agronomy

Review

Leveraging Convolutional Neural Networks for Disease Detection in Vegetables: A Comprehensive Review

Muhammad Mahmood ur Rehman [1], Jizhan Liu [1,2,*], Aneela Nijabat [3], Muhammad Faheem [4], Wenyuan Wang [1] and Shengyi Zhao [1]

[1] School of Agricultural Engineering, Jiangsu University, Zhenjiang 212013, China; mmrehman@ujs.edu.cn (M.M.u.R.)
[2] National Digital Agriculture Equipment (AI & Agribot) Innovation Sub-Center, Zhenjiang 212013, China
[3] Department of Botany, University of Mianwali, Mianwali 42200, Pakistan
[4] Department of Farm Machinery and Power, University of Agriculture, Faisalabad 38000, Pakistan
* Correspondence: liujizhan@163.com

Abstract: Timely and accurate detection of diseases in vegetables is crucial for effective management and mitigation strategies before they take a harmful turn. In recent years, convolutional neural networks (CNNs) have emerged as powerful tools for automated disease detection in crops due to their ability to learn intricate patterns from large-scale image datasets and make predictions of samples that are given. The use of CNN algorithms for disease detection in important vegetable crops like potatoes, tomatoes, peppers, cucumbers, bitter gourd, carrot, cabbage, and cauliflower is critically examined in this review paper. This review examines the most recent state-of-the-art techniques, datasets, and difficulties related to these crops' CNN-based disease detection systems. Firstly, we present a summary of CNN architecture and its applicability to classify tasks based on images. Subsequently, we explore CNN applications in the identification of diseases in vegetable crops, emphasizing relevant research, datasets, and performance measures. Also, the benefits and drawbacks of CNN-based methods, covering problems with computational complexity, model generalization, and dataset size, are discussed. This review concludes by highlighting the revolutionary potential of CNN algorithms in transforming crop disease diagnosis and management strategies. Finally, this study provides insights into the current limitations regarding the usage of computer algorithms in the field of vegetable disease detection.

Keywords: deep learning; vegetables; disease detection; early identification

Citation: Mahmood ur Rehman, M.; Liu, J.; Nijabat, A.; Faheem, M.; Wang, W.; Zhao, S. Leveraging Convolutional Neural Networks for Disease Detection in Vegetables: A Comprehensive Review. *Agronomy* **2024**, *14*, 2231. https://doi.org/10.3390/agronomy14102231

Academic Editors: Gniewko Niedbała and Yuxing Han

Received: 31 July 2024
Revised: 27 August 2024
Accepted: 22 September 2024
Published: 27 September 2024

1. Introduction

The world's population is expected to be 10 billion by 2050 [1]. To feed this large number of people, we need a higher production rate with a lower yield loss. The most important thing after planting seeds in the soil is to take care of the crop. If one plant is affected by a contagious disease, then all the harvest will be lost. Vegetables are sensitive, perishable, and vulnerable to various diseases, which cause a huge economic loss as compared to other food crops. This is why early disease detection in plants and particularly in vegetables is the most crucial part of a good harvest [2]. In the past, detection was carried out using only a manual method where one had to compare and identify different samples of affected and unaffected samples of a plant and describe the severity of the attack. This process was not very accurate and took a lot of time. In this new era of technology, computers have much more to offer in plant disease detection. However, the effectiveness of this detection completely relies on the collection of data [3]. The present technologies that work with computer vision are based on spots on leaves and fruits. These are the primary keys for analyzing information about the disease in the plant [4]. It is quite clear now to all agro-ecologists that a plant disease affects the photosynthesis ability of the plant, therefore affecting growth and fruit production [5,6]. Most plant diseases, almost 85%, are caused by fungal or fungal-like organisms. In some other cases, it can be bacteria, viruses, viroid species, and some specific Nematodes [7,8]. The main problem with these diseases is that they are revealed in the last stage of infection or the middle stage when little can be done to protect the crops [9]. The data collected from the U.S Environmental Protection Agency, UNECE, and the website of the Government of Alberta has resulted in the below chart (Figure 1), which indicates the loss of vegetables due to diseases every year [10].

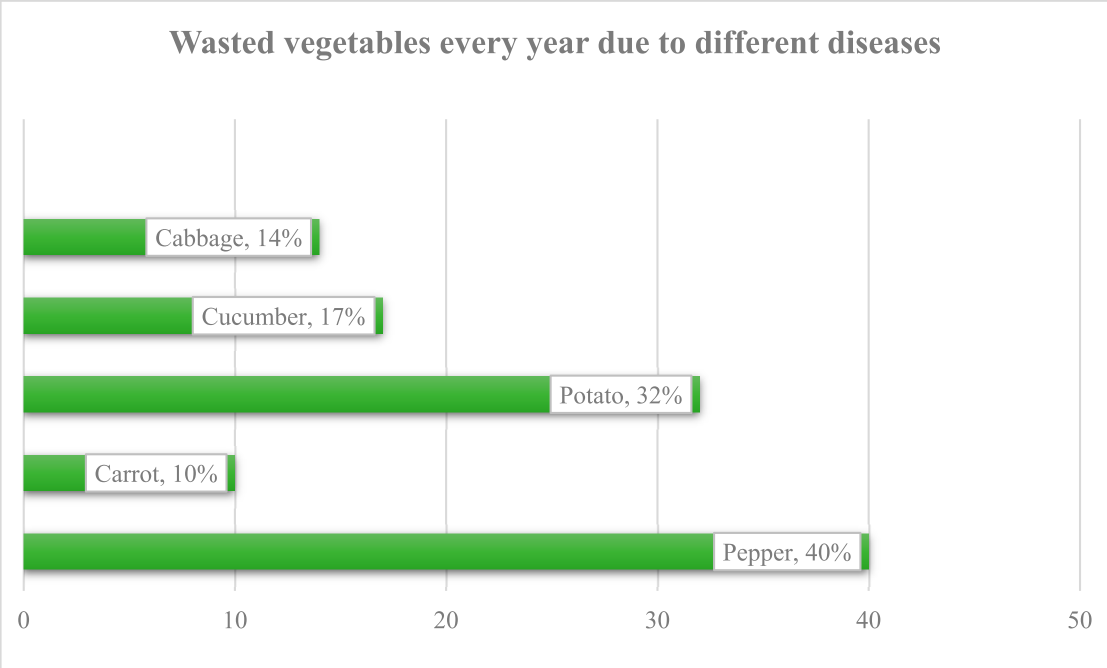


Figure 1. Percentage of vegetable wasted every year due to disease attacks (average data from 2009 to 2020).

In herbaceous plants, e.g., vegetables, the early detection of disease is of paramount importance [11,12]. Crops like cabbages and strawberries as well as vegetables with a thin layer of cellulose on their outer surface are prone to rot if any contagious diseases are caught. These diseases affect their skin and reduce photosynthesis in their leaf, which causes the deformation of crops. By the early detection process, the spreading of contagious diseases can be controlled to some extent [13]. Images of different affected parts can be analyzed using CNNs [14], and the severity of the attack can be inferred. Dechant et al. tried to draw a map of maize disease using different CNN models in combination [15]. The most commonly used dataset is Plant Village [16]. In most research, VGG (Visual Geometry Group)–CNN [17] models were used to determine blight in radish with k-mean clusters to express disease markers [18]. The results indicated that this model can be used in the detection of different crop diseases including those in tomato, tobacco, banana, etc. [19]. Normally, the whole leaf is considered or analyzed to identify the disease. Figure 2 indicates all the steps involved in the process of disease detection. A different approach was taken in other research, where individual lesions were taken into consideration and the DL model was used to identify the disease [20]. The DL model was first introduced in 1943 and went through three specific stages of development. The first generation of neural networks was introduced in 1943 as a linear model that could only deal with limited data [21]. The ReLU (Rectified Linear Unit) [22] model, introduced in 2011, could effectively deal with the gradient disappearance problem; this was more effective when AlexNet was introduced in 2012 [23]. From that moment on, CNNs have gained much more attention among scientists [24,25]. There has been much more development since then in this field of research. Some of the causes of plant diseases are shown in Figure 2. This hierarchy was developed from the ideas generated by [26].

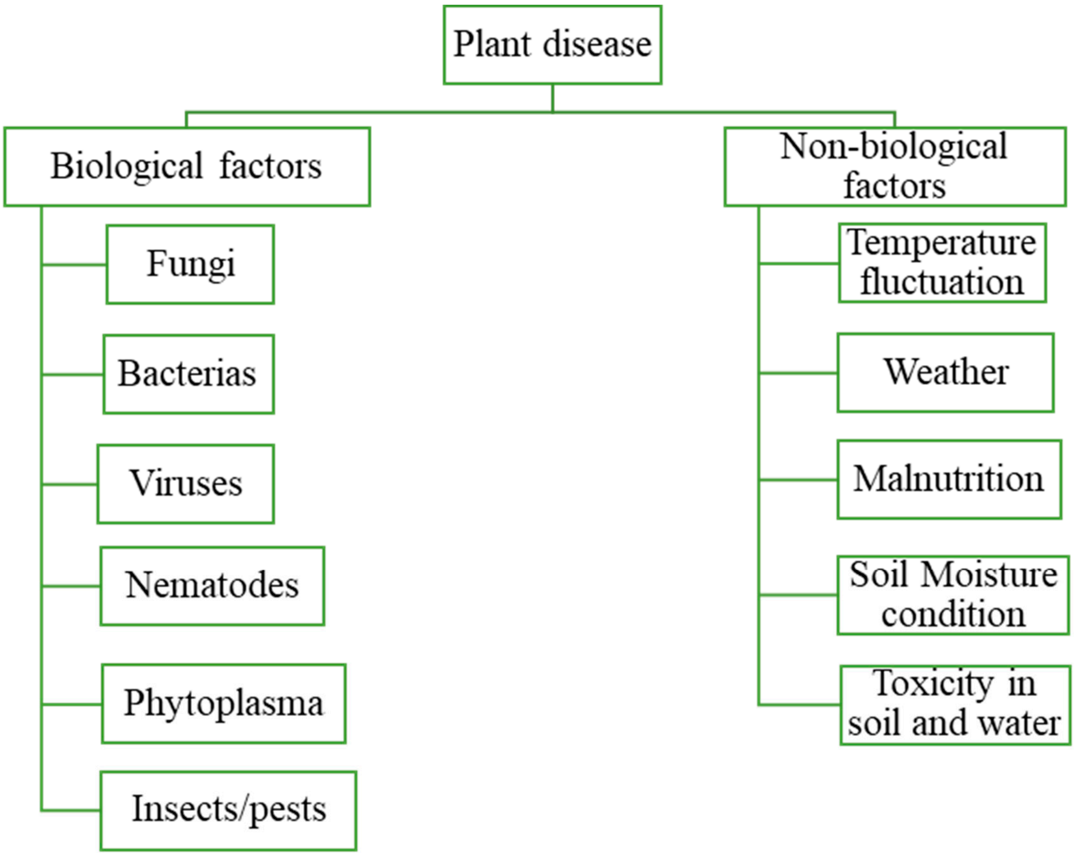


Figure 2. The factors that affect plant diseases, modified from [26].

The purpose of this review is to highlight and understand the latest research. If the current problems are addressed effectively, then the field of CNNs can grow in the identification of vegetable diseases more effectively [27]. This review analyzes some of the recent research from 2015 to 2024 on vegetables: so, all the information here is the most up to date compared to any other research in previous years. Some other articles from the last decade of the 20th century have been used for basic data presentation. The focus of the review is to provide insight based on the data that have been discussed in recent detection algorithms to find patterns in different models' accuracy. The review aims to provide a clear idea about different models to help future researchers to decide which models should be prioritized. This review focuses on answering questions about different models' efficiency on different vegetable crops. If further studies are conducted based on this research, then more accuracy can be achieved, and researchers would not have to waste time on models that have become obsolete. The review is structured in the following way: Introduction to deep learning: this section provides a short overview of DL technology and some frequently used models and algorithms such as EfficientNet, VGG16, ResNet50, MobileNet, and InceptionV3. After that, the Methodology section describes the steps and processes that have been used to collect and analyze the data for the review. Different CNN models are important in disease detection in vegetable plants, including some of the most popular vegetables that are being monitored for data collection. Data from different studies have been used to make predictions and form patterns. Based on the analysis, the Future Perspectives and Research Gaps section is produced, where most of the limitations of recent research have been included so that the reader can identify them effortlessly. The study, concludes with possible recommendations for future research. This is the first review that highlights the use of CNN techniques for disease detection in particular perishable vegetables and concludes with the most recent findings and limitations of CNN algorithms in vegetable disease detection.

2. Methodology

Like all the other reviews in different research fields, this review focuses on the recent progress of CNN application in the field of agriculture and specifically on vegetables. After carefully reviewing more than 300 papers on the matter, around 200 papers were selected to represent the data. The primary concern of this research was to focus on the accuracy percentage of different CNN models in the field of agriculture. Most importantly, this review reports most of the recent work that was conducted in the context of vegetable disease detection. The review comprises data collected from different prominent journals in the field of digitalization of agriculture engineering. *Computer and Electronics in Agriculture*, *Journal of Plant Pathology*, *Agriculture*, *Frontier in Plant Science*, and *IEE* are some of the major journals that provided the data for this review. All the vegetable images are collected from the PlantVillage database/platform.

At the initial stage, keywords were chosen to collect relevant research. CNN, CNN in disease detection, the role of CNN in vegetable disease detection, etc., are some of the keywords that were used for data collection. The search was made mostly through Google Scholar, as well as IEEE and some other research databases. We tried our best to produce the review according to recently provided data in this field. So, the search results were filtered by 2015–2024, but some exceptional cases appeared as some explanations were needed to provide a strong background for the research. That is why some data were taken from articles published in the late 20th century.

Figure 3 represents the percentage value of every model used in vegetable disease detection. A total of 258 occurrences were found in the almost 200 research articles that were used in this review. All the papers were studied to find the uses of each model in every article. The most frequently found model was VGG and the least was DenseNet. The other models that we see in the chart are a combination of different models that had too small contributions individually in the articles that were reviewed. Some of these models are FCNN, ReLU, Global Pooling, Dilated CNN, YOLO (You Only Look Once), ACNN (Active Control Neural Network), k-means clustering, Naïve Bayes, EFDet (Efficient Detection Model), DCNN, RBFN (Radial Bias Function Network), and Pearson Correlation Coefficient. These models were not exactly used on a primary basis but were combined with GoogleNet, MobileNet, AlexNet, or VGG models.

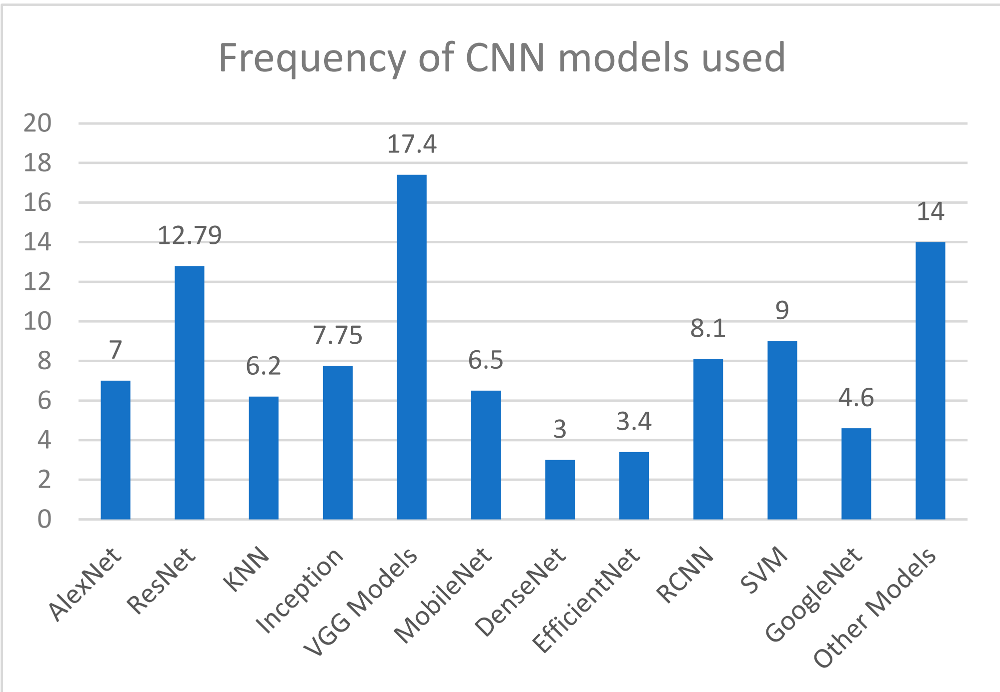


Figure 3. The percentage of uses of models in different studies reviewed.

In Figure 4, we have summarized almost 200 papers to produce this chart according to different models. The figure depicts more than 7 models used very frequently in the detection of more than 9 vegetable diseases. The vegetables include bitter gourd, cabbages, carrot, brinjal, and cauliflower, where the model showed 90.05% accuracy. It is known that the availability of more data is more beneficial for accuracy detection. As can be seen in Figure 4, tomato has more sources of data, and it has shown remarkably better testing accuracy. This applies to all the other vegetables that are reviewed in this paper.

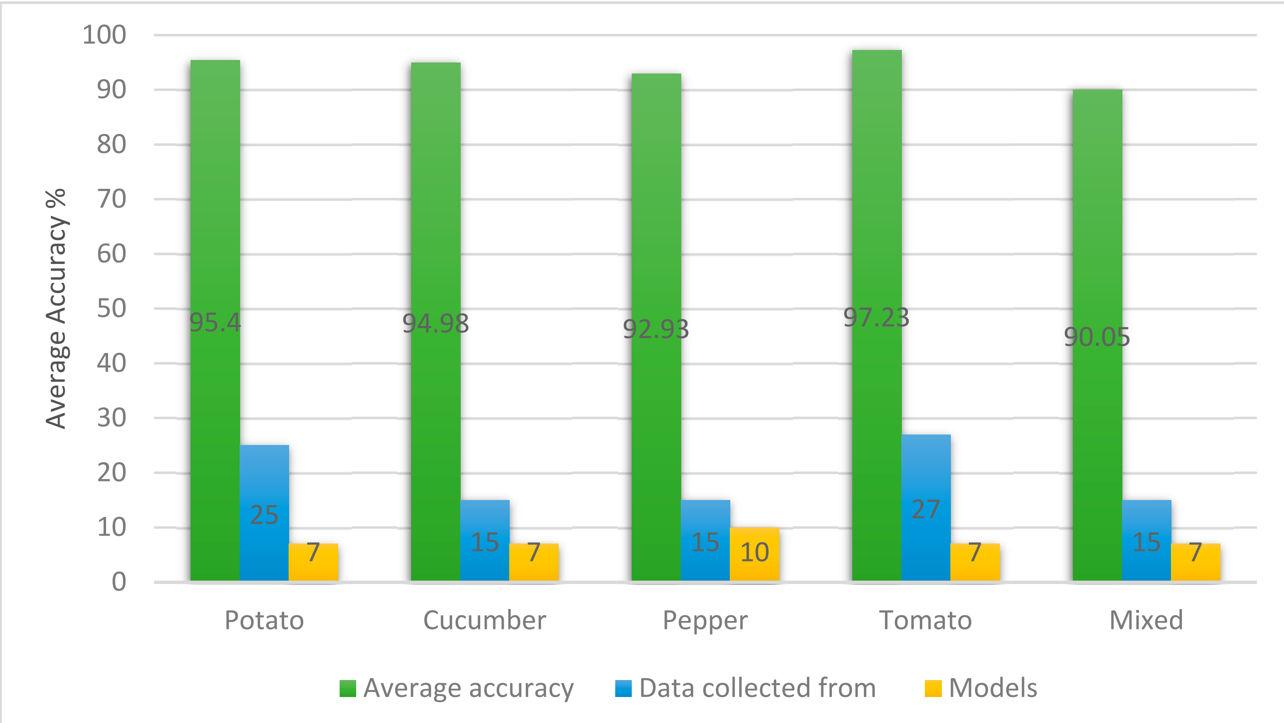


Figure 4. Disease detection accuracy among various models and plant types in reviewed papers.

CNNs have recently become very popular among researchers due to their versatility in the field of science. The main purpose of choosing CNNs as the primary focus is to provide a clearer insight into CNN architectures and the models that are closely related to this field. Convolutional networks have more stability and reliability in image detection, which is the main purpose of vegetable disease detection. The performance of these models has become so remarkably efficient that they can reduce the loss of crops to some extent. Other models such as VGG, Inception, Resnet, EfficientNet, MobileNet, etc., have been prioritized due to their ability to detect diseases with almost 100% accuracy.

The performance of a model is dependent on the number of images that have been fed through it. The more images it identifies successfully, the more accurate it becomes. This review will focus more on the models that are used in this field. The detailed uses and performance will be discussed in detail for the detection of different plant diseases.

We approached this research with 5 questions in mind:

- What is the role of CNNs in disease detection and their performance?
- Are enough data available to research vegetable diseases?
- What are the contributing models that can add value to the uses of machine learning technology in the field of agriculture?
- What is the current status of efficiency in disease detection through machine learning?
- What are the problems and limitations faced by the researchers community?

We have discussed most of the points thoroughly in relation with the vegetables and models. By the end of the review, the limitations of previous research are partially identified. The availability of data sources is also discussed, and it was found that the most convenient database was Plant Village. Results produced from self-collected data might provide better insights, but not all self-produced data are publicly accessible, so it is hard to assume based on someone's model just by seeing the results.

2.1. Introduction to DL

As one of the most reputable interdisciplinary fields within artificial intelligence, specifically in DL, CNNs are considered advanced structures for various tasks in computer vision. Compared to alternative networks, CNNs demonstrate superior performance in this domain. One of the most distinguishing features of CNNs is their ability to achieve invariance, enabling comprehensive image perception. Even when dealing with images that contain diverse attributes, CNNs can still effectively recognize them [28]. CNNs utilize convolution to extract features through a specific-sized kernel [29]. This kernel operates with predetermined strides, dictating the intervals used in the architecture's execution to generate a feature map. Following this, a pooling process is employed to reduce the size of the feature map. Eventually, the image undergoes flattening and conversion into either a fully or partially connected layer. Then, a classification layer is utilized to classify the image, determining its probability of belonging to predefined classes (Figure 5).

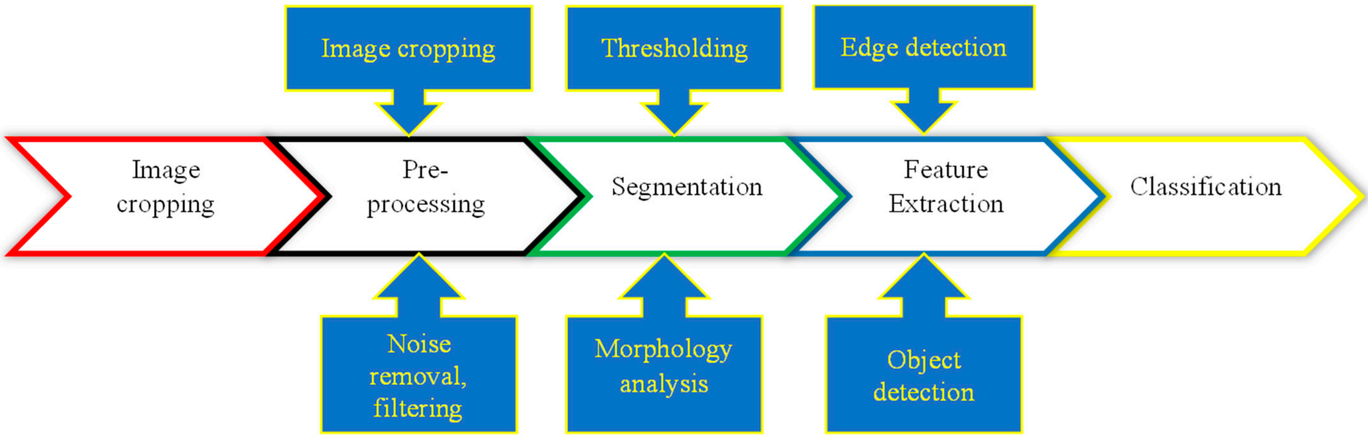


Figure 5. The process flow of image recognition using CNN architecture.

The model draws ideas through statistics, information theory, philosophy, control theory, and probability [30]. The model's main purpose is to identify patterns. The most fascinating feature of this model is that it can learn from the environment and the data it has been given. In a nutshell, it is a technology that learns through trial and error with or without a teacher [31]. The application of DL in agriculture was introduced very recently [32]. DL models such as CNNs can learn very quickly and make an output swiftly [33]. Previously, plant disease detection was conducted by humans, which was accomplished by just seeing and comparing diseased leaves and healthy samples. The precision of CNNs in image processing and pattern recognition is beyond comparison to human decision-making skills [34,35]. This algorithm recognizes images through a process that is considered a mimic of human action. Technology copies human nerves by linking one neuron to another. The neurons have some parameters like weight, bias, and initiation function for image recognition. The algorithm is structured in two layers: one for feature extraction and another for making decisions, which comprises connected nodes [36].

Another CNN model is known as Deep Convolution Neural Network or DCNN. The model extracts high-dimensional features with more precision [37]. The model comprises two stages of networks such as Region CNN [38], fast RCNN [39], and Faster RCNN [40]. FSNet was introduced by Zhang et al. for fungal spore detection during the storage process of grains [40].

2.1.1. Efficient NET

EfficientNet comprises a series of CNNs highly regarded for their outstanding performance in comparison to other models. The set includes eight distinct models, designated from B0 to B7. As the model number increases, both the number of parameters and prediction accuracy also increase [41]. One notable advantage of EfficientNet is its ability to achieve exceptional results while conserving time and computational resources, outperforming many existing models. This efficiency is achieved through a smart strategy known as intelligent scaling, which involves adjustments in depth, width, and resolution. An important aspect of EfficientNet is its support for EDGE-enabled devices and mobile phones for DL tasks. A compound scaling technique is employed to uniformly scale the networks' resolution, depth, and width using a compound coefficient (φ) in a well-established manner. This method facilitates the efficient and effective deployment of DL models across a diverse range of devices.

2.1.2. VGG19 (Visual Geometry)

This is an architecture that has gained a lot of interest among researchers. It is renowned for its exceptional performance and image processing capability. The model consists of 19 layers in total. The design is made with a very elaborate pattern. The architecture is made up of 3×3 convolution layers on top of one another with a stride of 1. After that, there is a max pooling layer with a window size of 2×2; in this structure, the stride is 2 [42]. The model is trained with a cross-entropy function and optimized by stochastic gradient descent. The main strength of this model is its simplicity and uniformity. The model can easily interpret data with a high requirement for resources and memory capacity [43].

2.1.3. ResNET50

This model is popular because of its residual learning ability [44]; the model was developed by Microsoft Corporation. The algorithm of this architecture consists of 50 layers. Residual information is distributed in the layers of the network and thus, it solves the issue of vanishing gradients, which facilitates training in much deeper networks. The layers contain multiple convolutional sub-layers, which helps skip connections that bypass one or multiple layers at a time. The architecture also includes some fully connected layers, average pooling, and a SoftMax output layer for classification. It has gained such exceptional features because of its ability to be trained in a deep network [45].

2.1.4. MobileNet

This is another CNN model capable of precise calculations, and it can be used in mobile phones [46]. The model depends on much fewer resources due to its lightweight algorithm and functionality. It is more accurate than most other CNN models but cannot handle a large amount of data [47]. The depth-wise separable convolutional layers are the most creative part of this model. The model is characterized by the application of a mono filter to each input channel autonomously. Then, there is a point-wise convolution followed by a 1×1 convolution to merge the depth-wise convolution results. MobileNet performs better because of this architecture while maintaining a reasonable level of accuracy and efficiency. As the version of the model is updated, the performance increases significantly. The model MobileNet gained much popularity because of its efficiency in architecture [48]. This is not only limited to computers or mobile phones; it can be embedded in many other devices. It can operate easily on any device because of the lightweight algorithm and resource requirements [49].

2.1.5. Inception V3

The CNN model has been extensively used for image recognition tasks. The model has been trained with the ImageNet dataset and achieved good accuracy in the training period. The architecture of this model consists of multiple layers of convolutional, pooling, and activation functions [50]. Inception modules are included, which facilitates the network to learn for feature application on a higher scale. The training efficiency is increased by batch normalization and factorized 1 × 1 convolutions. The model is also designed to be convertible to different tasks and datasets, making it more reliable and useful in transfer learning [51].

3. Importance of Different CNN Models in Disease Detection of Vegetable Plants

3.1. Potato

Potato is the most consumed vegetable in the world and probably the highest produced crop in the world after rice and wheat. So, with a high amount of production and consumption, potato holds many vulnerabilities towards disease and pests. A proposition for utilizing DL in the detection of potato leaf diseases is suggested in [52,53]. Sofuoglu et al. suggested a deep learning model to predict potato leaf disease from images. The model was based on convolutional neural network architecture. The methodology applied filters to the images provided and then extracted the notable features. It also reduced the dimension of the images while preserving some important information about the sample. The predetermined resolution was 256 × 256 pixels. Then, the images were fed through a circle of Conv2D, ReLU, and MaxPooling2D. The final step was performing classification using the softmax activation function, and the highest probability and result were calculated through dense_1 [26]. The accuracy found in this research was remarkably better (98.28%) than other research (89.67%). In another study, the accuracy was found to be between 99 and 100% in some classes. The classes were Healthy, Black, Scurf, Common Scab, Black Leg, and Pink Rot. The research suggested a model similar to a pre-trained model such as VGG19 [53]. Another method employing DL was introduced for the classification of diseases affecting potato leaves [54]. Potato leaf blight stands out as a highly destructive plant ailment on a global scale [55], significantly impacting the yield and quality of potato crops and posing substantial challenges to individual farmers and the agricultural sector. The dataset used for training encompasses three distinct categories of potato leaves: those deemed healthy, those afflicted with early blight, and those with late blight. The proposed model achieved an impressive mean testing accuracy of 98% [56]. DL finds application across various domains such as image classification, object detection, semantic segmentation, and image retrieval, with its adoption steadily on the rise [57]. Table 1 indicates the accuracy of different studies that were conducted using various methods for disease detection.

Table 1. The accuracy percentage of different methods of disease detection in different parts of potato.

Detection Type	Method	Data Source	Dataset Size	Accuracy	Ref.
Alteralia Solaris, Pytophora infestans	DL, transfer learning	Plant Village	50,000	94.94%	[58]
Overall yield prediction	R-CNN	Self-collected	12,000	90.8–93.0%	[59]
Early blight	SVM and PLS-DA	Self-collected	32	92%	[60]
Surface bump detection	CNN	Self-collected	296	86.6%	[61]
Surface health detection	ABC, BUZO, PSO, DT, SVM	Self-collected	200	88.83%	[62]
Overall potato defects	LS-SVM	Self-collected	417	90.70%	[63]
Common scab	GA PLS	Self-collected	140	99%	[64]
Potato grading	Fuzzy C-mean	Self-collected	100	95%	[65]

Table 1. *Cont.*

Detection Type	Method	Data Source	Dataset Size	Accuracy	Ref.
Skin injury	LS-SVM (LeastSquare Support Vector Machine), BLR (Binary Logistic Regression)	Self-collected	120	90%	[66]
Defect detection	Fuzzy logic, GA	Ardabil, Iran	500	88.10%	[67]
Overall potato grading	MLP, SVM, RBF	Ardabil, Iran	50 bags	95%, 96%, 86%	[68]
Blight detection	CNN, SoftMax	Plant village	1000	99.53%	[69]
Blight	Mask R-CNN	Self-collected	1423	98%	[70]
Blight	GoogleNet, VGGNet, EfficientNet, PyTorch	Self-collected	5199	94%	[71]
Blight	AlexNet, VGGNet, ResNet, LeNet and Sequential model	Kaggle, Dataquest and Self-collected images	3000	97%	[72]
Early blight	Random Forest	Plant Village	450	97%	[73]
Late blight	ShuffleNetV2	Potato Leaf Disease Dataset	7039	94%	[74]
Overall leaf disease	SVM, CNN, VGG16	Self-collected	-	CNN-98%	[75]
Blight diseases	PLDPNet	Plant-Village	10 classes	98.66%	[76]
Target spot, Lycopersicon, Tuberosum, Capsicum Annuum	Night-CNN	Plant Village	50,000	95.23%	[77]
Dry rot diseases	Ann, SVM	Self-collected	25	97%	[78]
Late blight	CropdocNet	Self-collected	34 groups	95.75%	[79]
Potato leaf diseases	SVM, k-means cluster	Plant Village	54,306	95.99%	[80]
Potato blight	YOLOv5	Plant Village	4062	99.75%	[81]
Scab, Black Scurf	CNN, MatLab	Self-collected	400 Potatoes	95.85%	[82]

Sadiq et al. have developed different approaches with a range of models to detect potato leaf diseases. Four models were trained to perform disease tests on the potato plants. VGG16, EfficientNet B4, Inception V3, and Inception resNetV2 all models were trained using a comprehensive dataset consisting of both healthy and unhealthy potatoes. The EfficientNet B4 model showed more efficiency than all the others in this case 100%. The VGG16 showed 99%, Inception V3 98% and Inception ResNet V2 [83] at 94% [84]. Another group of researchers devised the same models for their research on cotton leaves and found the accuracy to be 98.53%. Which is almost as efficient as the previous one mentioned [85].

Verma et al. found the efficiency to be 97% when a combination of libraries/algorithms such as Keras, ReLu, and finally SoftMax was used to achieve maximum likelihoods. The training tool "Adam" was used to optimize the results. This increases the learning rate and decreases the understanding time [86]. There are some common potato diseases which are mentioned in Figure 6.

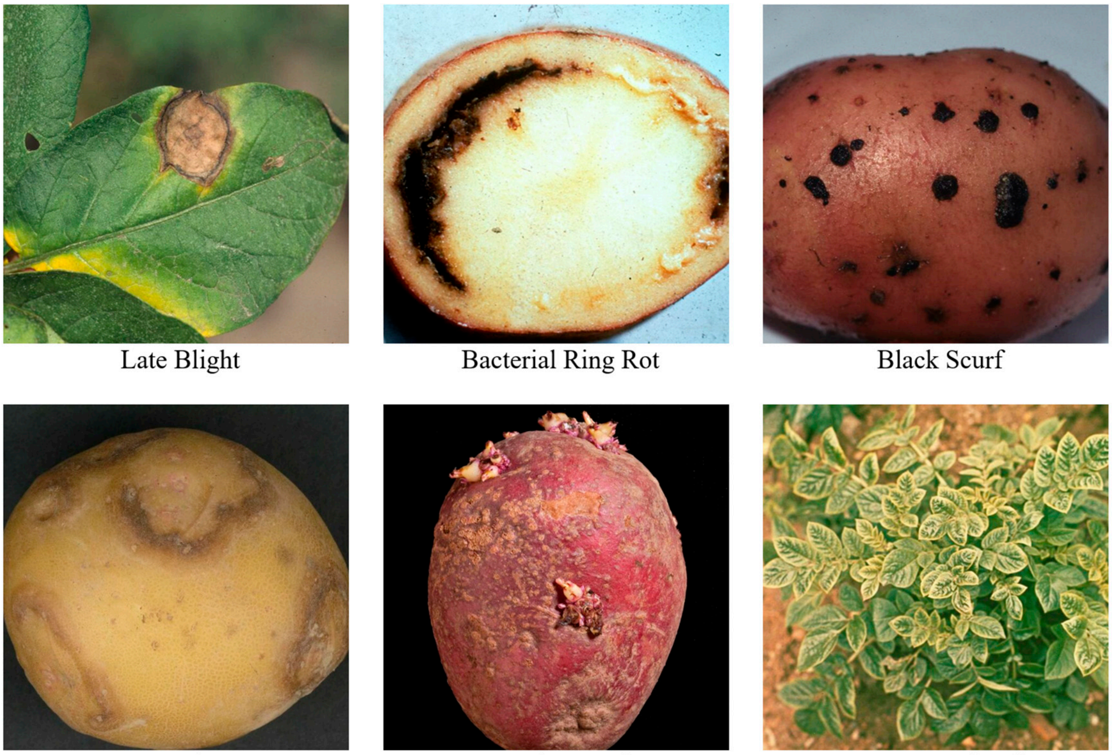


Figure 6. Some of the most common potato diseases.

3.2. Cucumber

Cucumbers are one of the most important crops for humans yet are not safe from bacteria and diseases caused by other microorganisms. Some diseases are responsible for making crop production to be reduced by 30–40%. Powdery Mildew (PM) predominantly impacts cucumber during its later growth stages, leading to considerable yield loss [87]. *Podosphaera xanthii* (*P. fusca*) and *Erysiphe cichoracearum* are the primary culprits behind this disease. They initially target lower parts of the plant due to their preference for shaded areas, manifesting first on older leaves [88]. Abundant conidia are produced within the powdery mycelium, facilitating rapid spread via wind to neighboring foliage or plants, capable of traveling considerable distances and remaining viable for up to 7–8 days [89]. Symptoms manifest as circular white powdery patches on both the upper and lower leaves [90,91]. Disease development occurs within a temperature range of 27–35 °C and relative humidity exceeding 70%, with visible symptoms appearing 3–7 days after initial infection [92,93].

A bit of difference can be seen between the detection of diseases in potato and cucumber. The algorithms that are used in potatoes are not all suitable for cucumbers as the plants are a bit different from each other. Researchers conducted a comparative examination of six pre-trained DL architectures, VGG16, VGG19, ResNet50, ResNet101, InceptionV3, and Xception, for identifying diseases in cucumber plants [94]. Figure 7 shows some examples of leaves with different diseases [95].

The pre-trained models underwent fine-tuning via transfer learning and were assessed based on various metrics including training accuracy, testing accuracy, and epoch count. The findings revealed that VGG16, despite its relatively smaller layer count, outperformed the other models across all evaluation criteria. Specifically, VGG16 achieved a testing accuracy of 98% and a training accuracy of 99.91% after eight epochs. Moreover, it was noted that models with more layers, such as ResNet50 and ResNet101 [96], displayed fluctuations in accuracy during training, likely due to their large size relative to the dataset [97]. Xu et al. represented their research as a bit different from most others. They found strong positive associations between greenness and spectrum in specific bands. Analysis of disease spot images and classification revealed a direct relationship between disease severity in leaves, spectral reflectivity, and fluorescence intensity. Enhancement techniques such as MSC and SPA improved the R2 of the NIR spectrum to 0.8742 in the quantitative prediction model, although the fluorescence spectrum model yielded less satisfactory results. Qualitative discriminant models employing KNN and ensemble subspace discriminant methods achieved an identification accuracy of 97.5% after validation for both spectra types [98]. Table 2 shows some of the recent research in disease detection with the help of different models and summarizes the accuracy and size of the sample, which means the number of images analyzed and the source of the collected images.

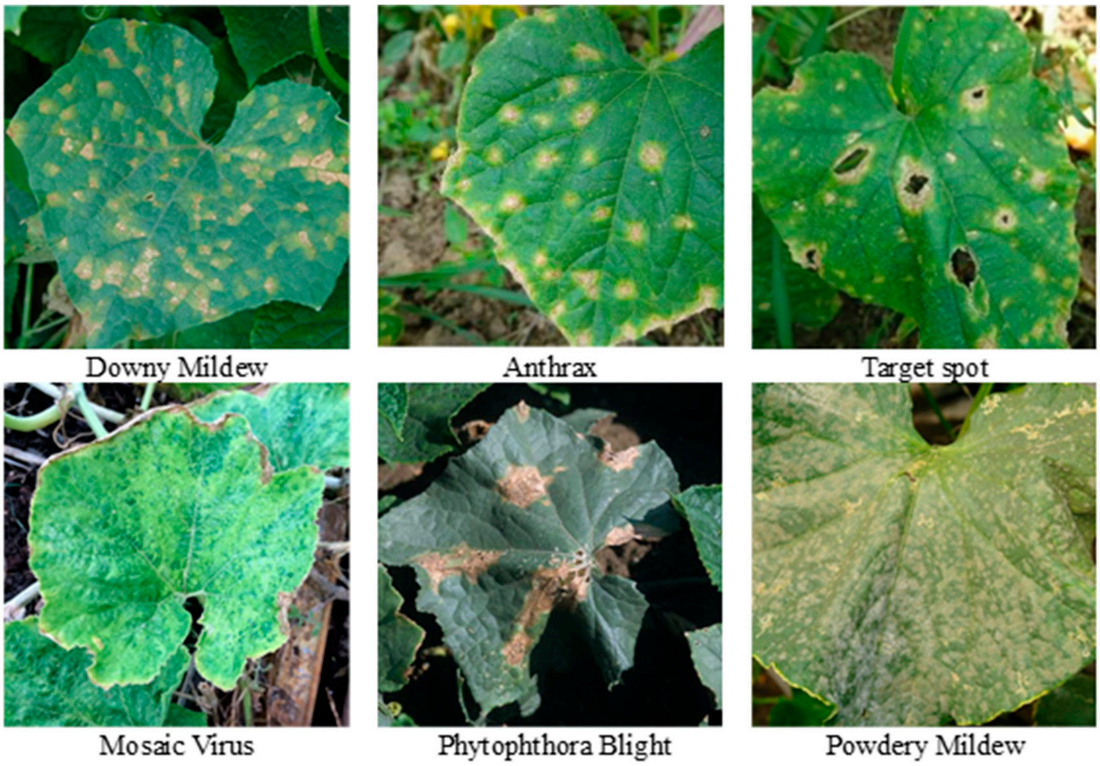


Figure 7. Different leaf diseases of cucumber, modified from [95].

Table 2. Summary of recent research in cucumber disease detection.

Number of Diseases Analyzed	DL Models	Data Source	Sample Size	Accuracy (Max)	Ref.
Fungal diseases	Residual Next-50, YOLO Net V5, KNN	Self-collection from multiple farms	35,000	97.81%	[99]
Downy and Powdery Mildew	DA, SVM, KNN	Collected from two greenhouse	931	SVM—96% KNN—95.8% DA—92.8%	[100]
Leaf diseases (Angular Spot, Powdery Mildew, Downy Mildew, blight, Anthracnose)	ES-KNN F-KNN C-SVM Q-SVM ESD MG-SVM W-KNN EB-Tree	Self-collected	339	ES-KNN—95.2% F-KNN—94.6% C-SVM—95.6% Q-SVM—94.9% ESD—64.2% MG-SVM—93.3% W-KNN—87.1% EB-Tree—89.4%	[101]
Anthracnose, Powdery Mildew, Downy Mildew, Angular Spot, mosaic, and blight	VGG16, ResNet50, ResNet101, and DenseNet201	The Cucumber Leaf Diseases Scan Dataset	2000 in every class	VGG16—93.8% ResNet50—94.6% ResNet101—97.7% DenseNet201—98.50%	[102]

Table 2. *Cont.*

Number of Diseases Analyzed	DL Models	Data Source	Sample Size	Accuracy (Max)	Ref.
Mildew diseases	MATLAB	Tokat Gaziosmanpaşa University Agricultural Applications and Research Center	200	Determination coefficient (R2 = 0.995, $p < 0.01$) Pearson's correlation coefficient (r = 0.997, $p < 0.01$)	[103]
Powdery Mildew and Downy Mildew	YOLO v4	Vietnam National University of Agriculture (VNUA).	7640	80.76%	[104]
Downy Mildew, anthrax, and Powdery Mildew.	MTC-YOLOv5n	Self-collected	374	84.9%	[105]
Downy Mildew, Bacterial Angular Spot	YOLO V3-V5 EfficientDetD1 YOLO V3-ASFF	Xiaotangshan National Precision Agriculture Research Demonstration Base in Beijing	7488	85.52%	[106]
Umbilical rot, gray mold, spotted fly, Anthracnose, target spot	YOLOv5s CSP FPN NMS	Self-collected	1000	93.1%	[107]
Pests and diseases	PD R-CNN	Self-Collected	10,000 in every class	91.51%	[108]
Leaf diseases	KNN	Self-collected	1262	Ex1-94.30% Ex2-94.50% Ex3-94.2%	[109]
Downy Mildew	DeepLabV3+ U-Net	Xiaotangshan National Precision Agriculture Research Demonstration Base	1000	93.27%	[110]
Angular leaf spot Blight Powdery Mildew Downey Mildew Anthracnose Cornrespora	SVM Complex Tree KNN	Public database	1010	93.50%	[111]
Anthracnose, Angular Spot Black spot, brown spot Downy Mildew Gray mold Powdery Mildew Target spot virus	Alexnet and VGG16	Northwest A&F University, China [112]	849	93.75%	[22]

Small samples were never used before in the detection of cucumber diseases. One of the first approaches was to use small samples with an image–text label-based multi-modal model. Cao et al. introduced a model where they used all the models together: image–text multi-modal contrastive learning, image self-supervised contrastive learning, and label information were all combined to measure the distance between common image–text label spaces. The model achieved an outstanding 94.84% accuracy in disease detection [95]. Banerjee and his team used a model which was pre-trained by citrus images. Here, they used three convolution layers with two pooling layers and two fully connected layers, and later, they used a support vector classifier machine (SVM). The model's performance was evaluated using different scores of precision, recall, F1 score, support, accuracy, and average metrics. The overall accuracy was 86.03%, and it had a weighted F1 score of 86.10%. The model previously showed a precision score of 86.96% for Citrus Nematode and 84% for the Dothiorella blight class. It predicted seven classes of bacterial diseases: angular leaf spot, bacterial rind necrosis, bacterial soft rot, Bacterial Wilt, bacterial fruit blotch, and brown spot [113].

3.3. Pepper

Significant research efforts have concentrated on recognizing and categorizing diseases in bell pepper crops, employing sophisticated DL methodologies like convolutional neural networks (CNNs) and transfer learning [114]. Dedicated researchers have introduced a range of creative frameworks and techniques, such as feature fusion, ensemble models, and hybrid approaches, to improve the accuracy of disease detection [115]. The adoption of DL methods has yielded highly promising results, revolutionizing the field of bell pepper disease classification [116]. The authors suggested a model that can indicate diseases with the help of the Canny edge detection algorithm. They also used data augmentation techniques such as image flipping and rotation. For the classification, the authors used Mobilenet_v2, Inception_v3, and Resnet_v2. By analyzing 1250 images, the model obtained 98.88% accuracy, which is a remarkable achievement [117]. Bhagat et al. used SVM and grid search-based SVM algorithms to classify peppers as healthy and unhealthy [118]. The accuracy was found to be extended by 4% from 80% to 84% by transforming it from SVM to grid search-based SVM [119]. Figure 8 shows some of the most dangerous diseases in peppers, modified from [120].

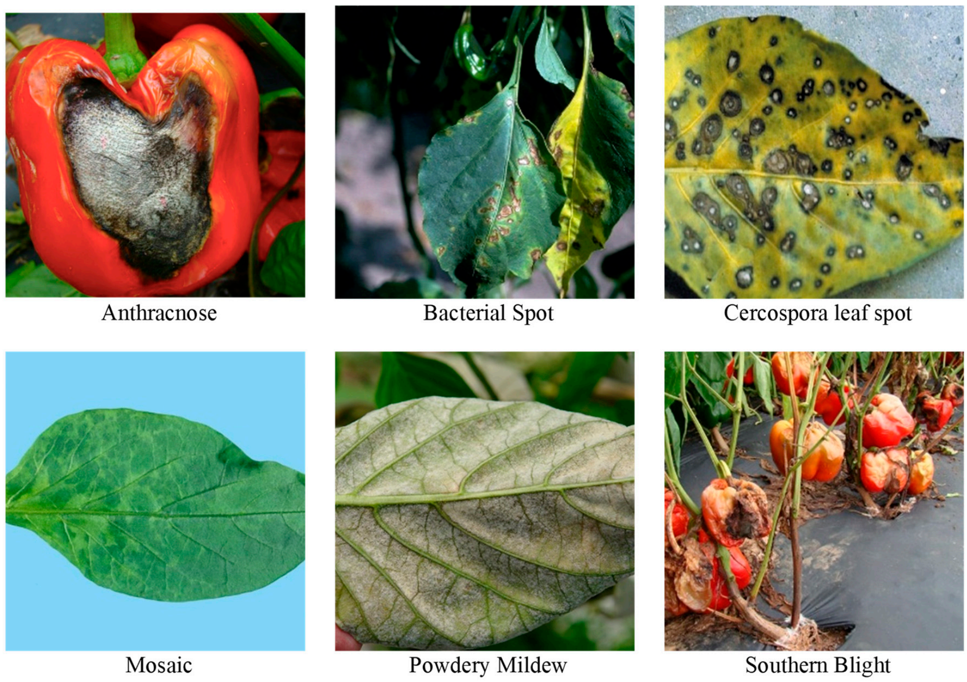


Figure 8. Most common pepper diseases.

In another study, Zeng et al. analyzed 2478 images to detect diseases, of which 1478 were healthy and 1000 were infected. The model identified the diseased and healthy plants with 99.55% accuracy [121]. Das used two CNN architectures in his research: VGG16 and VGG19. He used a total of 2475 images, where 1478 were healthy and 997 were unhealthy. The VGG19 model was more efficient than the other one. The VGG16 model showed 97% accuracy with a precision of 99%, where the recall percentage was 93% and the F1 score 96%. On the other hand, the VGG19 model showed 96% accuracy with 99% precision and 91% recall, where the F1 score was 95% [122]. Dai et al. introduced a new improved model which showed promising progress. The model accuracy was recorded to be 97.87%, which is 6% higher than that of GoogleNet based on Inception-V1 and Inception-V3. The memory used by the model was recorded to be 10.3 MB, which was a reduction to 52.31% from 86.69%. The proposed model was compared with different models such as AlexNet, ResNet-50, and MobileNet-V2. The output of this comparison showed that the inference time decreased by 61.49%, 41.78%, and 23.81%, respectively [120].

As we know, increasing the number of model layers increases its efficiency and accuracy to some extent. In their research, Mustafa et al. found out that to be true: they used a five-layer model for automatic detection using leaf images. They used 20,000 images to train their CNN model. This model showed an astonishing result of 99.99% accuracy in disease detection [28]. In another study, two methods were compared and combined to identify 26 diseases by using 14 plant leaves, and the results found were quite accurate [123]. There was another study conducted with the same technique, which was used to identify 13 diseases [124]. The same research was conducted by another author, and the results were compared with traditional computer models; this resulted in the fact that CNN is better than most other computer models for disease detection [125]. Bezabih et al. proposed a model where they used noise removal and segmentation as well as feature extraction and classification. This was a unique approach in recent research. The model resulted in a 100% classification accuracy and 97.29% validation accuracy, as well as 95.82% testing accuracy [27].

Table 3 makes a comparison between different models used in pepper disease detection. The efficiency found in this research is remarkably good for both early and late detection.

Table 3. Comparison between different CNN models in pepper disease detection.

Number of Diseases Analyzed	DL Model	Data Source	Sample Size	Accuracy (Max)	Ref.
34	VGG16, VGG19, Resnet50	National Institute of Horticultural and Herbal Science	28,011	85.6% for diseases and 98.42% for pests	[126]
1 (PLBD)	R-CNN	Self-collection	10,000	99.39%	[127]
Overall leaf diseases	Inception V3, Mobilenet, VGG19, ResNet, EfficientNetB4	Kaggle	20,000	84.25%, 79.69%, 79.99%, 77.34%, 82.65%	[49]
2	CNN	Plant Village	4627	91.28%	[128]
Bacterial and fungal diseases	VGG19, Xception, NasNet Mobile, MobileNet-V2, Resnet-152-V2 and Inception-ResNet-V2	Self-collected	386	96.26%	[129]
Bacterial diseases	ANN, Recurrent Neural Network, ResNet50 VGG16, Inception V3	Plant Village	2442	VGG16—99.72% ResNet50—99.31% InceptionV3—95.77%	[130]
Leaf diseases	MobileNet	Self-collected	2478	99.55%	[121]
14 diseases	Multilayer Perception Neural Network	Self-collected	33	98.91%	[131]
19 diseases	VGG and ResNet50	National Institute of Horticulture and Herbal Science, South Korea	23,868	96.02%	[132]
Bacterial infection	SVM, KNN, DarkNet-19	Kaggle	2475	98.8%	[133]
Black pepper diseases, nutrient deficiency	VGG16 and Inception V3	Sarawak Farms	947 converted into 9532	98.47%	[134]
Fusarium, mycorrizhal fungus	ANN, Naïve Bayes, KNN	GAP Agriculture Institute, Turkey	80	KNN—100% ANN—97.5% Naïve Bayes—90%	[135]
Bacterial and viral diseases	VGG16, VGG19, ResNet50, ResNet101, ResNet152, InceptionResNetV2, DenseNet121	Plant Village	1596	97.49%	[136]
Pepperbell Bacterial Spot	Faster R-CNN	Plant Village	460	98.06%	[137]
Bacterial disease	VGG16, AlexNet	Self-collected	3139	95.82%	[27]

3.4. Tomato

Tomatoes are one of the most consumed vegetables on earth. They are filled with nutrients and vitamins and are almost as popular as potatoes in every corner of the earth. But every year, there is a huge loss in the production of tomatoes because of bacterial attacks on the plant [138]. There have been several reports of tomato diseases. Nine diseases have been reported so far by different researchers such as target spot, two-spotted spider mite, Bacterial Spot, early blight, Septoria Leaf Spot, target spot, mosaic virus, and late blight [139,140]. Timely recognition of these diseases can add a benefit to the tomato production procedure and can reduce economic losses and supply losses [141]. There has been a lot of research going on in the detection of tomato diseases [142]. DL models have been found to be more useful than most other models that have been used in machine learning algorithms [143,144]. Mohanty et al. used AlexNet and GoogleNet to identify a huge number of diseases (26), where they took 14 crop samples for identification [145]. Another researcher used the same models to identify nine plant diseases with 14,828 pictures taken from different plants. A Deep Convolution Neural Network-based project combined AlexNet, GoogleNet, and Visual Geometry Group models for identification of diseases from 58 distinct classes of 25 plants. Here, it was clear that the VGG [146] model achieved a higher identification rate compared to AlexNet and GoogleNet [147]. Aishwarya et al. used the Plant Village dataset to train their model. The dataset comprised 54,303 images of plant leaves that were in 38 categories classified by species and diseases. The healthy portion of the dataset contained 16,012 images and the diseased part was classified into 10 categories for convenience [148]. Figure 9 shows some of the most dangerous bacterial and viral diseases of tomatoes.

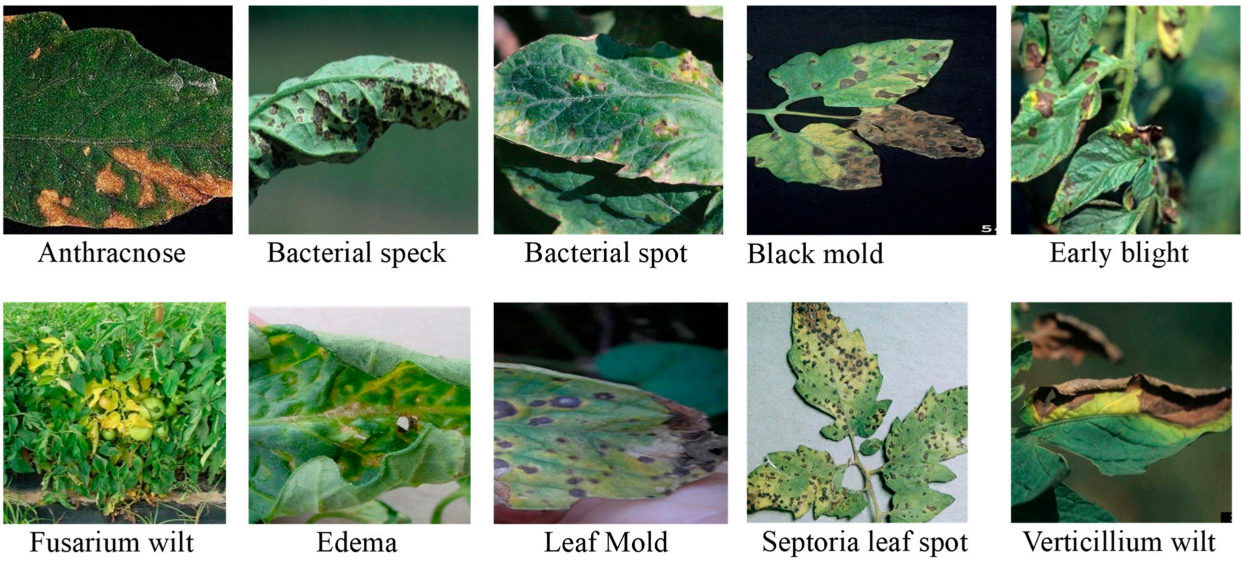


Figure 9. Different tomato diseases caused by fungal, bacterial or viral attacks.

Table 4 indicates testing accuracy between different models, and once again, it proves the superiority of CNN in the disease detection process. Compared to every other testing model, CNN shows the highest accuracy in most of the cases.

Table 4. Comparison between different CNN models in tomato disease detection.

Number of Diseases	Models	Dataset Source	Dataset Size	Accuracy	Ref.
8 distinct diseases	CNN, GoogleColab	Public dataset	3000	98.49%	[149]
12 diseases	CNN	Self-collected	1981	93.37%	[150]
10 diseases	CNN, MobileNet	Public dataset	7176	89.2%	[151]
10 disease classes	DenseNet	Kaggle	10,000	95.7%	[152]

Table 4. *Cont.*

Number of Diseases	Models	Dataset Source	Dataset Size	Accuracy	Ref.
8 distinct diseases	Deep CNN, ResNet50, DesnseNet121, RRDN	AI Challenger	13,185	95%	[153]
5 diseases	C-GAN, DenseNet121	PlantVillage	16,012	DenseNe121—98.65%	[154]
5 diseases	YOLOX-S, PLPNet	Self-collected	203	PLPNet—94.5%	[155]
Overall leaf diseases	GoogleNet, VGG16	PlantVillage	10,735	GoogleNet—99.23%	[156]
Early blight, late blight, and Leaf Mold	Attention-based Residual CNN	PlantVillage	95,999	98%	[157]
9 different diseases	T-LeafNet, AlexNet, MobileNetV2 and VGG16	Plant Village	10,000	VGG16—99.21%	[158]
Early and late blight	ResNet9	PlantVillage	1331	99.25%	[159]
5 distinct diseases	VGG16 [160], VGG-19, ResNet and Inception V3	Laboratory-based data, available in (https://github.com/PrajwalaTM/tomato-leaf-disease-detection accessed on 21 January 2024	2364	99%	[161]
Virus-based diseases	YOLOv5, R-CNN	Self-collected	150	91.07%	[162]
9 types	ResNet50, Xception, MobileNet, ShuffleNet, Dense121_Xception	PlantVillage	13,112	97.10%	[163]
Overall leaf diseases	VGG16, VGG19	Tomato diseases multiple data source	32,535	94.88%	[164]
Leaf diseases	CNN	PlantVillage	14,903	99.25%	[165]
Leaf spot	MobileNet, YOLOv5	Collected by a web crawler	2385	94.13%	[166]
10 different classes	PCA DeepNet, Adversarial Network	PlantVillage	18,128	99.60%	[1]
Fungi, bacteria, mold, virus, and mite diseases	EfficientNet	PlantVillage	18,161	99.95%	[160]
Phoma rot, Leaf Miner, target spot	OpenCV, AlexNet, ANN	Public database	-	98.12%	[167]
Target spot, Bacterial Spot, Septoria Spot	VGG16, ResNet152, EfficientNet-B4	PlantVillage	5524	98%	[168]
Bacterial Spot, early blight, late blight, Leaf Mold, mosaic virus, Septoria Leaf Spot, two-spotted spider mite, target spot, and Yellow Leaf Curl Virus	MobileNetV2, NasNetMobile, Xception, MobileNetV3, AlexNet, GoogLeNet and ResNet1	PlantVillage	18,160	99%	[169]
Bacterial spot, early blight, late blight, Leaf Mold, Septoria Leaf Spot, two-spotted spider mite, target spot, tomato mosaic virus, and tomato yellow leaf curl	MobileNetV3Small, EfficientNetV2L, InceptionV3 and MobileNetV2	PlantVillage	18,160	99.60%	[170]
Tomato leaf diseases	ResNet50, InceptionV3, AlexNet, MobileNetV1, MobileNetV2 and MobileNetV3	PlantVillage	16,004	99.81%	[171]
9 distinct diseases	VGG16, InceptionV3, MobileNet	Plant Village	10,000	CNN—91.2%	[172]

Table 4. *Cont.*

Number of Diseases	Models	Dataset Source	Dataset Size	Accuracy	Ref.
Early blight, Yellow Leaf Curl Virus	Inception V3 and Inception ResNet V2	Plant Village	5225	Inception V3—99.22%	[173]
Bacterial Spot, early blight, late blight, Leaf Mold, Septoria Leaf Spot, two-spotted spider mite, target spot, mosaic virus, Yellow Curl Virus	LightMixer	Plant Village	18,835	99.3%	[174]
Six diseases	CNN, K-NN, SVM	Plant Village	600	CNN—99.6%	[175]

Chug et al. introduced a revolutionary model to identify disease; the team used a hybrid model to identify crop diseases. A framework of 40 different hybrid deep learning models was proposed. Eight different pre-trained architectures were used, such as EfficientNet (B0–B7) as a feature extractor. Five machine learning methods were used, including k-Nearest Neighbors, AdaBoost, Random Forest, logistic regression, and stochastic gradient boosting as a classifier. The model's accuracy ranged between 87.55% and 100% in disease detection. The PlantVillage-TomEBD and PlantVillageBBLS datasets were used to evaluate the model's accuracy. For early blight detection, IARI-TomEBD was used. The novel optuna framework increased the model's performance remarkably according to [176]. A lot of researchers have used CNN architectures to deal with maize disease: Darwish et al. used VGG16 and VGG19 to distinguish between healthy and unhealthy maize leaves and achieved 98.2% accuracy [177]. Another researcher used grid and random search to identify maize disease and achieved 96.25% accuracy [178]. Yulita et al. used a public dataset from Kaggle to identify diseases in tomato plants on the DenseNet training model. A total of 1000 images were collected to identify 10 diseases in the plant leaves. The model's accuracy was reported to be 85.32% without the picture being augmented, and later after augmentation, the accuracy increased to 92.53% [152]. Recently, more research has been conducted on MobileNet to achieve greater efficiency [179].

3.5. Bitter Gourd

Bitter gourd, also known as *Momordica charantia*, is prone to diseases because of its physical structure. The outer layer of its body holds a very thin layer of tissue that can be penetrated by any microorganisms like bacteria and viruses. The most common diseases that can be seen in bitter gourd are Powdery Mildew, Downy Mildew, Anthracnose, Bacterial Wilt, and some mosaic viruses. Figure 10 represents the yellow mosaic virus of bitter gourd. Liu et al. worked on predicting the Powdery Mildew disease using a small-sized leaf. They increased the original R-CNN model-recommended size of the area during training. The result indicated that the DL network model VGG-16 [180] has the best performance. The accuracy of detection was mentioned as 89.9%, 83.0%, 81.9%, and 79.5% for healthy leaves, Powdery Mildew, gray spot, and vine blight, respectively. After increasing the size of candidate value, the efficiency increased by 7% and the result was recorded at 99.9% [181]. In another study, 55 bitter gourd samples were used to identify diseases. The Feed-Forward Neural Network algorithm, Learning Vector Quantization, and Radial Function Network were used for the experiment. The average accuracy that was reported was 94.67% [182]. Hasan et al. used a more complicated technique. They created three different models by modifying their algorithm layers by number and value to identify diseases more efficiently. The prepared model showed 99.70% accuracy. The project also used Tensorflow, Scikit-Learn, Pandas, and Keres. The structure programming language was Python [183]. Figure 10 demonstrates the yellow mosaic virus mentioned by Mondal et al. in their research and other common bitter gourd diseases [184].

Figure 10. Common bitter gourd diseases.

3.6. Brinjal

Brinjals are very much affected by some of the most harmful diseases, mainly wilt diseases such as Verticillium Wilt, Fusarium Wilt, and Bacterial Wilt. There are some more diseases like Phomopsis Blight, Powdery Mildew, Bacterial Leaf Spot, and root rot. Abisha et al. worked on the brinjal plant, which was affected by *Alternaria melongenea* and Tobacco Mosaic. Initially, they filtered the images with a Gaussian filter to reduce the noise. Later, they used DCNN and RBFNN to classify the leaves as having a disease. The mean accuracy found was 93.30% with fusion and 76.70% without fusion [185]. In another study, the group used SLIC clustering to detect diseases more efficiently and classify the diseased leaves according to their respective attacking microorganisms. The model identified 300 diseased leaves with 98.38% accuracy [186]. Jain et al. used three pre-trained models to identify the diseases in eggplant leaves. The models were AlexNet, GoogleNet, and ResNet. Five diseases were identified successfully with 77.08% accuracy by the ResNet model [187]. A different approach was taken by Venkataramana et al., who used a novel DL integration supported by Support Vector Machine [188]. Some of the most dangerous leaf diseases of brinjals (Figure 11) were also listed by [189].

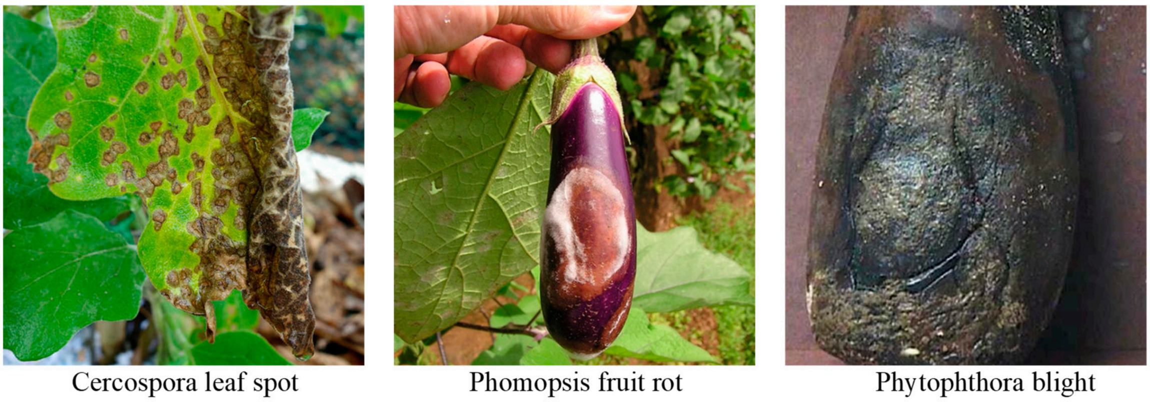
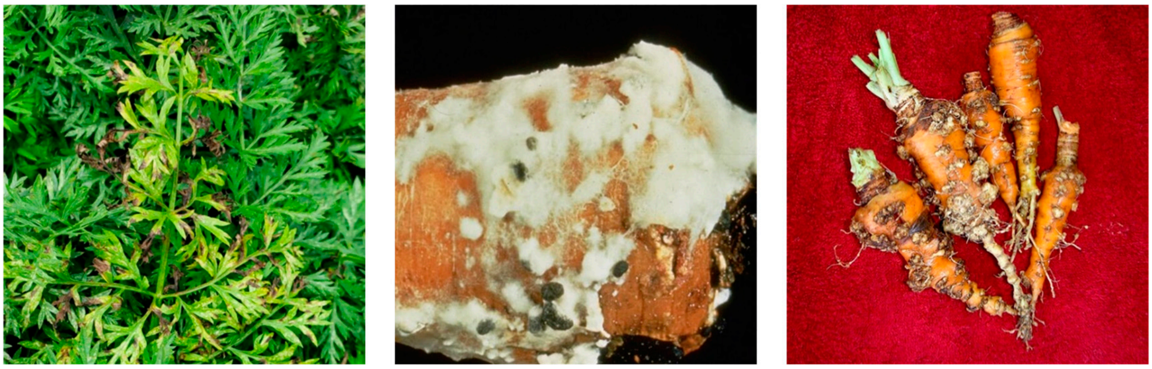


Figure 11. Leaf and fruit diseases of brinjal, commonly observed in vegetable fields.

3.7. Carrot

Carrots are a very important vegetable with rich nutrients, but they are often attacked by root nematode, Sclerotinia Rot, black root rot, alternaria leaf spot and cavity spot, as some of the diseases shown in Figure 12. All these diseases are very harmful to carrot production. Contagious and diverse diseases are highly dangerous for a vegetable that grows underground [190]. Methun et al. worked on the disease detection of carrots and found a rather good efficiency with CNN. They used the FCNN model to classify the data and Inception V3 for result analysis. The accuracy was found to be 97.4% [191]. In another study, the researcher tried to identify carrot cavities with CNN models as well as predict diseases by analyzing the leaf of the plant. The group developed an application called

Carrot Cure to identify diseases and report them with efficiency. The CNN model showed a 99.8% accuracy [192].



Alternaria Leaf Blight Sclerotinia Rot Root Knot

Figure 12. Visual representation of Sclerotinia Rot and Root Knot. Among these, Root Knot is more common than the other one.

3.8. Cabbages and Cauliflower

Cabbages and cauliflower are attacked by several bacteria and viruses over their lifetime. Some mentionable diseases are Black Leg, Clubroot, Downy Mildew, Powdery Mildew, Fusarium Wilt, Alternaria leaf spot, bacterial soft rot, and Xanthomas leaf spot, as some of them shown in Figure 13. Some of the diseases can be detected efficiently with the help of AI or machine learning models. Reya et al. used four models, VGG16, VGG19, MobileNet V2, and Inception V3, to identify diseases in cabbages. The VGG16 showed promising results, with an accuracy of 95.55% [193]. The main purpose of DL is not just to identify the disease but also to separate and dictate whether the plant is healthy or not. So, the researcher's purpose is not limited to only detecting diseases but identifying healthy leaves too [194]. The most common diseases that can be found in Bangladesh, one of the biggest cabbage producers, some of them alike including cauliflower are presented below

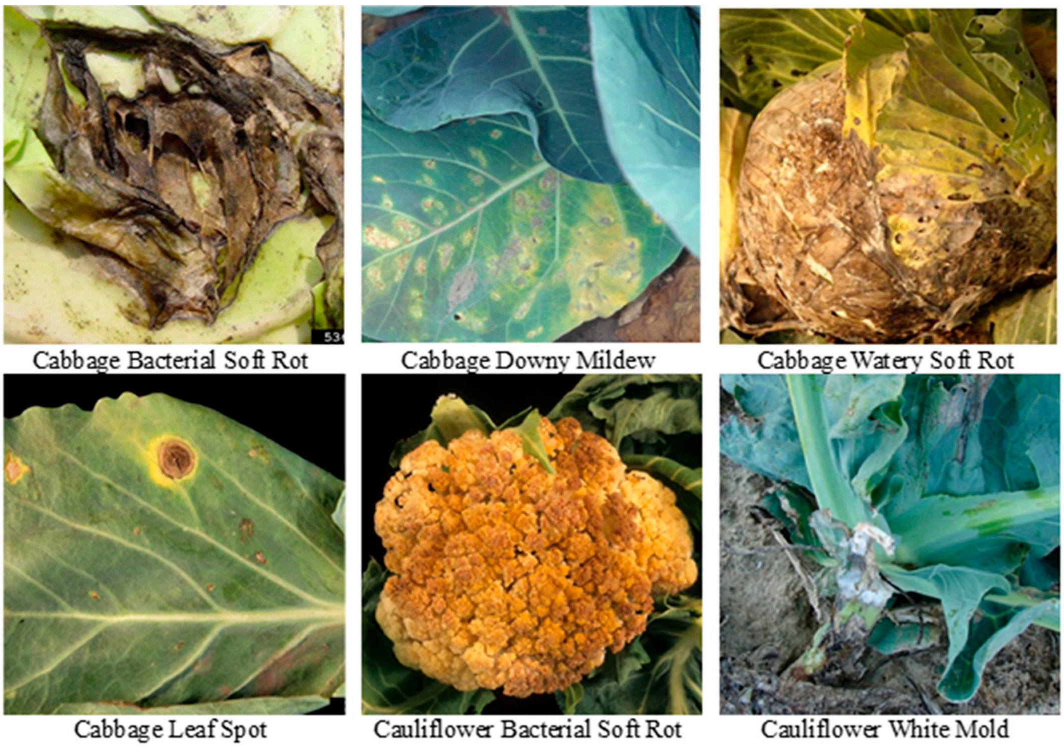


Figure 13. Most common cabbage and cauliflower diseases.

In a different approach in India, a group of researchers used Adaptive Threshold Algorithms to compare different samples and identify fungal diseases. The adaptive thresholding algorithms showed more promising results than only the threshold algorithm. The accuracy of the prior one was found to be 80.5% at 93.5% sensitivity. And the latter one was found to be 62.7% at 43.1% sensitivity [195]. Song et al. used nondestructive classification to detect soft rot in napa cabbages by processing hyperspectral imaging in near-infrared imaging. The group determined the microbiological and physiochemical qualitative properties. To predict the cabbage condition, the Support Vector Machine, the second-derivative Savitzky–Golay method, and wavelength selection were used. Among these models, the SVM model showed 99% success in finding diseases, 96% sensitivity, and 88% specificity. The effective wavelengths were 970, 978, 1180, and 1070 [196]. Kanna et al. used multiple models to predict Bacterial Spot rot, Black Rot, and Downy Mildew in cauliflower. Ten deep transfer learning models were used in this experiment: efficient netB0, Xception, Efficient NetB1, MobileNetV2, DenseNet201, EfficientNetB3, InceptionResnetV2, EficientNetB4, RestNet152V2, and Efficient NetB4. EfficientNetB1 achieved a remarkable accuracy of 99.90% [197]. Shakil et al. used k-means clustering for segmentation; the statistical matrix was named gray-level co-occurrence. At this level, the synthetic minority oversampling method was used, followed by a machine learning approach to evaluate the detection performance. The logistic regression turned out to be the most accurate in this case: the accuracy was 90.77% [198].

Table 5 summarizes the other vegetables that have been affected by the most common diseases. The accuracy of the models shown in the table is promising in the field of disease detection using DL.

Table 5. Summary of bitter gourd, brinjal, cabbages, carrot, and cauliflower diseases recognition accuracy and models used in different studies.

Name of the Crops	Model Used	Dataset Size	Accuracy	Ref
Bitter gourd	CNN, DL	4965	99.31%	[183]
Bitter gourd	Naïve Bayes Classifier	75	95%	[184]
Brinjal	AlexNet, ResNet, GoogleNet	5 datasets	68.75% 77.08% 75%	[187]
Brinjal	VGG16	2815	94.3%	[199]
Brinjal	DCNN, RBFNN	1100	93.30% 87%	[185]
Brinjal	DenseNet, Xception, RestNet152V2	2766	99.06%	[200]
Brinjal	CNN, SVM	-	99.4%	[188]
Cabbages	VGG16, VGG19, MobileNet V2, Inception V3	1500	95.55%	[193]
Cabbages	MATLAB	544	80.5%	[195]
Carrot	VGG16, VGG19, MobilNet	10,655	97.4%	[191]
Carrot	FCNN	1063	98.40%	[192]
Cauliflower	GLCM, SMOTE, LR	708	90.77%	[198]

4. Future Perspectives and Research Gaps

Numerous factors contribute to the efficacy of a particular CNN in detecting vegetable diseases, encompassing the availability and quality of annotations, the characteristics of the available images, the environmental conditions during image acquisition, and the variability of disease symptoms across instances. While numerous methodologies have been proposed for leaf disease identification, significant challenges persist.

4.1. Limitations

- Adequate sample sizes are crucial for ensuring robust generalization of features within DL networks.
- Despite advancements, a limited number of diseases have been addressed thus far, underscoring the need for expanded research encompassing a broader array of diseases.

- Current machine learning models rely solely on manual feature extraction for performance evaluation, highlighting the imperative for automated feature extraction to facilitate optimal classification. Total automation requires more accuracy in detection and the ability of the model to identify the features by itself.
- Discriminating between crucial features in plant leaves using conventional image processing techniques poses considerable difficulty due to the substantial variability in disease characteristics. Automated analysis of disease patterns necessitates the utilization of diverse datasets.
- The available datasets are sometimes outdated and can no longer match the current mutated viruses or diseases. Some diseases have similar symptoms, but the cures are different, or some can even be highly contagious and treated as mild because of misinterpretation of results.
- Disease-level prediction is another limitation that we have that is hindering the use of AI in the field.
- Real-time monitoring is not available in all farms, which is why the subject on which this research is being conducted cannot be monitored for progress or decline.
- Most of the data that are being used now are being used by many researchers at the same time. Due to this, we are losing so much time on data that have already been analyzed by another group elsewhere in the world.
- The contour of the images can be confusing to the AI model sometimes, so proper identification is hindered because of changes in contour.
- Some algorithms require more space and take more time for execution, which should be modified to obtain robust responses.

4.2. Recommendations

- Detection of the stage of the disease is of paramount importance. The model should indicate the stage of disease such as curable, non-curable, or rotten. That way, farmers can take proper action without wasting any time.
- Feature extraction must be improved to identify and monitor the data properly.
- Real-time farm monitoring should be enabled to take care of crops properly. That way, the farmers will know when to use medicine when the plant is being affected, and how long it takes to recover or fully lose the harvest.
- Similar symptoms of diseases are very confusing. Some highly contagious diseases can be treated with a little caution; the model should be able to make proper identification with precision.
- Farmers should know how much time they have left to save the crop or how much time they have to cure all the crops; that is why it will be of great help if proper identification of the disease stage is made.
- Pesticides and other chemicals that are used are dependent on the severity of the attack; the model should identify what concentration of pesticides should be used to properly save the crops. Otherwise, the expenses can increase, which will not be good if there is a loss in production.
- IoT can be of much help in this section; by integrating the output algorithms that are being used with the farm management system and IoT, the data can be shared seamlessly and properly used in different parts of the world at the same time. This will provide proper real-time monitoring and proper decision-making in different changes in conditions. Proper communication through different channels will increase efficiency in detection as well as decision-making for proper treatment.
- Multidimensional concatenation will be a great contribution because of its recognized knowledge of plant insects.

5. Conclusions

This study presents a review of the emergence of smart agricultural solutions that incorporate computer vision; vision transformers (ViTs) are a relatively new and intriguing breakthrough. It is concluded in this review that convolutional neural networks (CNNs) and DL have made encouraging progress in the field of vegetable disease detection, providing a potent instrument for precise and effective diagnosis. The literature assessment indicates that these systems can overcome conventional limitations related to manual feature extraction and categorization. The main problem is the data source and testing environment. Most of the research is conducted based on public datasets, while they should be conducted on self-collected data directly from fields. As the weather and geological locations have a great impact on the characteristics of a disease, data from one part of the world may not be useful for another part. So, when researchers are training a model based on data found in the US and using that model to identify disease in India, then the accuracy can show major dissimilarity. The wide diversity of vegetable diseases and changes in symptoms between cases require the creation of more resilient and flexible models. This calls for improving feature extraction methods, reorganization of model topologies, and incorporating cutting-edge approaches like ensemble learning and transfer learning. Furthermore, boosting the performance and real-world applicability of DL models across various environmental conditions and vegetable species requires expanding and diversifying their datasets to strengthen their generalization capabilities. In addition, it is critical to tackle issues with computing complexity and real-time implementation to promote broad adoption in agricultural contexts. This review identifies the similarities and dissimilarities among different models' accuracy in disease detection in vegetables, as vegetables are very perishable, delicate, and vulnerable to various diseases, which cause huge economic losses as compared to other food crops. The use of CNN techniques helps minimize these economic losses through disease detection at early stages. This review also identified the necessity of data sharing by different communities all over the world. In general, to fully utilize CNNs and DL for revolutionary breakthroughs in plant disease detection and agricultural sustainability, interdisciplinary cooperation between computer scientists, plant pathologists, and agronomists will be essential, as well as ongoing research and innovation in model development. The issues that have been found through this study should properly be explored as much as possible in future works. In particular, IoT can contribute a lot more than one might think, as researchers have not thought about it yet or have not found a proper channel to implement it; this can have the most valuable impact on properly detecting diseases and being able to take proper action at the proper time.

Author Contributions: M.M.u.R., W.W.: data analysis, investigation, methodology and formal analysis; M.M.u.R.: methodology and data curation; M.M.u.R.: writing—original draft preparation; J.L., A.N., M.F. and S.Z.: conceptualization, writing—review and editing; J.L.: supervision; J.L.: funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: The author(s) declare financial support was received for the research, authorship, and/or publication of this article. This study was funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions (No. PAPD-2023-87), Young Scientists Fund of the National Natural Science Foundation of China (No. 32401693) and Jiangsu Funding Program for Excellent Postdoctoral Talent (2024ZB873).

Data Availability Statement: No new data were created or analyzed in this study.

Acknowledgments: The authors highly acknowledge the support from Priority Academic Program Development of Jiangsu Higher Education Institutions (No. PAPD-2023-87), Young Scientists Fund of the National Natural Science Foundation of China (No. 32401693) and Jiangsu Funding Program for Excellent Postdoctoral Talent (2024ZB873).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Roy, K.; Chaudhuri, S.S.; Frnda, J.; Bandopadhyay, S.; Ray, I.J.; Banerjee, S.; Nedoma, J. Detection of Tomato Leaf Diseases for Agro-Based Industries Using Novel PCA DeepNet. *IEEE Access* **2023**, *11*, 14983–15001. [CrossRef]
2. Latif, G.; Abdelhamid, S.E.; Mallouhy, R.E.; Alghazo, J.; Kazimi, Z.A. Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model. *Plants* **2022**, *11*, 2230. [CrossRef] [PubMed]
3. Ma, J.; Du, K.; Zhang, L.; Zheng, F.; Chu, J.; Sun, Z. A segmentation method for greenhouse vegetable foliar disease spots images using color information and region growing. *Comput. Electron. Agric.* **2017**, *142*, 110–117. [CrossRef]
4. Barbedo, J.G.A. A review on the main challenges in automatic plant disease identification based on visible range images. *Biosyst. Eng.* **2016**, *144*, 52–60. [CrossRef]
5. Islam, A.; Sama Raisa, S.R.; Khan, N.H.; Rifat, A.I. A Deep Learning Approach for Classification and Segmentation of Leafy Vegetables and Diseases. In Proceedings of the 2023 International Conference on Next-Generation Computing, IoT and Machine Learning (NCIM), Gazipur, Bangladesh, 16–17 June 2023; IEEE: New York, NY, USA, 2023; pp. 1–6.
6. Lichtenthaler, H.K. Vegetation Stress: An Introduction to the Stress Concept in Plants. *J. Plant Physiol.* **1996**, *148*, 4–14. [CrossRef]
7. Golhani, K.; Balasundram, S.K.; Vadamalai, G.; Pradhan, B. A review of neural networks in plant disease detection using hyperspectral data. *Inf. Process. Agric.* **2018**, *5*, 354–371. [CrossRef]
8. Meshram, S.; Adhikari, T.B. Microbiome-Mediated Strategies to Manage Major Soil-Borne Diseases of Tomato. *Plants* **2024**, *13*, 364. [CrossRef]
9. Strange, R.N.; Scott, P.R. Plant Disease: A Threat to Global Food Security. *Annu. Rev. Phytopathol.* **2005**, *43*, 83–116. [CrossRef]
10. Tiamiyu, Q.O.; Adebayo, S.E.; Ibrahim, N. Recent advances on postharvest technologies of bell pepper: A review. *Heliyon* **2023**, *9*, e15302. [CrossRef]
11. Shrestha, G.; Deepsikha; Das, M.; Dey, N. Plant Disease Detection Using CNN. In Proceedings of the 2020 IEEE Applied Signal Processing Conference (ASPCON), Kolkata, India, 7–9 October 2020; IEEE: New York, NY, USA, 2020; pp. 109–113. [CrossRef]
12. Arid, H.; Bellamine, I.; Elmoutaouakkil, A. Plant leaf diseases classification using Deep Learning. In Proceedings of the 2023 7th IEEE Congress on Information Science and Technology (CiSt), Agadir, Morocco; Essaouira, Morocco, 16–22 December 2023; IEEE: New York, NY, USA, 2023; pp. 166–170.
13. de Luna, R.G.; Dadios, E.P.; Bandala, A.A. Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition. In Proceedings of the TENCON 2018—2018 IEEE Region 10 Conference, Jeju, Republic of Korea, 28–31 October 2018; IEEE: New York, NY, USA, 2018; pp. 1414–1419.
14. Singla, P.; Kalavakonda, V.; Senthil, R. Detection of plant leaf diseases using deep convolutional neural network models. *Multimed. Tools Appl.* **2024**, *83*, 54533–54549. [CrossRef]
15. DeChant, C.; Wiesner-Hanks, T.; Chen, S.; Stewart, E.L.; Yosinski, J.; Gore, M.A.; Nelson, R.J.; Lipson, H. Automated Identification of Northern Leaf Blight-Infected Maize Plants from Field Imagery Using Deep Learning. *Phytopathology* **2017**, *107*, 1426–1432. [CrossRef] [PubMed]
16. Goyal, P.; Verma, D.K.; Kumar, S. Plant Leaf Disease Detection Using an Optimized Evolutionary Gravitational Neocognitron Neural Network. *Natl. Acad. Sci. Lett.* **2024**, *47*, 347–354. [CrossRef]
17. Sinshaw, N.T.; Assefa, B.G.; Mohapatra, S.K. Transfer Learning and Data Augmentation Based CNN Model for Potato Late Blight Disease Detection. In Proceedings of the 2021 International Conference on Information and Communication Technology for Development for Africa (ICT4DA), Bahir Dar, Ethiopia, 22–24 November 2021; IEEE: New York, NY, USA, 2021; pp. 30–35.
18. Wu, J. Cluster Analysis and K-means Clustering: An Introduction. In *Advances in K-Means Clustering*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 1–16.
19. Ha, J.G.; Moon, H.; Kwak, J.T.; Hassan, S.I.; Dang, M.; Lee, O.N.; Park, H.Y. Deep convolutional neural network for classifying Fusarium wilt of radish from unmanned aerial vehicles. *J. Appl. Remote Sens.* **2017**, *11*, 1. [CrossRef]
20. Arnal Barbedo, J.G. Plant disease identification from individual lesions and spots using deep learning. *Biosyst. Eng.* **2019**, *180*, 96–107. [CrossRef]
21. McCulloch, W.S.; Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biophys.* **1943**, *5*, 115–133. [CrossRef]
22. Agarwal, M.; Gupta, S.; Biswas, K.K. A new Conv2D model with modified ReLU activation function for identification of disease type and severity in cucumber plant. *Sustain. Comput. Inform. Syst.* **2021**, *30*, 100473. [CrossRef]
23. Alom, M.Z.; Taha, T.M.; Yakopcic, C.; Westberg, S.; Sidike, P.; Nasrin, M.S.; Van Esesn, B.C.; Awwal, A.A.S.; Asari, V.K. The History Began from AlexNet: A Comprehensive Survey on Deep Learning Approaches. 2018. Available online: http://arxiv.org/abs/1803.01164 (accessed on 25 August 2024).
24. Li, L.; Zhang, S.; Wang, B. Plant Disease Detection and Classification by Deep Learning—A Review. *IEEE Access* **2021**, *9*, 56683–56698. [CrossRef]
25. Singh, M.; Shah, S.K.; Kumbhar, V.; Singh, T.P.; Tomar, D. Enhanced Convolutional Neural Network Model for Crop Disease Identification using UAV Imagery. In Proceedings of the 2023 IEEE Pune Section International Conference (PuneCon), Pune, India, 14–16 December 2023; IEEE: New York, NY, USA, 2023; pp. 1–7.
26. Sofuoglu, C.I.; Birant, D. Potato Plant Leaf Disease Detection Using Deep Learning Method. *Tarim. Bilim. Derg.* **2024**, *30*, 153–165. [CrossRef]

27. Bezabih, Y.A.; Salau, A.O.; Abuhayi, B.M.; Mussa, A.A.; Ayalew, A.M. CPD-CCNN: Classification of pepper disease using a concatenation of convolutional neural network models. *Sci. Rep.* **2023**, *13*, 1–12. [CrossRef]
28. Mustafa, H.; Umer, M.; Hafeez, U.; Hameed, A.; Sohaib, A.; Ullah, S.; Madni, H.A. Pepper bell leaf disease detection and classification using optimized convolutional neural network. *Multimed. Tools Appl.* **2023**, *82*, 12065–12080. [CrossRef]
29. Hafeez, U.; Umer, M.; Hameed, A.; Mustafa, H.; Sohaib, A.; Nappi, M.; Madni, H.A. A CNN based coronavirus disease prediction system for chest X-rays. *J. Ambient. Intell. Humaniz. Comput.* **2023**, *14*, 13179–13193. [CrossRef] [PubMed]
30. Mentor, K.P. *Introduction to Machine Learning*, 3rd ed.; MIT Press: Cambridge, MA, USA, 2014.
31. El Naqa, I.; Murphy, M.J. *Machine Learning in Radiation Oncology*; Springer: Cham, Switzerland, 2015; pp. 3–11. [CrossRef]
32. Saleem, M.H.; Potgieter, J.; Arif, K.M. Correction to: Automation in Agriculture by Machine and Deep Learning Techniques: A Review of Recent Developments. *Precis. Agric.* **2021**, *22*, 2092–2094. [CrossRef]
33. Yuan, Y.; Chen, J.; Polat, K.; Alhudhaif, A. An innovative approach to detecting the freshness of fruits and vegetables through the integration of convolutional neural networks and bidirectional long short-term memory network. *Curr. Res. Food Sci.* **2024**, *8*, 100723. [CrossRef] [PubMed]
34. Banerjee, S.; Chand Mondal, A. An Intelligent Approach towards Plant Leaf Disease Detection through Different Convolutional Neural Networks. *Int. J. Intell. Syst. Appl. Eng.* **2024**, *12*, 536–546. Available online: https://orcid.org/0000-0002-7361-1553 (accessed on 25 August 2024).
35. Islam, A.; Raisa, S.R.S.; Khan, N.H. Enhanced Leafy Vegetable Analysis: Image Classification and Disease Instance Segmentation Using Deep Learning Techniques. *SSRN* **2020**, *20*, 10–14.
36. Li, R.; Liang, H.; Shi, Y.; Feng, F.; Wang, X. Dual-CNN: A Convolutional language decoder for paragraph image captioning. *Neurocomputing* **2020**, *396*, 92–101. [CrossRef]
37. Zhang, Y.; Zhang, W.; Yu, J.; He, L.; Chen, J.; He, Y. Complete and accurate holly fruits counting using YOLOX object detection. *Comput. Electron. Agric.* **2022**, *198*, 107062. [CrossRef]
38. Girshick, R.; Donahue, J.; Darrell, T.; Malik, J. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. In Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA, 23–28 June 2014; IEEE: New York, NY, USA, 2014; pp. 580–587.
39. Girshick, R. Fast R-CNN. In Proceedings of the 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, Chile, 7–13 December 2015; IEEE: New York, NY, USA, 2015; pp. 1440–1448.
40. Zhang, Y.; Li, J.; Tang, F.; Zhang, H.; Cui, Z.; Zhou, H. An Automatic Detector for Fungal Spores in Microscopic Images Based on Deep Learning. *Appl. Eng. Agric.* **2021**, *37*, 85–94. [CrossRef]
41. Wang, J.; Liu, Q.; Xie, H.; Yang, Z.; Zhou, H. Boosted EfficientNet: Detection of Lymph Node Metastases in Breast Cancer Using Convolutional Neural Networks. *Cancers* **2021**, *13*, 661. [CrossRef]
42. Younis, A.; Qiang, L.; Nyatega, C.O.; Adamu, M.J.; Kawuwa, H.B. Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches. *Appl. Sci.* **2022**, *12*, 7282. [CrossRef]
43. Verma, P.; Kaur, G.; Machavaram, R.; Bhattacharya, M. Intelligent cotton ball maturity prediction model for smart agriculture. In *AIP Conference Proceedings, Proceedings of the Second International Conference on Computing and Communication Networks (ICCCN 2022), Manchester, UK, 19–20 November 2022*; AIP Publishing: College Park, MD, USA, 2024; p. 050004.
44. Sarwinda, D.; Paradisa, R.H.; Bustamam, A.; Anggia, P. Deep Learning in Image Classification using Residual Network (ResNet) Variants for Detection of Colorectal Cancer. *Procedia Comput. Sci.* **2021**, *179*, 423–431. [CrossRef]
45. Fulton, L.; Dolezel, D.; Harrop, J.; Yan, Y.; Fulton, C. Classification of Alzheimer's Disease with and without Imagery Using Gradient Boosted Machines and ResNet-50. *Brain Sci.* **2019**, *9*, 212. [CrossRef] [PubMed]
46. Qabulio, M.; Memon, M.S.; Iqbal, S.; Kumar, P.; Tsetse, A. Effective Tomato Leaf Disease Identification Model using MobileNetV3Small. *Int. J. Inf. Syst. Comput. Technol.* **2024**, *3*, 57–72. [CrossRef]
47. Ahsan, M.M.; Nazim, R.; Siddique, Z.; Huebner, P. Detection of COVID-19 Patients from CT Scan and Chest X-ray Data Using Modified MobileNetV2 and LIME. *Healthcare* **2021**, *9*, 1099. [CrossRef] [PubMed]
48. Singh, R.; Sharma, N.; Gupta, R. Rice Leaf Disease Detection using MobileNet Transfer Learning Model. In Proceedings of the 2023 Second International Conference on Trends in Electrical, Electronics, and Computer Engineering (TEECCON), Bangalore, India, 23–24 December 2023; IEEE: New York, NY, USA, 2023; pp. 131–136.
49. Alarfaj, A.A.; Altamimi, A.; Aljrees, T.; Basheer, S.; Umer, M.; Samad, M.A.; Alsubai, S.; Ashraf, I. Multi-Step Preprocessing with UNet Segmentation and Transfer Learning Model for Pepper Bell Leaf Disease Detection. *IEEE Access* **2023**, *11*, 132254–132267. [CrossRef]
50. Pal, M.; Mahal, A.; Mohapatra, R.K.; Obaidullah, A.J.; Sahoo, R.N.; Pattnaik, G.; Pattanaik, S.; Mishra, S.; Aljeldah, M.; Alissa, M.; et al. Deep and Transfer Learning Approaches for Automated Early Detection of Monkeypox (Mpox) Alongside Other Similar Skin Lesions and Their Classification. *ACS Omega* **2023**, *8*, 31747–31757. [CrossRef]
51. Mujahid, M.; Rustam, F.; Álvarez, R.; Luis Vidal Mazón, J.; Díez, I.D.L.T.; Ashraf, I. Pneumonia Classification from X-ray Images with Inception-V3 and Convolutional Neural Network. *Diagnostics* **2022**, *12*, 1280. [CrossRef]
52. Nagaraju, M.; Chawla, P. Systematic review of deep learning techniques in plant disease detection. *Int. J. Syst. Assur. Eng. Manag.* **2020**, *11*, 547–560. [CrossRef]

53. Tiwari, D.; Ashish, M.; Gangwar, N.; Sharma, A.; Patel, S.; Bhardwaj, S. Potato Leaf Diseases Detection Using Deep Learning. In Proceedings of the 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 13–15 May 2020; IEEE: New York, NY, USA, 2020; pp. 461–466.
54. Sun, W.; Wang, C.; Gu, J.; Sun, X.; Li, J.; Liang, F. Veg-DenseCap: Dense Captioning Model for Vegetable Leaf Disease Images. *Agronomy* **2023**, *13*, 1700. [CrossRef]
55. Kumar, A.; Trivedi, N.K.; Tiwari, R.G. Disease Identification in Potato Leaves Using a Multi-Tier Deep Learning Model. In Proceedings of the 2023 3rd Asian Conference on Innovation in Technology (ASIANCON), Ravet, IN, India, 25–27 August 2023; IEEE: New York, NY, USA, 2023; pp. 1–6.
56. Arshaghi, A.; Ashourian, M.; Ghabeli, L. Potato diseases detection and classification using deep learning methods. *Multimed. Tools Appl.* **2023**, *82*, 5725–5742. [CrossRef]
57. Gené-Mola, J.; Sanz-Cortiella, R.; Rosell-Polo, J.R.; Morros, J.-R.; Ruiz-Hidalgo, J.; Vilaplana, V.; Gregorio, E. Fruit detection and 3D location using instance segmentation neural networks and structure-from-motion photogrammetry. *Comput. Electron. Agric.* **2020**, *169*, 105165. [CrossRef]
58. Dasgupta, S.R.; Rakshit, S.; Mondal, D.; Kole, D.K. Detection of Diseases in Potato Leaves Using Transfer Learning. In *Computational Intelligence in Pattern Recognition. Advances in Intelligent Systems and Computing*; Springer: Singapore, 2020; pp. 675–684. [CrossRef]
59. Lee, H.-S.; Shin, B.-S. Potato Detection and Segmentation Based on Mask R-CNN. *J. Biosyst. Eng.* **2020**, *45*, 233–238. [CrossRef]
60. Van De Vijver, R.; Mertens, K.; Heungens, K.; Somers, B.; Nuyttens, D.; Borra-Serrano, I.; Lootens, P.; Roldán-Ruiz, I.; Vangeyte, J.; Saeys, W. In-field detection of Alternaria solani in potato crops using hyperspectral imaging. *Comput. Electron. Agric.* **2020**, *168*, 105106. [CrossRef]
61. Su, Q.; Kondo, N.; Al Riza, D.F.; Habaragamuwa, H. Potato Quality Grading Based on Depth Imaging and Convolutional Neural Network. *J. Food Qual.* **2020**, *2020*, 1–9. [CrossRef]
62. Arshaghi, A.; Ashourian, M.; Ghabeli, L. Feature selection based on buzzard optimization algorithm for potato surface defects detection. *Multimed. Tools Appl.* **2020**, *79*, 26623–26641. [CrossRef]
63. Zhang, W.; Zhu, Q.; Huang, M.; Guo, Y.; Qin, J. Detection and Classification of Potato Defects Using Multispectral Imaging System Based on Single Shot Method. *Food Anal. Methods* **2019**, *12*, 2920–2929. [CrossRef]
64. Al Riza, D.F.; Suzuki, T.; Ogawa, Y.; Kondo, N. Diffuse reflectance characteristic of potato surface for external defects discrimination. *Postharvest Biol. Technol.* **2017**, *133*, 12–19. [CrossRef]
65. Amrinder Singh Brar, E.; Singh, K. Potato Defect Detection using Fuzzy C-mean Clustering based Segmentation. *Indian. J. Sci. Technol.* **2016**, *9*, 1–6. [CrossRef]
66. Gao, Y.; Geng, J.; Rao, X.; Ying, Y. CCD-Based Skinning Injury Recognition on Potato Tubers (*Solanum tuberosum* L.): A Comparison between Visible and Biospeckle Imaging. *Sensors* **2016**, *16*, 1734. [CrossRef]
67. Moallem, P.; Razmjooy, N.; Mousavi, B.S. Robust potato color image segmentation using adaptive fuzzy inference system. *Iran. J. Fuzzy Syst.* **2014**, *11*, 47–65.
68. Razmjooy, N.; Daviran, R. Potato defect detection using Computer vision and Neural Networks. *Majlesi Conf. Electr. Eng.* **2016**, 1–6.
69. Lee, T.Y.; Lin, I.A.; Yu, J.Y.; Yang, J.M.; Chang, Y.C. High Efficiency Disease Detection for Potato Leaf with Convolutional Neural Network. *SN Comput. Sci.* **2021**, *2*, 1–11. [CrossRef]
70. Johnson, J.; Sharma, G.; Srinivasan, S.; Masakapalli, S.K.; Sharma, S.; Sharma, J.; Dua, V.K. Enhanced field-based detection of potato blight in complex backgrounds using deep learning. *Plant Phenomics* **2021**, *2021*, 1–13. [CrossRef]
71. Afzaal, H.; Farooque, A.A.; Schumann, A.W.; Hussain, N.; McKenzie-Gopsill, A.; Esau, T.; Abbas, F.; Acharya, B. Detection of a potato disease (Early blight) using artificial intelligence. *Remote Sens.* **2021**, *13*, 411. [CrossRef]
72. Asif, M.K.R.; Rahman, M.A.; Hena, M.H. CNN based disease detection approach on potato leaves. In Proceedings of the 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS 2020), Thoothukudi, India, 3–5 December 2020; pp. 428–432. [CrossRef]
73. Iqbal, M.A.; Talukder, K.H. Detection of Potato Disease Using Image Segmentation and Machine Learning. In Proceedings of the 2020 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), Chennai, India, 4–6 August 2020; pp. 43–47. [CrossRef]
74. Feng, J.; Hou, B.; Yu, C.; Yang, H.; Wang, C.; Shi, X.; Hu, Y. Research and Validation of Potato Late Blight Detection Method Based on Deep Learning. *Agronomy* **2023**, *13*, 1659. [CrossRef]
75. Binnar, V.; Sharma, S. Plant Leaf Diseases Detection Using Deep Learning Algorithms. In *Machine Learning, Image Processing, Network Security and Data Sciences, Proceedings of the 3rd International Conference on Machine Intelligence and Signal Processing, Arunachal Pradesh, India, 23–25 September 2021*; Springer: Singapore, 2023; Volume 946, pp. 217–228. [CrossRef]
76. Arshad, F.; Mateen, M.; Hayat, S.; Wardah, M.; Al-Huda, Z.; Gu, Y.H.; Al-antari, M.A. PLDPNet: End-to-end hybrid deep learning framework for potato leaf disease prediction. *Alex. Eng. J.* **2023**, *78*, 406–418. [CrossRef]
77. Joshi, B.M.; Bhavsar, H. Deep Learning Technology based Night-CNN for Nightshade Crop Leaf Disease Detection. *Int. J. Intell. Syst. Appl. Eng.* **2023**, *11*, 215–227.
78. Farokhzad, S.; Modaress Motlagh, A.; Ahmadi Moghaddam, P.; Jalali Honarmand, S.; Kheiralipour, K. A machine learning system to identify progress level of dry rot disease in potato tuber based on digital thermal image processing. *Sci. Rep.* **2024**, *14*, 1–10. [CrossRef]

79. Shi, Y.; Han, L.; Kleerekoper, A.; Chang, S.; Hu, T. Novel CropdocNet Model for Automated Potato Late Blight Disease Detection from Unmanned Aerial Vehicle-Based Hyperspectral Imagery. *Remote Sens.* **2022**, *14*, 396. [CrossRef]
80. Singh, A.; Kaur, H. Potato plant leaves disease detection and classification using machine learning methodologies. In Proceedings of the 1st International Conference on Computational Research and Data Analytics (ICCRDA 2020), Rajpura, India, 24 October 2020; IOP Publishing: London, UK, 2021; Volume 1022. [CrossRef]
81. Rashid, J.; Khan, I.; Ali, G.; Almotiri, S.H.; Alghamdi, M.A.; Masood, K. Multi-level deep learning model for potato leaf disease recognition. *Electronics* **2021**, *10*, 2064. [CrossRef]
82. Oppenheim, D.; Shani, G.; Erlich, O.; Tsror, L. Using deep learning for image-based potato tuber disease detection. *Phytopathology* **2019**, *109*, 1083–1087. [CrossRef]
83. Catal Reis, H.; Turk, V. Potato leaf disease detection with a novel deep learning model based on depthwise separable convolution and transformer networks. *Eng. Appl. Artif. Intell.* **2024**, *133*, 108307. [CrossRef]
84. Sadiq, S.; Malik, K.R.; Ali, W.; Iqbal, M.M. Deep Learning-Based Disease Identification and Classification in Potato Leaves. *J. Comput. Biomed. Inform.* **2023**, *5*, 13–25.
85. Memon, M.S.; Kumar, P.; Iqbal, R. Meta Deep Learn Leaf Disease Identification Model for Cotton Crop. *Computers* **2022**, *11*, 102. [CrossRef]
86. Verma, R.; Mishra, R.; Gupta, P.; Pooja; Trivedi, S. CNN based Leaves Disease Detection in Potato Plant. In Proceedings of the 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 3–4 March 2023; IEEE: New York, NY, USA, 2023; pp. 1–5. [CrossRef]
87. 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. [CrossRef] [PubMed]
88. Wspanialy, P.; Moussa, M. Early powdery mildew detection system for application in greenhouse automation. *Comput. Electron. Agric.* **2016**, *127*, 487–494. [CrossRef]
89. Rana, C. *Important Diseases of cucurbitaceous crops and their management In Handbook of Cucurbits Growth, Cultural Practices and Physiology*; CRC Press: Boca Raton, FL, USA, 2016; pp. 301–323.
90. Bandamaravuri, K.B.; Nayak, A.K.; Bandamaravuri, A.S.; Samad, A. Simultaneous detection of downy mildew and powdery mildew pathogens on Cucumis sativus and other cucurbits using duplex-qPCR and HRM analysis. *AMB Express* **2020**, *10*, 135. [CrossRef]
91. Pawar, P.; Turkar, V.; Patil, P. Cucumber disease detection using artificial neural network. In Proceedings of the 2016 International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, 26–27 August 2016; IEEE: New York, NY, USA, 2016; pp. 1–5.
92. Ni, L.; Punja, Z.K. Management of powdery mildew on greenhouse cucumber (*Cucumis sativus* L.) plants using biological and chemical approaches. *Can. J. Plant Pathol.* **2021**, *43*, 35–42. [CrossRef]
93. Mostafa, Y.S.; Hashem, M.; Alshehri, A.M.; Alamri, S.; Eid, E.M.; Ziedan, E.-S.H.E.; Alrumman, S.A. Effective Management of Cucumber Powdery Mildew with Essential Oils. *Agriculture* **2021**, *11*, 1177. [CrossRef]
94. Sultana, N.; Shorif, S.B.; Akter, M.; Uddin, M.S. A dataset for successful recognition of cucumber diseases. *Data Br.* **2023**, *49*, 109320. [CrossRef]
95. Cao, Y.; Chen, L.; Yuan, Y.; Sun, G. Cucumber disease recognition with small samples using image-text-label-based multi-modal language model. *Comput. Electron. Agric.* **2023**, *211*, 107993. [CrossRef]
96. Kamdi, S.Y.; Biradar, V. Monitoring and control system for the detection of crop health in agricultural application through an ensemble based deep learning strategy. *Multimed. Tools Appl.* **2023**, *83*, 56391–56422. [CrossRef]
97. Bhola, A.; Verma, S.; Kumar, P. A comparative analysis of deep learning models for cucumber disease classification using transfer learning. *J. Curr. Sci. Technol.* **2023**, *13*, 23–35. [CrossRef]
98. Xu, J.T.; Zhang, Z.; Guo, Y.H.; Liu, Y.F.; Ning, X.F. Detection of Cucumber Powdery Mildew Based on Spectral and Image Information. *J. Biosyst. Eng.* **2023**, *48*, 115–122. [CrossRef]
99. Bansal, A.; Sharma, R.; Sharma, V.; Jain, A.K.; Kukreja, V. Detecting Severity Levels of Cucumber Leaf Spot Disease using ResNext Deep Learning Model: A Digital Image Analysis Approach. In Proceedings of the 2023 4th International Conference for Emerging Technology (INCET), Belgaum, India, 26–28 May 2023; IEEE: New York, NY, USA, 2023; pp. 1–6. [CrossRef]
100. Ibrahim Eldesoky, A.; Omran, E.-S.; Abd El-Nabi, H. Detecting Mildew Diseases in Cucumber Using Image Processing Technique. *Misr J. Agric. Eng.* **2023**, *40*, 243–258. [CrossRef]
101. Hussain, N.; Khan, M.A.; Tariq, U.; Kadry, S.; Yar, M.A.E.; Mostafa, A.M.; Alnuaim, A.A.; Ahmad, S. Multiclass cucumber leaf diseases recognition using best feature selection. *Comput. Mater. Contin.* **2022**, *70*, 3281–3294. [CrossRef]
102. Khan, M.A.; Alqahtani, A.; Khan, A.; Alsubai, S.; Binbusayyis, A.; Ch, M.M.I.; Yong, H.S.; Cha, J. Cucumber Leaf Diseases Recognition Using Multi Level Deep Entropy-ELM Feature Selection. *Appl. Sci.* **2022**, *12*, 593. [CrossRef]
103. Zhang, X.; Wang, P.; Wang, Y.; Hu, L.; Luo, X.; Mao, H.; Shen, B. Cucumber powdery mildew detection method based on hyperspectra-terahertz. *Front. Plant Sci.* **2022**, *13*, 1–12. [CrossRef] [PubMed]
104. Uoc, N.Q.; Duong, N.T.; Son, L.A.; Thanh, B.D. A Novel Automatic Detecting System for Cucumber Disease Based on the Convolution Neural Network Algorithm. *GMSARN Int. J.* **2022**, *16*, 295–301.
105. Li, S.; Li, K.; Qiao, Y.; Zhang, L. A multi-scale cucumber disease detection method in natural scenes based on YOLOv5. *Comput. Electron. Agric.* **2022**, *202*, 107363. [CrossRef]

106. Liu, C.; Zhu, H.; Guo, W.; Han, X.; Chen, C.; Wu, H. EFDet: An efficient detection method for cucumber disease under natural complex environments. *Comput. Electron. Agric.* **2021**, *189*, 106378. [CrossRef]
107. Li, J.; Qiao, Y.; Liu, S.; Zhang, J.; Yang, Z.; Wang, M. An improved YOLOv5-based vegetable disease detection method. *Comput. Electron. Agric.* **2022**, *202*, 107345. [CrossRef]
108. Hua, S.; Xu, M.; Xu, Z.; Ye, H.; Zhou, C. Multi-feature decision fusion algorithm for disease detection on crop surface based on machine vision. *Neural Comput. Appl.* **2022**, *34*, 9471–9484. [CrossRef]
109. Kainat, J.; Sajid Ullah, S.; Alharithi, F.S.; Alroobaea, R.; Hussain, S.; Nazir, S. Blended Features Classification of Leaf-Based Cucumber Disease Using Image Processing Techniques. *Complexity* **2021**, *2021*, 1–12. [CrossRef]
110. Wang, C.; Du, P.; Wu, H.; Li, J.; Zhao, C.; Zhu, H. A cucumber leaf disease severity classification method based on the fusion of DeepLabV3+ and U-Net. *Comput. Electron. Agric.* **2021**, *189*, 106373. [CrossRef]
111. Kianat, J.; Khan, M.A.; Sharif, M.; Akram, T.; Rehman, A.; Saba, T. A joint framework of feature reduction and robust feature selection for cucumber leaf diseases recognition. *Optik* **2021**, *240*, 166566. [CrossRef]
112. Zhang, S.; Wu, X.; You, Z.; Zhang, L. Leaf image based cucumber disease recognition using sparse representation classification. *Comput. Electron. Agric.* **2017**, *134*, 135–141. [CrossRef]
113. Banerjee, D.; Kukreja, V.; Hariharan, S.; Jain, V.; Dutta, S. CNN-SVM Model for Accurate Detection of Bacterial Diseases in Cucumber Leaves. In Proceedings of the 2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC), Jalandhar, India, 26–28 May 2023; IEEE: New York, NY, USA, 2023; pp. 7–12. [CrossRef]
114. Sharma, G.; Anand, V.; Malhotra, S.; Kukreti, S.; Gupta, S. CNN-Based Intelligent Classification of Bell Pepper Plant Diseases: A Novel Approach for Precision Agriculture. In Proceedings of the 2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), Bangalore, India, 29–31 December 2023; IEEE: New York, NY, USA, 2023; pp. 1–5.
115. Classification of capsicum leaf disease from a complex cluster of leaves using an improved multiple layers ShuffleNet CNN model. *Int. J. Adv. Technol. Eng. Explor.* **2023**, *10*, 515–532. [CrossRef]
116. Kudari, M.; Nandeppanavar, A.S.; Korrapaty, S.S. Vegetable Classification Using Deep Learning Approach. In Proceedings of the 2023 IEEE North Karnataka Subsection Flagship International Conference (NKCon), Belagavi, India, 19–20 November 2023; IEEE: New York, NY, USA, 2023; pp. 1–5.
117. Jha, P.; Dembla, D.; Dubey, W. Implementation of Transfer Learning Based Ensemble Model using Image Processing for Detection of Potato and Bell Pepper Leaf Diseases. *Int. J. Intell. Syst. Appl. Eng.* **2024**, *12*, 69–80.
118. Bhagat, M.; Kumar, D.; Haque, I.; Munda, H.S.; Bhagat, R. Plant Leaf Disease Classification Using Grid Search Based SVM. In Proceedings of the 2nd International Conference on Data, Engineering and Applications (IDEA), Bhopal, India, 28–29 February 2020; IEEE: New York, NY, USA, 2020; pp. 1–6.
119. Bhagat, M.; Kumar, D.; Mahmood, R.; Pati, B.; Kumar, M. Bell Pepper Leaf Disease Classification Using CNN. In Proceedings of the 2nd International Conference on Data, Engineering and Applications (IDEA), Bhopal, India, 28–29 February 2020; IEEE: New York, NY, USA, 2020; pp. 1–5.
120. Dai, M.; Sun, W.; Wang, L.; Dorjoy, M.M.H.; Zhang, S.; Miao, H.; Han, L.; Zhang, X.; Wang, M. Pepper leaf disease recognition based on enhanced lightweight convolutional neural networks. *Front. Plant Sci.* **2023**, *14*, 1–18. [CrossRef]
121. Zeng, Y.; Zhao, Y.; Yu, Y.; Tang, Y.; Tang, Y. Pepper Disease Detection Model Based on Convolutional Neural Network and Transfer Learning. In *IOP Conference Series: Earth and Environmental Science, Proceedings of the 2021 2nd International Conference on Agricultural Science and Technology and Food Engineering, Qingdao, China, 28–30 May 2021*; IOP Publishing: London, UK, 2021; Volume 792, p. 012001. [CrossRef]
122. Kumar Das, P. Leaf Disease Classification in Bell Pepper Plant using VGGNet. *J. Innov. Image Process.* **2023**, *5*, 36–46. [CrossRef]
123. Mohanty, S.P.; Hughes, D.P.; Salathé, M. Using deep learning for image-based plant disease detection. *Front. Plant Sci.* **2016**, *7*, 1–10. [CrossRef] [PubMed]
124. 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*, 1–11. [CrossRef]
125. Pawara, P.; Okafor, E.; Surinta, O.; Schomaker, L.; Wiering, M. Comparing Local Descriptors and Bags of Visual Words to Deep Convolutional Neural Networks for Plant Recognition. In Proceedings of the 6th International Conference on Pattern Recognition Applications and Methods, Porto, Portugal, 24–26 February 2017; SCITEPRESS—Science and Technology Publications: Setúbal, Portugal, 2017; pp. 479–486.
126. Yin, H.; Gu, Y.H.; Park, C.J.; Park, J.H.; Yoo, S.J. Transfer learning-based search model for hot pepper diseases and pests. *Agric.* **2020**, *10*, 439. [CrossRef]
127. Sharma, R.; Kukreja, V.; Bordoloi, D. Deep Learning Meets Agriculture: A Faster RCNN Based Approach to pepper leaf blight disease Detection and Multi-Classification. In Proceedings of the 2023 4th International Conference for Emerging Technology (INCET), Belgaum, India, 26–28 May 2023; IEEE: New York, NY, USA, 2023; pp. 1–5. [CrossRef]
128. Aldhyani, T.H.H.; Alkahtani, H.; Eunice, R.J.; Hemanth, D.J. Leaf Pathology Detection in Potato and Pepper Bell Plant using Convolutional Neural Networks. In Proceedings of the 2022 7th International Conference on Communication and Electronics Systems (ICCES 2022), Coimbatore, India, 22–24 June 2022; IEEE: New York, NY, USA, 2022; pp. 1289–1294. [CrossRef]

129. Haque, I.; Islam, M.A.; Roy, K.; Rahaman, M.M.; Shohan, A.A.; Islam, M.S. Classifying Pepper Disease based on Transfer Learning: A Deep Learning Approach. In Proceedings of the 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 9–11 May 2022; IEEE: New York, NY, USA, 2022; pp. 620–629. [CrossRef]
130. Thakur, P.; Chug, A.; Singh, A.P. Plant Disease detection of Bell Pepper Plant Using Transfer Learning over different Models. In Proceedings of the 2021 8th International Conference on Signal Processing and Integrated Networks (SPIN 2021), Noida, India, 26–27 August 2021; IEEE: New York, NY, USA, 2021; pp. 384–389. [CrossRef]
131. Nuanmeesri, S.; Sriurai, W. Multi-Layer Perceptron Neural Network Model Development for Chili Pepper Disease Diagnosis Using Filter and Wrapper Feature Selection Methods. *Eng. Technol. Appl. Sci. Res.* **2021**, *11*, 7714–7719. [CrossRef]
132. Gu, Y.H.; Yin, H.; Jin, D.; Park, J.H.; Yoo, S.J. Image-Based Hot Pepper Disease and Pest Diagnosis Using Transfer Learning and Fine-Tuning. *Front. Plant Sci.* **2021**, *12*, 1–11. [CrossRef]
133. ÖZCAN, A.; DÖNMEZ, E. Bacterial Disease Detection for Pepper Plant by Utilizing Deep Features Acquired from DarkNet-19 CNN Model. *DÜMF Mühendislik Derg.* **2021**, *4*, 573–579. [CrossRef]
134. Khew, C.Y.; Teow, Y.Q.; Lau, E.T.; Hwang, S.S.; Bong, C.H.; Lee, N.K. Evaluation of Deep Learning for Image-based Black Pepper Disease and Nutrient Deficiency Classification. In Proceedings of the 2021 2nd International Conference on Artificial Intelligence and Data Sciences (AiDAS), IPOH, Malaysia, 8–9 September 2021; IEEE: New York, NY, USA, 2021; pp. 1–6. [CrossRef]
135. Karadağ, K.; Tenekeci, M.E.; Taşaltın, R.; Bilgili, A. Detection of pepper fusarium disease using machine learning algorithms based on spectral reflectance. *Sustain. Comput. Inform. Syst.* **2020**, *28*, 100299. [CrossRef]
136. Kundu, N.; Rani, G.; Dhaka, V.S. A comparative analysis of deep learning models applied for disease classification in bell pepper. In Proceedings of the 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC), Waknaghat, India, 6–8 November 2020; IEEE: New York, NY, USA, 2020; pp. 243–247. [CrossRef]
137. SERT, E. A deep learning based approach for the detection of diseases in pepper and potato leaves. *Anadolu J. Agric. Sci.* **2021**, *36*, 167–178. [CrossRef]
138. Bellout, A.; Dliou, A.; Latif, R.; Saddik, A. Deep Learning technique for predicting tomato leaf disease. In Proceedings of the 2023 IEEE International Conference on Advances in Data-Driven Analytics And Intelligent Systems (ADACIS), Marrakesh, Morocco, 23–25 November 2023; IEEE: New York, NY, USA, 2023; pp. 1–6.
139. Mahilraj, J.; Sivaram, P.; Sharma, B.; Lokesh, N.; Bobinath, B.; Moriwal, R. Detection of Tomato leaf diseases using Attention Embedded Hyper-parameter Learning Optimization in CNN. In Proceedings of the 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 3–4 March 2023; IEEE: New York, NY, USA, 2023; pp. 1–6. [CrossRef]
140. Sheenam; Kumar, A. Advanced CNN-Based Approach for Accurate Tomato Plant Disease Recognition. In Proceedings of the 2023 3rd International Conference on Intelligent Technologies (CONIT), Hubli, India, 23–25 June 2023; IEEE: New York, NY, USA, 2023; pp. 1–5.
141. Harinadha, P.; Mohan, C.K. Tomato Plant Leaf Disease Detection Using Transfer Learning-based ResNet110. In Proceedings of the 2023 International Conference on Data Science and Network Security (ICDSNS), Tiptur, India, 28–29 July 2023; IEEE: New York, NY, USA, 2023; pp. 1–8.
142. Singh, T. Identification of Tomato Crop Diseases using an Efficient CNN Model. In Proceedings of the 2023 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Kirtipur, Nepal, 11–13 October 2023; IEEE: New York, NY, USA, 2023; pp. 566–571.
143. Brahimi, M.; Boukhalfa, K.; Moussaoui, A. Deep Learning for Tomato Diseases: Classification and Symptoms Visualization. *Appl. Artif. Intell.* **2017**, *31*, 299–315. [CrossRef]
144. Deng, J.; Dong, W.; Socher, R.; Li, L.-J.; Li, K.; Li, F.-F. ImageNet: A large-scale hierarchical image database. In Proceedings of the 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, USA, 20–25 June 2005; IEEE: New York, NY, USA, 2009; pp. 248–255.
145. Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Reed, S.; Anguelov, D.; Erhan, D.; Vanhoucke, V.; Rabinovich, A. Going deeper with convolutions. In Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, USA, 7–12 June 2015; IEEE: New York, NY, USA, 2015; pp. 1–9.
146. Kontogiannis, S.; Konstantinidou, M.; Tsioukas, V.; Pikridas, C. A Cloud-Based Deep Learning Framework for Downy Mildew Detection in Viticulture Using Real-Time Image Acquisition from Embedded Devices and Drones. *Information* **2024**, *15*, 178. [CrossRef]
147. Ferentinos, K.P. Deep learning models for plant disease detection and diagnosis. *Comput. Electron. Agric.* **2018**, *145*, 311–318. [CrossRef]
148. Aishwarya, N.; Praveena, N.G.; Priyanka, S.; Pramod, J. Smart farming for detection and identification of tomato plant diseases using light weight deep neural network. *Multimed. Tools Appl.* **2023**, *82*, 18799–18810. [CrossRef]
149. Trivedi, N.K.; Gautam, V.; Anand, A.; Aljahdali, H.M.; Villar, S.G.; Anand, D.; Goyal, N.; Kadry, S. Early detection and classification of tomato leaf disease using high-performance deep neural network. *Sensors* **2021**, *21*, 7987. [CrossRef]
150. Fuentes, A.; Yoon, S.; Lee, M.H.; Park, D.S. Improving Accuracy of Tomato Plant Disease Diagnosis Based on Deep Learning with Explicit Control of Hidden Classes. *Front. Plant Sci.* **2021**, *12*, 682230. [CrossRef]
151. Elhassouny, A.; Smarandache, F. Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks. In Proceedings of the 2019 International Conference of Computer Science and Renewable Energies (ICCSRE 2019), Agadir, Morocco, 22–24 July 2019; IEEE: New York, NY, USA, 2019; pp. 1–4. [CrossRef]

152. Yulita, I.N.; Amri, N.A.; Hidayat, A. Mobile Application for Tomato Plant Leaf Disease Detection Using a Dense Convolutional Network Architecture. *Computation* **2023**, *11*, 20. [CrossRef]
153. Zhou, C.; Zhou, S.; Xing, J.; Song, J. Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network. *IEEE Access* **2021**, *9*, 28822–28831. [CrossRef]
154. Abbas, A.; Jain, S.; Gour, M.; Vankudothu, S. Tomato plant disease detection using transfer learning with C-GAN synthetic images. *Comput. Electron. Agric.* **2021**, *187*, 106279. [CrossRef]
155. Tang, Z.; He, X.; Zhou, G.; Chen, A.; Wang, Y.; Li, L.; Hu, Y. A Precise Image-Based Tomato Leaf Disease Detection Approach Using PLPNet. *Plant Phenomics* **2023**, *5*, 0042. [CrossRef] [PubMed]
156. Kibriya, H.; Rafique, R.; Ahmad, W.; Adnan, S.M. Tomato Leaf Disease Detection Using Convolution Neural Network. In Proceedings of the 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST 2021), Islamabad, Pakistan, 12–16 January 2021; IEEE: New York, NY, USA, 2021; pp. 346–351. [CrossRef]
157. Karthik, R.; Hariharan, M.; Anand, S.; Mathikshara, P.; Johnson, A.; Menaka, R. Attention embedded residual CNN for disease detection in tomato leaves. *Appl. Soft Comput. J.* **2020**, *86*, 105933. [CrossRef]
158. Ecemiş, İ.N.; İlhan, H.O. The performance comparison of pre-trained networks with the proposed lightweight convolutional neural network for disease detection in tomato leaves. *J. Fac. Eng. Archit. Gazi Univ.* **2023**, *38*, 693–705. [CrossRef]
159. Anim-Ayeko, A.O.; Schillaci, C.; Lipani, A. Automatic blight disease detection in potato (*Solanum tuberosum* L.) and tomato (*Solanum lycopersicum*, L. 1753) plants using deep learning. *Smart Agric. Technol.* **2023**, *4*, 100178. [CrossRef]
160. Chowdhury, M.E.H.; Rahman, T.; Khandakar, A.; Ayari, M.A.; Khan, A.U.; Khan, M.S.; Al-Emadi, N.; Reaz, M.B.I.; Islam, M.T.; Ali, S.H.M. Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques. *AgriEngineering* **2021**, *3*, 294–312. [CrossRef]
161. Ahmad, I.; Hamid, M.; Yousaf, S.; Shah, S.T.; Ahmad, M.O. Optimizing pretrained convolutional neural networks for tomato leaf disease detection. *Complexity* **2020**, *2020*, 1–6. [CrossRef]
162. Qi, J.; Liu, X.; Liu, K.; Xu, F.; Guo, H.; Tian, X.; Li, M.; Bao, Z.; Li, Y. An improved YOLOv5 model based on visual attention mechanism: Application to recognition of tomato virus disease. *Comput. Electron. Agric.* **2022**, *194*, 106780. [CrossRef]
163. Hong, H.; Lin, J.; Huang, F. Tomato Disease Detection and Classification by Deep Learning. In Proceedings of the 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE 2020), Fuzhou, China, 12–14 June 2020; IEEE: New York, NY, USA, 2020; pp. 25–29. [CrossRef]
164. Paul, S.G.; Biswas, A.A.; Saha, A.; Zulfiker, M.S.; Ritu, N.A.; Zahan, I.; Rahman, M.; Islam, M.A. A real-time application-based convolutional neural network approach for tomato leaf disease classification. *Array* **2023**, *19*, 100313. [CrossRef]
165. Kumar, A.; Vani, M. Image Based Tomato Leaf Disease Detection. In Proceedings of the 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kanpur, India, 6–8 July 2019; IEEE: New York, NY, USA, 2019; pp. 1–6. [CrossRef]
166. Liu, J.; Wang, X. Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model. *Plant Methods* **2020**, *16*, 1–16. [CrossRef]
167. Nagamani, H.S.; Sarojadevi, H. Tomato Leaf Disease Detection using Deep Learning Techniques. *Int. J. Adv. Comput. Sci. Appl.* **2022**, *13*, 305–311. [CrossRef]
168. Khalid, A.; Akbar, S.; Hassan, S.A.; Firdous, S.; Gull, S. Detection of Tomato Leaf Disease Using Deep Convolutional Neural Networks. In Proceedings of the 4th International Conference on Advancements in Computational Sciences, Lahore, Pakistan, 20–22 February 2023; IEEE: New York, NY, USA, 2023; pp. 1–6. [CrossRef]
169. Gonzalez-Huitron, V.; León-Borges, J.A.; Rodriguez-Mata, A.E.; Amabilis-Sosa, L.E.; Ramírez-Pereda, B.; Rodriguez, H. Disease detection in tomato leaves via CNN with lightweight architectures implemented in Raspberry Pi 4. *Comput. Electron. Agric.* **2021**, *181*, 105951. [CrossRef]
170. Ulutaş, H.; Aslantaş, V. Design of Efficient Methods for the Detection of Tomato Leaf Disease Utilizing Proposed Ensemble CNN Model. *Electronics* **2023**, *12*, 827. [CrossRef]
171. Tarek, H.; Aly, H.; Eisa, S.; Abul-Soud, M. Optimized Deep Learning Algorithms for Tomato Leaf Disease Detection with Hardware Deployment. *Electronics* **2022**, *11*, 140. [CrossRef]
172. Agarwal, M.; Singh, A.; Arjaria, S.; Sinha, A.; Gupta, S. ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network. *Procedia Comput. Sci.* **2020**, *167*, 293–301. [CrossRef]
173. Saeed, A.; Abdel-Aziz, A.A.; Mossad, A.; Abdelhamid, M.A.; Alkhaled, A.Y.; Mayhoub, M. Smart Detection of Tomato Leaf Diseases Using Transfer Learning-Based Convolutional Neural Networks. *Agriculture* **2023**, *13*, 139. [CrossRef]
174. Zhong, Y.; Teng, Z.; Tong, M. LightMixer: A novel lightweight convolutional neural network for tomato disease detection. *Front. Plant Sci.* **2023**, *14*, 1–12. [CrossRef]
175. Harakannanavar, S.S.; Rudagi, J.M.; Puranikmath, V.I.; Siddiqua, A.; Pramodhini, R. Plant leaf disease detection using computer vision and machine learning algorithms. *Glob. Transit. Proc.* **2022**, *3*, 305–310. [CrossRef]
176. Chug, A.; Bhatia, A.; Singh, A.P.; Singh, D. A novel framework for image-based plant disease detection using hybrid deep learning approach. *Soft Comput.* **2023**, *27*, 13613–13638. [CrossRef]
177. Darwish, A.; Ezzat, D.; Hassanien, A.E. An optimized model based on convolutional neural networks and orthogonal learning particle swarm optimization algorithm for plant diseases diagnosis. *Swarm Evol. Comput.* **2020**, *52*, 100616. [CrossRef]
178. Arora, J.; Agrawal, U.; Sharma, P. Classification of Maize leaf diseases from healthy leaves using Deep Forest. *J. Artif. Intell. Syst.* **2020**, *2*, 14–26. [CrossRef]

179. Nathanael, O.; Hutagalung, M.; Gamaliel, Y. Development of Convolutional Neural Network (CNN) Method for Classification of Tomato Leaf Disease Based on Android. In Proceedings of the 2023 1st IEEE International Conference on Smart Technology (ICE-SMARTec), Bandung, Indonesia, 17–19 July 2023; IEEE: New York, NY, USA, 2023; pp. 60–65.
180. Rizvi, S.M.H.; Naseer, A.; Rehman, S.U.; Akram, S.; Gruhn, V. Revolutionizing Agriculture: Machine and Deep Learning Solutions for Enhanced Crop Quality and Weed Control. *IEEE Access* **2024**, *12*, 11865–11878. [CrossRef]
181. Yu, Z.; Wang, J. *Advances in Intelligent Systems and Computing 1220 Advancements in Mechatronics and Intelligent Robotics*; Springer: Singapore, 2020; ISBN 9789811618420.
182. BEYENE, H.; JOSHI, D.N.A.; KOTECHA, D.K. Plant Diseases Prediction Using Image Processing and Machine Learning Techniques: Survey. *Int. J. Comput. Appl.* **2018**, *1*, 226–237. [CrossRef]
183. Hasan, M.M.; Alam, K.; Diganta, M.N.A.; Nur, A.U.; Habib, M.T.; Ahmed, F. Defected Bitter Gourd Detection Using Convolutional Neural Network; A Computer Vision Approach to Reduce Cost and Time. In Proceedings of the 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 6–8 July 2021; IEEE: New York, NY, USA, 2021; pp. 1–6. [CrossRef]
184. Abisha, S.; Mutawa, A.M.; Murugappan, M.; Krishnan, S. Brinjal leaf diseases detection based on discrete Shearlet transform and Deep Convolutional Neural Network. *PLoS ONE* **2023**, *18*, e0284021. [CrossRef] [PubMed]
185. Jena, B.; Routray, A.R.; Nayak, J. Detection of Brinjal Leaf Diseases based on Superpixel approach using SLIC Clustering. In Proceedings of the 2022 5th International Conference on Computational Intelligence and Networks (CINE), Bhubaneswar, India, 1–3 December 2022; IEEE: New York, NY, USA, 2022; pp. 1–6. [CrossRef]
186. Jain, S.; Ali, K.B. Brinjal Disease Classification Using Deep Learning. In Proceedings of the 2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO 2022), Noida, India, 13–14 October 2022; IEEE: New York, NY, USA, 2022; pp. 1–5. [CrossRef]
187. Venkataramana, A.; Suresh Kumar, K.; Suganthi, N.; Rajeswari, R. Prediction of Brinjal Plant Disease Using Support Vector Machine and Convolutional Neural Network Algorithm Based on Deep Learning. *J. Mob. Multimed.* **2022**, *18*, 771–788. [CrossRef]
188. Syed, S.F.; Phonsa, G. Machine Learning Approaches for Brinjal Leaf Disease Detection. In Proceedings of the 2nd International Conference on Sustainable Computing and Data Communication Systems (ICSCDS 2023), Erode, India, 23–25 March 2023; IEEE: New York, NY, USA, 2023; pp. 226–234. [CrossRef]
189. Sasirekha, S.; Suganthy, K.B. An Approach for Detection of Disease in Carrot Using K-Means Clustering. *Int. J. Res. Eng. Sci. Manag.* **2019**, *2*, 2–5.
190. Methun, N.R.; Yasmin, R.; Begum, N.; Rajbongshi, A.; Islam, M.E. Carrot Disease Recognition using Deep Learning Approach for Sustainable Agriculture. *Int. J. Adv. Comput. Sci. Appl.* **2021**, *12*, 732–741. [CrossRef]
191. Ray, S.D.; Natasha, M.K.T.K.; Hakim, M.A.; Nur, F. Carrot Cure: A CNN based Application to Detect Carrot Disease. In Proceedings of the 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI 2022), Tirunelveli, India, 28–30 April 2022; IEEE: New York, NY, USA, 2022; pp. 1043–1049. [CrossRef]
192. Reya, S.S.; Malek, M.A.; Debnath, A. Deep Learning Approaches for Cabbage Disease Classification. In Proceedings of the 2022 International Conference on Recent Progresses in Science, Engineering and Technology (ICRPSET), Rajshahi, Bangladesh, 26–27 December 2022; IEEE: New York, NY, USA, 2022; pp. 1–5. [CrossRef]
193. Kirola, M.; Joshi, K.; Chaudhary, S.; Singh, N.; Anandaram, H.; Gupta, A. Plants Diseases Prediction Framework: A Image-Based System Using Deep Learning. In Proceedings of the 2022 IEEE World Conference on Applied Intelligence and Computing (AIC 2022), Sonbhadra, India, 17–19 June 2022; IEEE: New York, NY, USA, 2022; pp. 307–313. [CrossRef]
194. Alex, S.; Premkumar, S. Detection of Fungal Disease in Cabbage Images Using Adaptive Thresholding Technique Compared with Threshold Technique. *Rev. Gestão Inovação Tecnol.* **2021**, *11*, 1112–1125. [CrossRef]
195. Song, H.; Yoon, S.R.; Dang, Y.M.; Yang, J.S.; Hwang, I.M.; Ha, J.H. Nondestructive classification of soft rot disease in napa cabbage using hyperspectral imaging analysis. *Sci. Rep.* **2022**, *12*, 14707. [CrossRef]
196. Kanna, G.P.; Kumar, S.J.K.J.; Kumar, Y.; Changela, A.; Woźniak, M.; Shafi, J.; Ijaz, M.F. Advanced deep learning techniques for early disease prediction in cauliflower plants. *Sci. Rep.* **2023**, *13*, 18475. [CrossRef]
197. Shakil, R.; Akter, B.; Shamrat, F.M.J.M.; Noori, S.R.H. A novel automated feature selection based approach to recognize cauliflower disease. *Bull. Electr. Eng. Inform.* **2023**, *12*, 3541–3551. [CrossRef]
198. Mondal, D.; Kumar, D.; Roy, K. Gradation of yellow mosaic virus disease of okra and bitter gourd based on entropy based binning and Naive Bayes classi fi er after identi fi cation of leaves. *Comput. Electron. Agric.* **2017**, *142*, 485–493. [CrossRef]
199. Krishnaswamy Rangarajan, A.; Purushothaman, R.; Pérez-Ruiz, M. Disease classification in aubergine with local symptomatic region using deep learning models. *Biosyst. Eng.* **2021**, *209*, 139–153. [CrossRef]
200. Saad, I.H.; Islam, M.M.; Himel, I.K.; Mia, M.J. An automated approach for eggplant disease recognition using transfer learning. *Bull. Electr. Eng. Inform.* **2022**, *11*, 2789–2798. [CrossRef]