detect parasites, illnesses, and vegetation while effectively monitoring plant health. There is less need for human observers thanks to this technology.

This study's main goal was to create an autonomous diagnostic system for identifying and categorizing diseases that damage cucumber plants. The objective of this research was to evaluate and compare the effectiveness of transfer learning approaches based on convolutional neural networks (CNNs) with standard deep learning (DL) techniques. This assessment considered several illnesses, including downy mildew and powdery mildew.

Recently, scientists have increasingly focused on the agricultural sector to harness innovative technology to successfully address the challenges associated with the detection or classification of plant diseases. Many solutions to this problem have been suggested. Technologies such as Global Pooling Dilated Convolutional Neural Networks (GPDCNN), Hyperspectral Imaging (HSI), and Support Vector Machines (SVM) have been employed in this context. This section provides a summary of published work that details the various research approaches used to study cucumber diseases.

To achieve classification objectives, Zhou et al. [5] advised employing image preprocessing methods and Support Vector Machines (SVM). Their approach for identifying cucumber downy mildew was 90% accurate. In a study, researchers [6] looked at three techniques for identifying diseases in cucumbers. The researchers used image processing methods to efficiently remove background noise, segment lesions, and convert the images to grayscale. When information was extracted for categorization, features such as shape, color, and texture were considered. The typical rate of recognition was higher than 96.0%. To determine the prevalence of cucumber downy mildew illness, the researchers used hyperspectral imaging [7]. They used several image processing methods, including augmentation, binarization, erosion, and dilation, to improve the visibility of the spot features in the fusion picture. The technique showed 90% overall detection accuracy. The method created by Pawar et al. [8] used first-order statistical moments algorithms and GLCM to extract nine texture attributes from images. An artificial neural network was then used for categorization. The researchers focused on three groups: healthy leaves, downy mildew, and powdery mildew. For the given data, the system's classification accuracy was 80.45%. In their work, Youwen et al. [9] introduced a unique technique for examining ailments that damage cucumber leaves, combining support vector machines (SVM) and artificial intelligence (AI) approaches. According to their results, SVMs outperformed neural networks in recognizing sick cucumber leaves. Additionally, combining form and texture data yielded better results than depending exclusively on shape attributes. Khan et al. [10] examined the use of a method for choosing deep features and an improved saliency approach. Five different cucumber illnesses were looked at in this research. A mean identification rate of 98.08 percent was reached in 10.52 seconds. Support Vector Machines (SVM) were utilized to categorize the deep features that were acquired using 2000 features and VGG19 in the final phase of this modified approach. Zhang et al. [11] found seven distinct illnesses in cucumber plant leaves. In this research, the affected region was segmented using the K-means clustering approach. The sparse representation (SR) approach was used to categorize lesions by extracting features related to both shape and color. The overall accuracy of the technique was 85.7%. Zhang et al. [12] provided a technique for the identification and categorization of cucumber illnesses, using superpixel clustering, a hybrid expectation-maximization (EM) approach, and support vector machines (SVMs). Their approach produced an accuracy higher than 90%. Ma et al. [13] gathered a collection of 1184 image datasets, which included four cucumber diseases. A deep convolutional neural network (CNN) was used. The authors showed that the suggested technique outperformed traditional classifiers, random forest (RF), and support vector machine (SVM), with a recognition accuracy of 93.4%. Zhang et al. [14] used Support Vector Machines (SVM) to categorize cucumber disease. Their process began with feature extraction via global-local singular value decomposition, after which a key-point vector was constructed for classification. A notable disadvantage of their technique was its high computational demand. The feature extraction process started by using global-local singular value decomposition, and then a key-point vector was built. Zhang et al. [15] suggested using global pooling dilated convolutional neural networks (CNNs) to identify six common diseases in cucumber plants, reporting high accuracy. Zhang et al. [16] used a sophisticated transfer learning method with the Efficient Net model. A classification model was developed to correctly detect four different forms of cucumber illness with 97.00% accuracy, and EfficientNet-B4 was shown to be the most effective technique.

Digital image processing has seen significant attention in recent years, as scholars have dedicated their efforts to comprehensively investigating its potential uses within the agricultural sector. This literature review provides the fundamental basis for understanding the current state of cucumber leaf recognition techniques, with an emphasis on the use of convolutional neural networks (CNNs). Several studies have examined various approaches for detecting plant diseases, highlighting the importance of precise and effective strategies for early diagnosis.

This review examines the literature to identify potential, problems, and gaps in the field of cucumber leaf detection. Understanding the development of CNNs in image recognition tasks helps in comprehending their application for identifying minute leaf irregularities that could be signs of illness. Additionally, investigating advancements in feature extraction, classification techniques, and image preprocessing offers insight into enhancing the reliability and accuracy of CNN-based detection models. This review aims to support agricultural sustainability and food security by exploring innovative techniques for cucumber leaf identification using CNNs.

1.1 Healthy Cucumber

Fresh cucumber leaves are essential markers of plant health since they show that there is no illness or stress present. The goal of fresh cucumber leaf research is to employ image analysis to develop baseline features that will help identify anomalies. A representative example of a healthy cucumber leaf is shown in Figure 1, which illustrates the characteristic vibrant green coloration and uniform texture indicative of optimal plant condition.

Figure 1. Healthy Cucumber leaf.

1.2 Powdery Mildew

Cucumber plants are frequently afflicted by powdery mildew, a fungal disease that causes white, powdery areas on the leaves, as shown in Figure 2. Research on the detection of powdery mildew in cucumbers emphasizes the crucial role of early detection in preventing both yield loss and widespread infection.

1.3 Effects of Powdery Mildew

Powdery mildew can seriously harm cucumber plants, lowering their vitality and yield. The appearance of powdery white patches on leaves, stems, and fruits is one obvious consequence. These patches are fungal spores, which can cause leaves to become yellow, wilt, and finally drop off. The disease weakens the plant

Figure 2. Powdery mildew Effect.

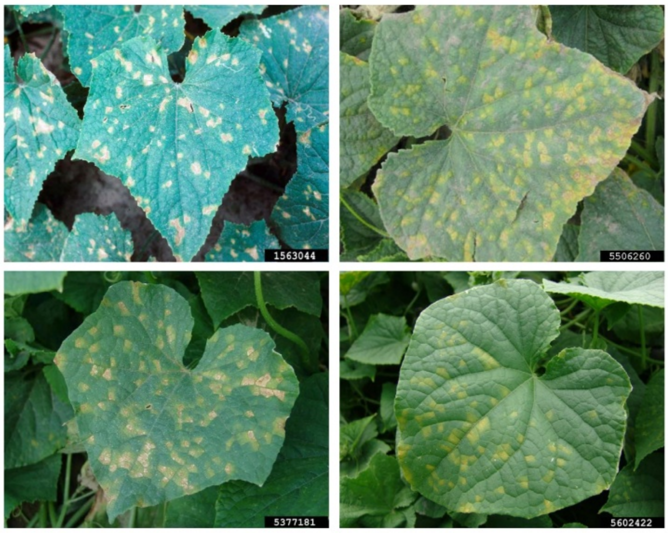

Figure 3. Effect of Downy Mildew.

as it spreads, resulting in stunted development and lower harvests. Furthermore, photosynthesis can be hampered. If left untreated, powdery mildew can seriously impair plant health, costing growers money. Therefore, timely management strategies are crucial.

1.4 Downy Mildew: Symptomatology and Diagnosis

The diagnosis of downy mildew is primarily based on its distinct and progressive symptomatology. Initial symptoms appear as small, pale green to yellow, angular lesions bounded by the leaf veins, giving them a "mosaic-like" appearance on the adaxial (upper) surface, as clearly demonstrated in Figure 3. As the disease progresses, these lesions enlarge, turn bright yellow, and eventually become necrotic, turning brown and causing tissue collapse.

The definitive diagnostic feature, however, is observed on the abaxial (lower) leaf surface. Under conditions of high humidity, typically in the early morning, a characteristic dense, downy, and fuzzy growth of purplish-gray to black coloration appears corresponding to the lesions above. This growth consists of the pathogen's sporangiophores and sporangia. Advanced infections lead to severe leaf curling, wilting, and premature defoliation, which expose fruits to sunscald and leads to overall plant decline. The accurate and timely identification of these visual cues is paramount for implementing effective fungicidal interventions before the disease causes irreversible damage to the crop.

1.5 Downy Mildew Effects: Pathogenesis and Physiological Impact

Downy mildew, caused by the oomycete pathogen Pseudoperonospora cubensis, presents a severe threat to cucumber cultivation worldwide. Unlike powdery mildew, this pathogen thrives under cool, moist conditions and is highly destructive. Its infection cycle begins when motile zoospores, released from sporangia, germinate on leaf surfaces under high humidity and penetrate the stomata.

The primary physiological impact is the rapid disruption of photosynthesis. The pathogen colonizes the mesophyll layer, leading to the formation of chlorotic lesions on the upper leaf surface corresponding to the sites of fungal sporulation on the underside. This directly damages chloroplasts and reduces the functional leaf area, severely reducing carbohydrate production. Consequently, the plant experiences a significant energy deficit, manifesting as stunted growth, reduced fruit size, and ultimately, lower yield. Furthermore, the infection induces systemic stress, weakening the plant's overall vigor and increasing its susceptibility to secondary infections and environmental stressors. Effective management is therefore critical not only to control the disease but also to maintain the plant's physiological integrity and productivity.

1.6 Causes of Powdery Mildew

Powdery mildew is a widespread fungal disease affecting cucumbers, caused by fungi from the Erysiphales order. It appears as white to grayish powdery patches on leaves, stems, and occasionally fruits. Contributing factors include high humidity,

Table 1. Symptoms and management of powdery mildew and downy mildew.

Aspect	Powdery Mildew	Downy Mildew
Symptoms	White powdery spots on leaves	Yellow spots on leaves, fuzzy growth on undersides
Leaf Damage	Leaves become distorted, curled	Yellowing, wilting, eventually leaves die
Growth Reduction	Reduced photosynthesis	Stunted growth, reduced yield
Fruit Quality	Reduced quality, smaller fruits	Fruits may become discolored, rot prematurely
Overall Plant Health	Weakened, susceptible to other diseases	Severe infections can lead to plant death
Management	Fungicides, proper spacing and ventilation	Fungicides, removal of infected debris, avoid leaf wetness

warmth, dense plantings, inadequate plant nutrition, and infected plant debris.

1.7 Causes of Downy Mildew

Downy mildew is another prevalent fungal disease. Cucumber leaves affected by this illness usually have yellow to brown lesions on their upper surface and fuzzy, grayish-purple growth on their undersides. Downy mildew develops and spreads due to moisture, poor air circulation, infected plant material, and favorable weather patterns.

1.8 Symptoms of Powdery Mildew and Downy Mildew

This section provides detailed information regarding the symptoms and causes of powdery mildew and downy mildew, relevant to our problem. A comprehensive comparison of the symptoms and management strategies for both diseases is presented in Table 1, which highlights key differences in leaf damage patterns, impact on fruit quality, and recommended control measures.

2 Methodology

2.1 Deep Convolutional Neural Network

Since their successful application to the MNIST dataset, convolutional neural networks (CNNs) have evolved remarkably [17]. CNNs are particularly effective at processing images because they can efficiently capture spatial hierarchies and relationships across layers. Given that studies have demonstrated CNNs can automatically extract relevant features from images, they are highly suited for tasks like image classification [18, 19]. The general architecture of a typical CNN model is illustrated in Figure 4.

Historically, a common strategy to improve model performance was to increase network depth. Based on this methodology, several well-known models have been proposed, such as AlexNet, VGG16, Inception_v3, ResNet50, and DenseNet. Studies based on the Plant Village dataset found that Inception_v3 achieved high accuracy [20]. Its inception process uses factorization to improve feature extraction while lowering computing complexity. Though more complex than VGG16, it is valuable due to its efficiency. However, as network depth increases, the degradation problem can occur, where accuracy saturates and then degrades rapidly. ResNet was introduced to address this issue by enabling deeper networks without problems like gradient vanishing [21].

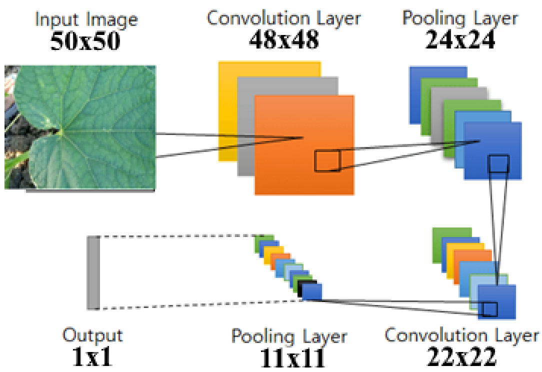

Figure 4. General network construction of a CNN model.

Using images of cucumber diseases, we compared VGG16, Inception_v3, and ResNet50. A deep CNN typically consists of convolutional, pooling, and fully connected layers, as shown in the network construction depicted in Figure 4. The convolutional layers extract features, and the fully connected layers serve as classifiers. To reduce parameter redundancy and boost performance, models like ResNet and DenseNet often use global average pooling instead of fully connected layers.

In situations with limited training data, transfer learning is frequently used. More accuracy and faster convergence can be achieved by fine-tuning pre-trained models [22] like VGG16, Inception_v3, and ResNet50. For our investigation, we retained the pre-trained architecture's feature extraction components but modified the classifier by adding batch normalization layers, dropout layers, simplifying fully connected layers, and using global max pooling.

The initial models selected were ResNet50, for its ability to effectively train very deep networks [23]; InceptionV3, for its proficiency in capturing multi-scale features; and VGG16, for its simplicity and consistently strong performance. Together, these models established robust baselines for subsequent comparisons. Overall, this benchmark encompasses a balanced mix of well-established and high-performing architectures in the field of computer vision.

2.2 Model Architecture

The proposed Convolutional Neural Network (CNN) model is based on the VGGNET architecture, which performs well in image classification tasks. The development of the model involved multiple steps. Experimentation was used to identify the optimal number of layers and nodes in each layer. A CNN is a Deep Learning method that analyzes visual input using the Multi-Layer Perceptron (MLP) concept and classifies data using supervised learning algorithms. The complete architecture of our proposed model is illustrated in Figure 5.

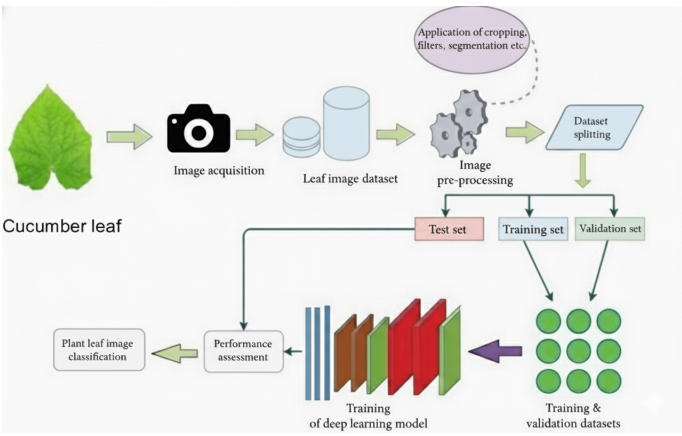

Figure 5. Proposed CNN model architecture.

Inspired by the VGG architecture, we created a custom Convolutional Neural Network (CNN) from the ground up. There are four convolutional blocks in the model. Each block has a 2x2 max-pooling layer after two convolutional layers with 32, 64, 128 and 256 filters, respectively, each employing a 3x3 kernel and ReLU activation. A flattening layer and two dense, fully connected layers with 128 and 64 units and ReLU activation comes next, with a dropout rate of 0.5 to avoid overfitting. The final output layer classifies the three classes (Healthy, Powdery Mildew, and Downy Mildew) using a softmax activation function.

2.3 Custom CNN Architecture

Table 2 contains information about the architecture of the custom CNN model built exclusively for this study. The model is composed of convolutional and pooling layers for feature extraction and fully connected layers for classification.

2.4 Preprocessing

Recognizing diseases in cucumber leaves relies on datasets with images of healthy and diseased leaves. Since there's not enough large dataset pertinent to diseases of cucumbers, the researchers had to rely on other datasets such as the ones provided by Kaggle. At this stage, preprocessing operations include conversion to grayscale, resizing, and noise reduction for the images. The images are resized to 50×50 pixels while maintaining the aspect ratio because important information and the area of focus should be preserved. Another aspect of preprocessing involves segmenting the background and the leaf to retain only the relevant features.

2.5 Dataset Description

A dataset of photos of both healthy and diseased cucumber leaves was acquired from Kaggle to efficiently identify the diseases. The two disease classes covered by the dataset are powdery mildew and downy mildew. Images in the original "Cucumber Plant Disease Dataset" have been categorized as either healthy or diseased. The dataset became unbalanced after augmentation, making it impossible to properly tune the model. The detailed distribution of the augmented dataset across different classes for training and testing purposes is provided in Table 3.

We visualized the output layer to learn more about how our neural network processes images. In order to capture the features that the model identified for each disease class, we created images that maximized the activity of nodes in the final layer. Important new information about the mechanisms behind the network's diagnosis was made possible by this visualization.

Table 2. Architecture of the proposed Custom CNN model.

Layer Type	Filter Size / Stride	No. of Filters / Units	Output Shape	Activation
Input	-	-	(50, 50, 3)	-
Convolutional	3x3 / 1	32	(50, 50, 32)	ReLU
Max Pooling	2x2 / 2	-	(25, 25, 32)	-
Convolutional	3x3 / 1	64	(25, 25, 64)	ReLU
Max Pooling	2x2 / 2	-	(12, 12, 64)	-
Convolutional	3x3 / 1	128	(12, 12, 128)	ReLU
Max Pooling	2x2 / 2	-	(6, 6, 128)	-
Flatten	-	-	(4608)	-
Dense (Fully Connected)	-	128	(128)	ReLU
Dropout (0.5)	-	-	(128)	-
Dense (Fully Connected)	-	64	(64)	ReLU
Dense (Output)	-	3	(3)	softmax

Table 3. Distribution of the augmented dataset for training and testing.

Class Name	Total Images After Augmentation	Training Images	Testing Images
Downy Mildew	2170	1520	650
Powdery Mildew	1430	1000	430

2.6 Data Augmentation

Every class in the dataset was expanded through augmentation to enhance dataset size and diversity for improved model performance. The augmentation process included techniques like rotation, flipping, and zooming, which exposed the models to a wider range of variations and conditions, leading to improved generalization capabilities. Examples of the augmented images for both powdery mildew and downy mildew are shown in Figure 6, demonstrating the effects of pre-processing and augmentation techniques. This detailed dataset setup laid a solid foundation for robust and reliable classification models.

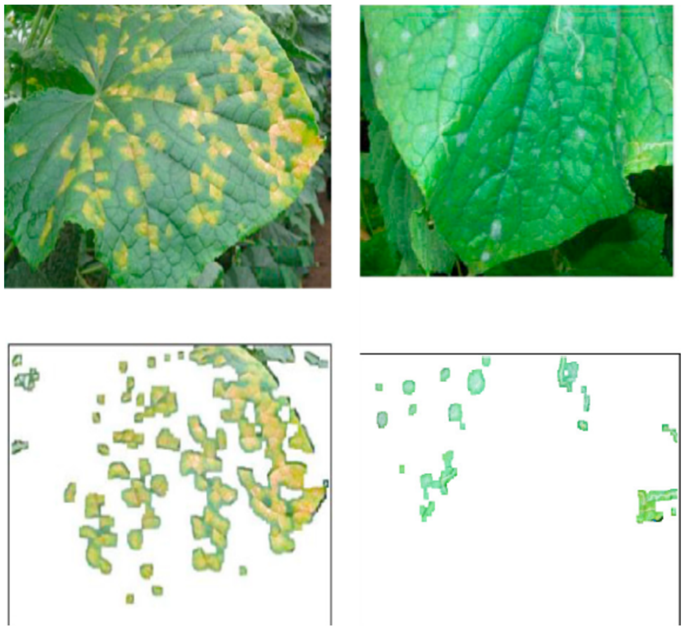

Figure 6. Images of powdery mildew (right) and downy mildew (left) are examples of pre-processed and augmented images. While segmentation and color normalization were used in pre-processing to separate the leaf and disease spots, augmentation techniques included flipping and rotation.

3 Experiments

Our model was trained on the training set, and its performance was assessed on the validation set at each epoch. This method ensures robustness and helps prevent overfitting.

We trained the models using mini-batch stochastic gradient descent with a momentum factor of 0.9. Each batch contained 32 samples. The weights of every network layer were initialized using the Glorot uniform initializer, and the biases were set to zero. Each layer began with a learning rate of 0.001, which decayed by 1e-6. The training and testing were run on a single PC with an Intel Core i9-7900X processor, 16GB of RAM, and an NVIDIA GeForce RTX 4090 GPU. We used the TensorFlow and Keras frameworks for model training. An early stopping method was employed, halting training if the validation loss did not improve for 30 epochs, to avoid overfitting and reduce training time.

All models converged within 300 epochs. ResNet50 demonstrated the fastest convergence, reaching a loss of 0.00281 by the 245th epoch. The training and

Table 4. Model convergence and results.

Name of Model	Final Validation Loss	Final Epoch Value	Test Accuracy(%)	Validation loss (Minimum)	Early Stopping Epoch	Best Validation Accuracy (%)
Custom CNN	0.0415	300	92.15	0.0398	300	91.84
VGG16	**0.00823**	**287**	**98.76**	**0.00857**	**165**	**97.63**
Inception V3	0.00493	272	97.43	0.00607	176	97.76
Resnet50	0.00283	245	97.93	0.00778	109	97.53

validation accuracy curves peaked near 1.0 after about 200 epochs.

A distinct performance hierarchy among the assessed models is shown by the results in Table 4. The transfer learning models performed noticeably better than the custom CNN, which attained a test accuracy of 92.15%, as expected. The benefit of using pre-trained models that incorporate features learned from large-scale datasets like ImageNet is highlighted by the custom CNN's lower accuracy, even though it offers a competent baseline. VGG16 demonstrated its effectiveness for this classification task by achieving the highest test accuracy of 98.76% among the transfer learning models. With test accuracies of 97.43% and 97.93%, respectively, InceptionV3 and ResNet50 also produced impressive, comparable results.

4 Discussion

The experimental results expressed in Table 4 show clear performance ranking, confirming the advantage of transfer learning for this specific task. The custom CNN model gave a good baseline with a test accuracy of 92.15%, proving that deep learning is an avenue worth pursuing for automated recognition of the disease. Its lower accuracy than that of the transfer learning techniques shows that there is a much larger benefit in extracting features learned from large-scale datasets such as ImageNet.

Among the transfer learning architecture, VGG16 showed the best result, with 98.76% on the test accuracy. This good performance can be attributed to its deep, sequential structure, which can easily derive hierarchical features from leaf images. The specific texture and color patterns of powdery and downy mildew seem to be perfectly modeled by the VGG16 filter stack. In contrast, InceptionV3 and ResNet50, although a little more sophisticated in their architecture design and computational efficiency, performed a bit lower on this dataset but still maintained quite competitive test accuracy at 97.43% and 97.93%, respectively. The importance of fine-tuning the pre-trained models became clear as initial experiments with frozen base layers showed a sharp decline in accuracy (>15%), confirming that adapting the learned features to the specific domain of cucumber leaves is crucial for good performance.

The real strength of this method is its high degree of accuracy and automation. This enables rapid diagnosis, making human experts less dependent on the system [24]. By using transfer learning, we can achieve state-of-the-art results even using a reasonably sized, domain-specific data set.

Certain limitations are inherent in this study; the foremost limitation is the size and scope of the data set employed, which covers only two common diseases. Model performance may differ in images obtained under varying real-world conditions (i.e. different lighting conditions or angles) or different disease presentations not appropriately represented in the training data (such as very early-stage symptoms). Future work will focus on expanding the dataset to include more varieties of diseases and severity levels while also investigating the robustness of the model in real-field conditions through implementation in the mobile application [25].

5 Conclusion

The efficacy of deep convolutional neural networks (CNNs) for cucumber leaf disease management has been tested in this research work. By employing cutting-edge developments in deep learning techniques, we have created a solid framework that enables the accurate recognition of particular diseases affecting cucumber plants from their leaf pictures. The results indicate the utility of CNNs for agricultural applications, particularly their promise for applications in plant disease diagnosis.

Based on our findings, we conclude that CNNs can successfully differentiate between these different cucumber leaf diseases, thereby aiding in early diagnosis and treatment. Adopting deep learning to deploy solution mechanisms has helped us avoid issues caused by the conventional detection methods, which include subjectivity and human error.

Apart from that, CNN application on detecting cucumber leaf diseases has great implications for the sustainable world. Farmers will lose less on crops and depend on fewer broad-spectrum chemical treatments by using timely and precise diagnoses that target interventions. The economic sustainability of cucumber production over a longer period would have an environmental conservation implication.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Lutfa, A., Happy, F. A., & Yeasmin, F. (2019). Production process and marketing system of cucumber: A socioeconomic study in Mymensingh district of Pakistan. *SAARC Journal of Agriculture, 17*(1), 135–147. [CrossRef]

[2] Khan, Z., Shah, A. H., Gul, R., Majid, A., Khan, U., & Ahmad, H. (2015). Morpho-agronomic characterization of cucumber germplasm for yield and yield associated traits. *International Journal of Agronomy and Agricultural Research, 6*(1), 1-6.

[3] Szeliski, R. (2010). *Computer vision: algorithms and applications*. Springer Science & Business Media.

[4] Gonzalez, R. C., & Woods, R. E. (2017). *Digital Image Processing*. Pearson Education.

[5] Zhou, B., Xu, J., Zhao, J., Li, A., & Xia, Q. (2015, August). Research on cucumber downy mildew detection system based on SVM classification algorithm. In *3rd international conference on material, mechanical and manufacturing engineering* (*IC3ME 2015*) (pp. 1681-1684). Atlantis Press. [CrossRef]

[6] Lin, K., Gong, L., Huang, Y., Liu, C., & Pan, J. (2019). Deep learning-based segmentation and quantification of cucumber powdery mildew using convolutional neural network. *Frontiers in plant science, 10*, 155. [CrossRef]

[7] Tian, Y., & Zhang, L. (2012). Study on the methods of detecting cucumber downy mildew using hyperspectral imaging technology. *Physics Procedia, 33*, 743–750. [CrossRef]

[8] Pawar, P., Turkar, V., & Patil, P. (2016, August). Cucumber disease detection using artificial neural network. In *2016 international conference on inventive computation technologies* (*ICICT*) (Vol. 3, pp. 1-5). IEEE. [CrossRef]

[9] Youwen, T., Tianlai, L., & Yan, N. (2008, May). The recognition of cucumber disease based on image processing and support vector machine. In *2008 congress on image and signal processing* (Vol. 2, pp. 262-267). IEEE. [CrossRef]

[10] Khan, M. A., Akram, T., Sharif, M., Javed, K., Raza, M., & Saba, T. (2020). An automated system for cucumber leaf diseased spot detection and classification using improved saliency method and deep features selection. *Multimedia Tools and Applications, 79*(25), 18627–18656. [CrossRef]

[11] Zhang, S., Wu, X., You, Z., & Zhang, L. (2017). Leaf image-based cucumber disease recognition using sparse representation classification. *Computers and Electronics in Agriculture, 134*, 135–141. [CrossRef]

[12] Zhang, S., Zhu, Y., You, Z., & Wu, X. (2017). Fusion of superpixel, expectation maximization and PHOG for recognizing cucumber diseases. *Computers and Electronics in Agriculture, 140*, 338–347. [CrossRef]

[13] Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., & Sun, Z. (2018). A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. *Computers and Electronics in Agriculture, 154*, 18–24. [CrossRef]

[14] Zhang, S., & Wang, Z. (2016). Cucumber disease recognition based on Global-Local Singular Value Decomposition. *Neurocomputing, 205*, 341–348. [CrossRef]

[15] Zhang, S., Zhang, S., Zhang, C., Wang, X., & Shi, Y. (2019). Cucumber leaf disease identification with global pooling dilated convolutional neural network. *Computers and Electronics in Agriculture, 162*, 422–430. [CrossRef]

[16] Zhang, P., Yang, L., & Li, D. (2020). EfficientNet-B4-Ranger: A novel method for greenhouse cucumber disease recognition under natural complex environment. *Computers and Electronics in Agriculture, 176*, 105652. [CrossRef]

[17] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278–2324. [CrossRef]

[18] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors, 18*(8), 2674. [CrossRef]

[19] Alginahi, Y. (2010). Preprocessing techniques in character recognition. *Character recognition, 1*, 1-19.

[20] Mia, M. R., Mia, M. J., Majumder, A., Supriya, S., & Habib, M. T. (2019). Computer vision based local fruit recognition. *International Journal of Engineering and Advanced Technology* (*IJEAT*), *9*(1), 2810–2820. [CrossRef]

[21] Habib, M. T., Mia, M. J., Uddin, M. S., & Ahmed, F. (2022). An in-depth exploration of automated jackfruit disease recognition. *Journal of King Saud University-Computer and Information Sciences*, *34*(4), 1200-1209. [CrossRef]

[22] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, *161*, 272-279. [CrossRef]

[23] Mukti, I. Z., & Biswas, D. (2019, December). Transfer learning based plant diseases detection using ResNet50. In *2019 4th International conference on electrical information and communication technology (EICT)* (pp. 1-6). IEEE. [CrossRef]

[24] Lou, Y., Hu, Z., Li, M., Li, H., Yang, X., Liu, X., & Liu, F. (2021, October). Real-time detection of cucumber leaf diseases based on convolution neural network. In *2021 IEEE 5th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)* (Vol. 5, pp. 1040-1046). IEEE. [CrossRef]

[25] Li, R., Su, X., Zhang, H., Zhang, X., Yao, Y., Zhou, S., ... & Lv, C. (2024). Integration of diffusion transformer and knowledge graph for efficient cucumber disease detection in agriculture. *Plants*, *13*(17), 2435. [CrossRef]

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