



Cucumber Leaf Diseases Recognition Based on Deep Convolutional Neural Networks

Muhammad Taimoor Shahid¹ and Muhammad Zohaib^{2,*}

¹Department of Software Engineering, The Islamia University of Bahawalpur, Bahawalpur 63100, Pakistan

²Department of Computer Science, National College of Business Administration & Economics, Bahawalpur 63100, Pakistan

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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*Corresponding author:

✉ Muhammad Zohaib

muhammadzohaib9120@gmail.com

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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. 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. 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. Computer vision is used in the agriculture sector to accurately detect parasites, leaf disease [2, 3], and vegetation while effectively monitoring plant health [4]. 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, Lin et al. [6] proposed a deep learning-based approach for the segmentation and quantification of powdery mildew on cucumber leaves using a convolutional neural network. The method enabled precise delineation of infected regions directly from leaf images, demonstrating that CNN-based architectures are capable of automatically learning discriminative features associated with fungal disease symptoms without relying on handcrafted feature engineering. The proposed framework achieved robust segmentation performance, confirming the strong potential of deep learning techniques for accurate and automated plant disease assessment in agricultural applications. In a related study, Tian and Zhang [7] investigated hyperspectral imaging technology as a non-destructive means of detecting cucumber downy mildew. By analyzing the spectral reflectance characteristics of infected and healthy leaf samples across multiple wavelength bands, the authors identified sensitive spectral features that could effectively distinguish diseased tissue from healthy tissue. Their findings demonstrated that hyperspectral imaging offers a promising and objective alternative to visual inspection for early-stage disease detection, laying a foundation for the development of more automated and sensor-based diagnostic systems in precision agriculture. 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 and Wang [14] used global-local singular value decomposition 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.



Figure 2. Powdery mildew Effect.

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 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.

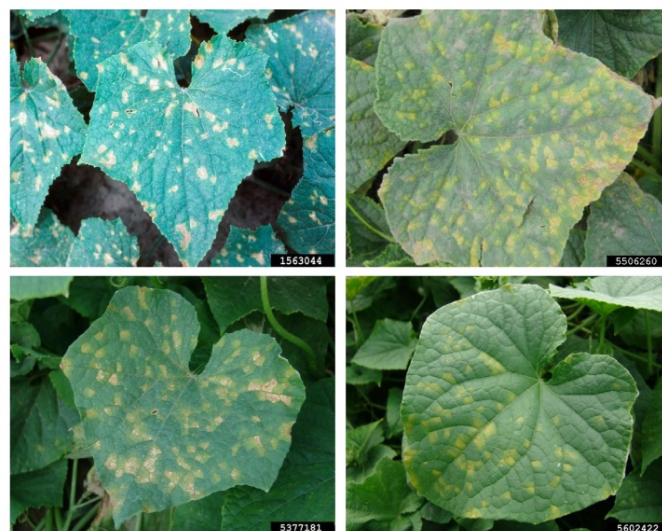


Figure 3. Effect of Downy Mildew.

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

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 underside
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

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

1.7 Causes of Downy Mildew

Downy mildew is another prevalent oomycete disease, caused by water mold pathogens that are distinct from true fungi despite sharing similar infection patterns. 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.

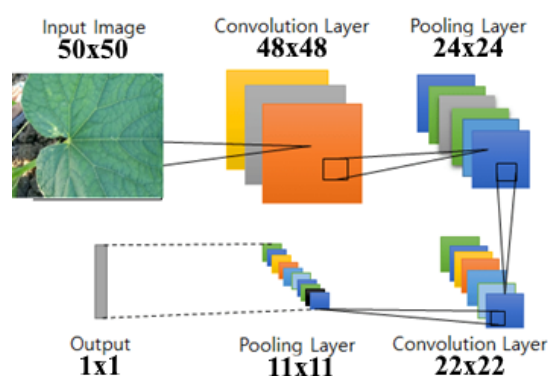
1.8 Symptoms of Powdery Mildew and Downy Mildew

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 machine learning techniques applied to agricultural image analysis have demonstrated strong feature extraction capabilities across diverse crop monitoring tasks [18], and that CNNs in particular have been shown to automatically learn discriminative features from cucumber leaf images for accurate disease classification [19], these approaches are highly suited for plant disease recognition. The general architecture of a typical CNN model is illustrated in Figure 4.

**Figure 4.** General network construction of a CNN model.

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 Swin Transformer. Studies applying VGG16 to cucumber disease image classification have

demonstrated high accuracy, confirming the model's strong feature extraction capability for distinguishing fungal disease patterns in leaf images [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. Swin Transformer-based architectures have been successfully adapted for cucumber leaf disease recognition, demonstrating that hierarchical vision transformers can effectively handle small sample sizes while maintaining high classification accuracy in agricultural settings [21].

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.

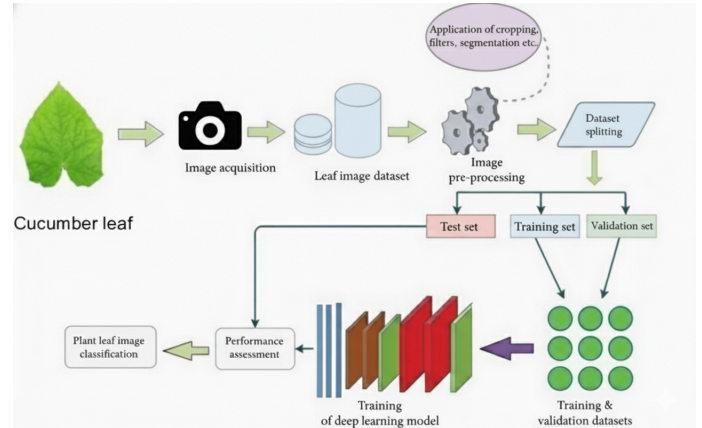


Figure 5. Proposed CNN model architecture.

Inspired by the VGG architecture, we created a custom Convolutional Neural Network (CNN) from the ground up. The model consists of three convolutional blocks with 32, 64, and 128 filters, respectively. Each block comprises a convolutional layer with a 3×3 kernel and ReLU activation, followed by a 2×2 max-pooling layer. A flattening layer then converts the feature maps into a one-dimensional vector of 4,608 elements, followed by two fully connected dense layers with 128 and 64 units and ReLU activation, with a dropout rate of 0.5 applied after the first dense layer to mitigate 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

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

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, with class sizes ranging from 1,430 to 2,170 images. To partition the data, a fixed 70% of each class was allocated for training and the remaining 30% for testing, applied independently per class to maintain proportional representation. The resulting distribution is detailed in Table 3. Note that rounding to whole numbers results in minor per-class deviations from the exact 70/30 ratio (within one image per class), which has negligible effect on model evaluation.

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

Class Name	Total Images After Augmentation	Training Images	Testing Images
Healthy	1800	1260	540
Downy Mildew	2170	1520	650
Powdery Mildew	1430	1000	430

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.

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.

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

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

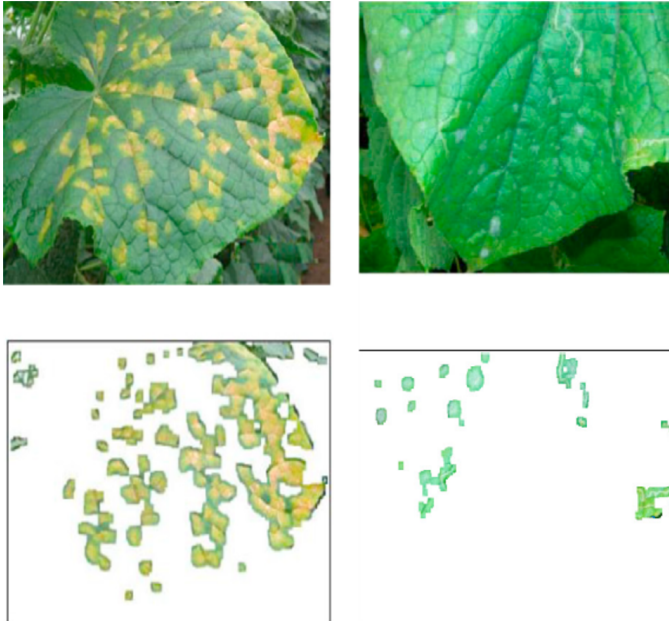


Figure 6. Images of powdery mildew (right) and downy mildew (left) are examples of pre-processed and augmented images. While segmentation and color normalization were used in pre-processing to separate the leaf and disease spots, augmentation techniques included flipping and rotation.

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 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, enabling rapid diagnosis

that substantially reduces dependence on human expert intervention. Real-time CNN-based detection systems for cucumber leaf diseases have demonstrated the practical feasibility of such automated pipelines in agricultural settings [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. Advanced frameworks integrating complementary knowledge representations with deep learning architectures offer a promising direction for further improving detection accuracy and generalization in complex agricultural environments [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.

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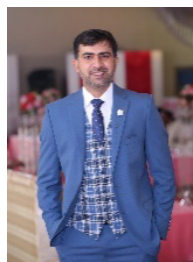
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Muhammad Taimoor Shahid received his bachelor's degree in software engineering from The Islamia University of Bahawalpur. His research interests lie in Software Engineering (SE), Artificial Intelligence (AI), Machine Learning (ML), Natural Language Processing (NLP), Computer Vision and Deep Learning, with a particular focus on developing and applying computational techniques to solve real-world problems. His work aims to

bridge the gap between theoretical research and practical implementations, driving innovation in AI technologies. (Email: chtaimoor943@gmail.com)



Muhammad Zohaib received his MPhil degree in Computer Science from the National College of Business Administration & Economics Bahawalpur. He received his bachelor's degree in computer science from University of Engineering and Technology Lahore. His research interests lie in Artificial Intelligence (AI), Machine Learning (ML), Deep Learning, Natural Language Processing (NLP), and real-time AI applications. He

is passionate about improving machine learning algorithms to enhance natural language understanding and image processing capabilities. (Email: muhammadzohaib9120@gmail.com)