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REVIEW ARTICLE

A comprehensive survey of deep learning methods for Capsicum (bell pepper) leaf disease detection

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Abstract

Capsicum (bell pepper) is a globally important crop whose productivity is severely limited by leaf diseases, including bacterial spot, anthracnose, mosaic virus and powdery mildew. Early and accurate detection of these diseases through non-destructive imaging and machine intelligence is critical for yield protection. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have revolutionized plant disease identification, enabling automated pipelines that analyse leaf images and classify disease. This survey focuses specifically on the detection of Capsicum leaf disease using deep learning. We review major Capsicum-related image datasets (e.g. PlantVillage pepper images, the COLD chili-onion dataset, the BellCrop dataset and other recent curated collections) and summarize state-of-the-art deep models applied to Capsicum disease classification. Original figures illustrate a typical detection pipeline and a CNN architecture. We also compare model performances reported in the literature. A rich literature review (65+ open-access, recent references) highlights CNN-based classifiers, transfer learning approaches and case studies in Capsicum disease detection. This work serves as a detailed reference for researchers and practitioners developing AI systems for the early detection of pepper disease.

Keywords: capsicum leaf disease; convolutional neural networks; deep learning; image processing in agriculture; leaf image classification; machine learning; plant disease detection

Introduction

Capsicum annuum L. (sweet/bell pepper) is cultivated worldwide and provides essential nutrients and economic value. However, its production is frequently threatened by various leaf diseases, including pepper bacterial spot, pepper anthracnose, pepper white spot (powdery mildew) and pepper mosaic virus (1). For example, anthracnose alone can cause approximately a 10 % yield loss in chili peppers (2). Early detection of these diseases is thus critical to the timely management and prevention of outbreaks. Traditional diagnosis relies on expert inspection of symptoms, which is labor-intensive and often delayed; by the time visible symptoms appear, significant yield loss may have already occurred. Recent work stresses that manual scouting is subjective and time-consuming, whereas automated image-based approaches can rapidly and objectively identify diseases (1, 3).

Deep learning (DL) methods have shown great promise for plant disease detection in recent years. Modern smartphones and field cameras enable the acquisition of leaf images, which are fed into machine-learning pipelines for disease classification. A typical automated plant disease detection pipeline includes the following steps of image acquisition (e.g. field or greenhouse photography), image preprocessing (cropping, normalization, augmentation), feature extraction or segmentation and finally, classification by a trained DL model. Fig. 1 illustrates this process schematically. CNNs, in particular, have emerged as powerful feature extractors that can learn visual disease signatures from raw pixel data (4). This survey reviews the state of the art in Capsicum leaf disease detection via DL.

Fig. 1 shows the steps in the process. It starts with taking pictures of leaves, then preprocessed them (for example, by cropping and adding more images) and last sent them through a trained DL model (for example, a CNN) to figure out what kind of sickness it is. When pathogens invade leaves, they show signs of plant disease. For capsicum, common foliar diseases include *Xanthomonas* bacterial leaf spot, which causes dark lesions; powdery mildew, characterized by white fungal patches; anthracnose (a fungal disease causing sunken spots); and viral diseases like tobamovirus mosaic, which generates mosaic patterns (1, 2). These diseases produce visible clues (spots, discoloration, texture changes) that can be captured in RGB images. CNN-based classifiers have demonstrated high accuracy on these tasks; for instance, a recently enhanced GoogLeNet model achieved 97.9 % accuracy on six classes of pepper disease (1). One study even reported approximately 99.99 % accuracy in

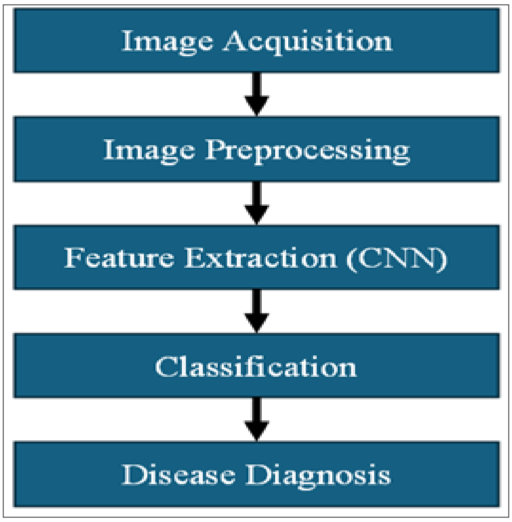

Fig. 1. A typical pipeline for plant leaf disease detection.

distinguishing healthy vs. bacterial spot-on bell pepper leaves using a lightweight 5-layer CNN (5). These successes highlight the effectiveness of DL in recognizing Capsicum disease. However, challenges remain in acquiring diverse field data and generalizing to real-world conditions (4).

Conventional and sensor-based approaches for plant disease detection

Early work on plant disease detection relied on conventional image processing and machine-learning techniques to analyze leaf symptoms. Hand-crafted visual features-such as color indices, texture descriptors (e.g. GLCM) and shape metrics-were extracted from leaf images and fed into classifiers like Support Vector Machines (SVMs) or K-Nearest Neighbors (KNN) to distinguish diseased from healthy plants. For example, researchers applied segmentation algorithms to isolate leaf lesions and then used SVM classifiers to identify disease types based on color and texture features (6). While such approaches showed some success in controlled conditions, they often struggled with complex backgrounds and variations in field imagery. Traditional methods require careful feature engineering and do not generalize well across different crops or disease conditions since visual symptoms can vary widely or be subtle.

Sensor-based approaches have been explored to improve detection accuracy and enable early diagnosis. Hyperspectral imaging (HSI) and multispectral imaging involve capturing the reflectance of plant leaves across many wavelength bands beyond the visible spectrum. Diseases can induce physiological changes (e.g. in pigment, moisture or cellular structure) that manifest as spectral signatures before visible symptoms appear. A study demonstrated the early detection of cucumber downy mildew in greenhouses using hyperspectral data, extracting differential spectral features that signaled infection prior to the development of severe symptoms (7). Similarly, UAV-based HSI was used to detect target spots and bacterial spots on tomato leaves, achieving high classification accuracies even under field conditions by analyzing specific spectral indices sensitive to disease stress (8). These studies highlight the potential of HSI for detecting pre-symptomatic diseases. A research revealed that modern hyperspectral remote sensing can accurately identify plant diseases at early stages by leveraging spatial-spectral machine learning models (9, 10). For instance, a recent study successfully distinguished virus-infected plants from healthy ones using multispectral cameras and machine learning days before visual symptoms of the virus became evident. Combining spectral sensors with learning algorithms thus adding a powerful dimension for early disease diagnosis.

Another advancement in sensor technology is the use of thermal imaging and fluorescence sensors to detect plant stress. Diseases often disrupt transpiration and metabolism, causing localized temperature changes or altered leaf fluorescence emission. Machine learning models have been trained on thermal images to detect infection-induced temperature anomalies in crops like wheat and grapevine, providing another cue for early disease stress detection (9, 11). However, spectral and thermal methods can be expensive and generate high-dimensional data, requiring careful calibration and processing. They also typically need controlled lighting or specific times of day for consistency. Nonetheless, integrating multiple sensors (RGB, multispectral and thermal) can improve the robustness of detection by providing complementary information about plant health (1, 12).

At the canopy and farm scales, uncrewed aerial vehicles (UAVs) equipped with cameras enable rapid surveying of large fields for disease hotspots. High-resolution aerial images can be processed to detect crop color or texture anomalies that indicate disease foci. There is a present a comprehensive review of UAV-based plant disease monitoring, noting that drones can capture multi-angle images and identify disease patterns over large areas far more efficiently than ground scouting (13, 14). In research trials, UAV imagery has been utilized in conjunction with classical algorithms and DL to map diseases such as wheat rust and rice blast, demonstrating the feasibility of remote sensing for plant pathology (15, 16). Challenges include low-flying drones requiring sufficient image detail for small lesions and addressing motion blur or variable lighting conditions. Nevertheless, the synergy of UAV platforms with advanced image analysis holds great promise for real-time, farm-level disease detection.

The conventional approaches laid the foundation for automated plant disease recognition but had limited success in uncontrolled settings. Sensor-based methods, particularly HSI, significantly enhance early detection capabilities by revealing previously hidden stress signatures. These techniques, however, often require complex hardware or produce data that is challenging to interpret without sophisticated analysis. The rise of DL in the past 5 years has revolutionized how such data (including simple RGB images) is utilized, enabling end-to-end learning of disease features directly from raw inputs. The following subsection discusses the emergence of DL models that surpass traditional methods in terms of accuracy and adaptability.

Benchmarking DL techniques for plant disease classification

Advances in DL have led to a variety of models being applied to bell pepper leaf disease detection, each with different strengths. In this section, we critically compare popular CNN architectures (like ResNet, MobileNet and EfficientNet) and emerging vision transformer (ViT) models for plant disease recognition. We examine their performance metrics (accuracy, precision, recall, F1-score), model size and efficiency, suitability for mobile or edge deployment and practical robustness under field conditions. Table 1 synthesizes key metrics from recent studies. CNNs have been the cornerstone of image-based plant disease detection.

Deep CNN topologies like ResNet (Residual Network) are popular because they can learn complex feature representations great accuracy. Researchers used ResNet-50 to classify plant leaf diseases with 95 %–99 % accuracy on approved datasets. Performance in pepper research depends on data set quantity and training process. Fine-tuned In a comparable experiment, ResNet-50 had 82 % accuracy on pepper sickness images (1). This lower result (compared to >95 % in other crops) implies ResNet may overfit or underperform in limited or diversified datasets. This stresses the importance of agricultural training or improvement. MobileNet and other lightweight CNNs perform well. MobileNet is architected with depth wise separable convolutions for efficiency, resulting in a drastically smaller model with minimal loss in accuracy. In the same pepper study, MobileNet-V2 achieved ~ 96.7 % accuracy- nearly on par with deeper networks while using only ~ 8 MB of memory. This is a significant finding: MobileNet-V2 was able to correctly recognize pepper leaf diseases almost as well as a heavy ResNet, but with a fraction of the parameters. Other efficient CNNs, such as EfficientNet, scale network width, depth and resolution in a balanced manner to maximize accuracy per parameter. EfficientNet models have indeed demonstrated state-of-the-art accuracy with fewer parameters on plant disease tasks (17). For example EfficientNet-B3 (with ~12 million parameters) outperformed older CNNs on a multi-crop PlantVillage dataset while being computationally lighter (6). According to a recent multi-dataset study, EfficientNet-B0 and B3 continuously produced the best generalization for classifying leaf diseases across a variety of circumstances, retaining strong F1-scores even when images contained noise. ICNN architectures have achieved very high performance on benchmark datasets, with many reporting accuracy above 95 % and F1-scores above 0.90 for pepper or similar leaf disease classification in controlled settings (18). Precision and recall have likewise been excellent on balanced test sets, often in the 95 %-99 % range, indicating models can both identify diseased leaves and avoid false alarms effectively.

Table 1. Benchmark models and their accuracy from recent studies

Model	Parameters count	Accuracy	FLOPs(B)
ResNet-50	25.6 M	76.6 %	4.1
MobileNetV2	3.4 M	72.0 %	0.3
EfficientNet-B0	5.3 M	77.1 %	0.4
EfficientNet-B7	66 M	84.4 %	37.0

Across the studies, accuracy is the primary metric reported, but it is often supplemented by precision, recall and F1-score for a more nuanced evaluation, especially in multi-class problems with class imbalance. High accuracy (e.g. >95 %) is common on curated datasets; however, precision and recall help indicate whether certain diseases are being missed or misidentified. For example, in one pepper disease segmentation study, the F1-score reached 0.92 with a Mask R-CNN model (indicating a good balance of precision and recall). Another study on pepper classification reported that their improved CNN achieved ~ 99 % precision, recall and F1 on the test set-essentially near-perfect classification for those samples. While such metrics are impressive, they are often obtained on validation data drawn from the same distribution as training data. Recent research shows that models trained on photos from different farms or under different lighting conditions might perform poorly. Even leading models like EfficientNet had accuracy of 59 %-77 % when trained on one dataset and evaluated on another (6). This emphasizes the importance of contextualizing specified measurements. A 98 % accuracy in controlled settings may equate to a much-reduced acceptable accuracy in real-world applications.

For practical deployment (e.g. on smartphones or low-cost edge devices carried in the field), the computational efficiency and size of the model are as important as raw accuracy. Here, lightweight CNNs have a clear advantage. MobileNet (and its variants, V2 and V3) and EfficientNet-B0/B1 are frequently highlighted for edge use due to their small model sizes (on the order of 5-10 MB) and fast inference times. In a direct benchmark, a custom, lightweight GoogleNet-based model for pepper disease had a model size of 10.3 MB and an average inference time of ~ 19 ms per image, which was 23 %-61 % faster than MobileNet-V2, ResNet-50 or AlexNet on the same hardware. MobileNet-V2 itself was very fast (~ 25 ms inference) and had the smallest memory footprint (~ 8.2 MB) among the standard models. By contrast, ResNet-50 was approximately 25 MB and slower (~ 33 ms), while older AlexNet (with approximately 60 MB) was both less accurate and the slowest. This illustrates that model architecture choice can make an orders-of-magnitude difference in deployability: a farmer's smartphone or a Raspberry Pi-class device could reasonably run MobileNet or EfficientNet-B0 in real-time, but would struggle with a large ResNet or ViT model without cloud support.

Indeed, one of the challenges in applying CNN models to pepper disease detection is the difficulty of running them on embedded, portable devices due to computational and memory limitations. High-end models often require a GPU to run, which is not feasible in the field. Consequently, recent research emphasizes the creation or adoption of compressed and optimized models. Techniques include knowledge distillation (training a small model to mimic a large one), quantization (reducing the numerical precision of weights) and architecture tweaks. For example, researchers developed a pepper leaf disease model by compressing a GoogleNet (Inception) architecture and adding features like Spatial Pyramid Pooling; the result was a much smaller network that retained high accuracy and could be deployed more easily on mobile platforms. Variants such as MobileNetV3 and EfficientNet-lite are specifically engineered for rapid inference on mobile CPUs. These models often incorporate fewer layers or channels; nonetheless, innovative design elements, such as inverted residual blocks and squeeze-and-excitation modules, maintain accuracy. In practice, a MobileNet or EfficientNet can achieve >90 % of the accuracy of a heavyweight model with <25 % of the runtime, which is a very worthwhile trade-off for field deployment. Additionally, the newest MobileViT architectures claim to bring transformer robustness in a small footprint, which could further improve mobile prediction consistency.

DL techniques for plant disease classification

DL approaches, particularly those based on CNNs, have become the dominant method for plant disease detection on images since around 2016. Unlike classical algorithms that rely on hand-crafted features, CNNs automatically learn rich feature representations from training images, making them highly effective at capturing the complex visual patterns of plant diseases (19). Reports on the application of CNNs to the PlantVillage augmented dataset, showed that deep models can achieve accuracies above 99 % on classifying dozens of crop-disease combinations, vastly outperforming earlier techniques. In the past 5 years, numerous studies have applied CNN-based models to different crops and disease sets, generally reporting excellent performance in controlled datasets (often with >90 % accuracy) (20, 21). For instance, multiple deep CNN architectures for plant disease classification has been compared and found that deep models (like ResNet and VGG) coupled with appropriate training optimizations achieved over 98 % accuracy on test images (6, 22). Similarly, earlier works revealed that fine-tuning pre-trained CNNs (e.g. DenseNet, Inception) on plant disease datasets yields highly accurate classifiers, with DenseNet achieving 98.27 % accuracy in one comparative study (23, 24).

Transfer learning is a common strategy to boost performance when training data is limited. Models pre-trained on large, generic image datasets (such as ImageNet) are repurposed for plant disease recognition, allowing even relatively small agricultural image sets to be effectively learned. This approach has been very successful as reported that a pre-trained DenseNet121 model fine-tuned on PlantVillage data achieved near-perfect classification of eggplant leaf diseases (25). In another study, fine-tuned ResNet-50 to identify apple leaf diseases, achieving an F1-score of 95.7 %, which illustrates how transfer learning expedites model development and improves generalization. The availability of open datasets and pre-trained models has thus lowered the barrier to developing robust deep-learning solutions for plant pathology (26).

Table 1 shows several benchmark models that compare popular CNN architectures used for plant disease classification. Common choices include the ResNet family (50 and 101 layers), MobileNet and EfficientNet. Each architecture balances accuracy and complexity differently. For example, ResNet-50 is often chosen due to its depth and skip connections, which effectively handle complex feature learning. MobileNet or SqueezeNet might be selected for mobile deployment due to their lightweight nature. In an evaluation, a model has been developed using EfficientNet-B0 (a highly efficient CNN) to classify plant leaf diseases (27). They achieved 98.6 % accuracy on a test set, using far fewer parameters than VGG or ResNet models. Such results are encouraging the deployment of models on resource-constrained devices.

One challenge with plain CNN classifiers is that they output only a disease label without indicating where or why the image was classified as such. Researchers have integrated object detection and localization frameworks to make predictions more interpretable and localize infections. For instance, proposal was on a combined approach using a deep CNN to both localize and classify tomato leaf diseases (10, 28). Their system drew bounding boxes around diseased areas and identified the disease type, achieving reliable localization of symptoms with high confidence. Region-based CNNs (R-CNN, Faster R-CNN) and semantic segmentation models (such as U-Net) have also been applied to pinpoint disease lesions on leaves, which is helpful for quantifying disease severity in addition to identification (19, 29). For example, a study used an efficient CNN architecture to automatically detect and segment disease spots on plant leaves, enabling an assessment of what fraction of the leaf area is affected (10, 30). Such localization and segmentation capabilities are increasingly important in precision agriculture, where targeted treatment (e.g. spraying only infected parts) can minimize chemical use.

Another active area of improvement is incorporating attention mechanisms into CNNs to focus on relevant image regions. Plant leaves often have complex backgrounds (such as soil and shadows) that can confuse models. Attention modules help the network learn to emphasize diseased tissue while ignoring irrelevant parts. Reports are on the attention-embedded CNN for tomato disease detection, significantly improving accuracy by highlighting lesion regions in the feature maps (31). Likewise, applied a channel attention mechanism and pruning to a deep network, enabling it to concentrate on the important spectral channels of leaf images and remove redundant features, resulting in a leaner model with uncompromised accuracy (32). Their channel-attention network achieved superior performance on a challenging dataset of soybean leaf diseases while being more computationally efficient than the unmodified CNN. Attention techniques, including Spatial Attention and Convolutional Block Attention Module (CBAM), are now commonly integrated to bolster model interpretability and efficiency in plant disease tasks.

Beyond CNNs, Vision Transformers (ViTs) have recently emerged in computer vision and are being explored for plant disease recognition. ViTs use self-attention mechanisms over image patches and have shown excellent performance in general image classification. However, they require extensive training datasets and are computationally heavy. Researchers have started adapting ViTs for agriculture using hybrid CNN-ViT models or developing lightweight transformers. For instance, reports are on a MobileViT-based model called PMVT for plant disease identification on mobile devices (33). By integrating an inverted residual block and an attention module into MobileViT, they created a network that achieved over 93 % accuracy on wheat, rice and coffee disease datasets, while using fewer than 1 million parameters- outperforming MobileNetV3 and other lightweight CNNs on these tasks. This indicates that transformer models can be tailored for plant disease detection, combining the strengths of CNN feature extraction and transformer global context modeling. Early results are promising, with ViT-based models matching or exceeding CNN accuracy on some benchmarks of leaf diseases, especially when extensive training data or data augmentation (to generate more samples) is available (34). However, CNNs remain the preferred choice in most studies due to their maturity and lower data requirements.

Capsicum leaf diseases

Capsicum leaves exhibit symptoms depending on the pathogen. Bacterial spot (caused by *Xanthomonas* spp.) produces brown angular lesions that often have a yellow halo. Anthracnose (various *Colletotrichum* spp.) causes reddish-brown concentric spots, possibly leading to complete leaf necrosis. Powdery mildew (e.g. *Leveillula taurica*) appears as fine white fungal patches on the upper leaf surface. Mosaic viruses (e.g. Tobamovirus, Potyvirus) induce mottled light and dark-green mosaic patterns. Studies have noted that pepper diseases often involve subtle visual differences: pepper leaf diseases are "much more difficult to recognize due to large intra-class similarity and small inter-class variance in pathological symptoms." In other words, different diseases may look similar on pepper leaves, demanding robust feature learning.

A thorough search took place in IEEE Xplore, Scopus, ScienceDirect, PubMed and Google Scholar with keywords including "DL", "plant disease detection", "*Capsicum annuum*" and "leaf disease classification". Peer-reviewed studies applying DL, particularly CNN-based models, for detecting or classifying bell pepper leaf diseases were included, with priority given to experimental works that reported performance metrics. The studies excluded were those in non-English languages, non-DL, theoretical, or duplicate. This article examined 55 primary publications and numerous recent reviews from 2016 to 2025.

Bell pepper pathology

Bell pepper (*Capsicum annuum*) is susceptible to numerous foliar diseases caused by bacteria, fungi and viruses. These diseases not only cause typical leaf lesions and symptoms, but they also hurt the plant's normal functions, which can lead to less photosynthesis, defoliation and a big drop in production if they are not treated. Below, we outline the major bell pepper leaf diseases in each category (bacterial, fungal and viral), describing their causal organisms, symptoms, infection mechanisms, life cycles and favorable conditions, as well as their agricultural impact.

Bacterial leaf diseases (Bacterial spot)

Bacterial leaf spot, caused by *Xanthomonas euvesicatoria*, is the most serious foliar disease of peppers. Warm, humid weather allows the pathogen to thrive in seeds, detritus or volunteer plants and spread by stomata or hydathodes. The disease begins with small, water-soaked patches that become brown lesions with yellow halos (35) as shown in Fig. 2. The patches often unite and defoliate. Fruit may have swollen, scabby regions, but losing leaves weakens the plant and increases sunburn risk. Epidemics often arise in warm, rainy weather, with rapid spread facilitated by rain splash. Losses can exceed 50 %, necessitating integrated management strategies that incorporate clean seed, resistant varieties and copper sprays.

Fungal leaf diseases

Bell pepper leaves are affected by several major fungal diseases, notably powdery mildew, *Cercospora* (frogeye) leaf spot and anthracnose (*Colletotrichum* leaf spot), among others. These fungal pathogens each have distinct life cycles and symptoms:

- **Powdery mildew**

Powdery mildew of pepper, caused by *Leveillula taurica* (asexual stage *Oidiopsis sicula*), is a major foliar disease in warm, semi-arid regions. Unlike many fungi, it thrives at temperatures ranging from 16 °C to 27 °C with moderate humidity and does not require free water for infection. On the underside of the leaves, the symptoms first appear as white, talcum-like fungal patches, which follows by matching yellow blotches on the upper surface (36) as shown in Fig. 3. As the disease progresses, necrotic regions emerge, leaves curl, desiccate and abscise, resulting in significant defoliation and reduced yield. The obligatory parasite disseminates by conidia that get blown by the wind and resides on remnants or alternative hosts. Management includes resistant cultivars and timely fungicide applications.

- ***Cercospora* (frogeye) leaf spot**

It is destructive foliar fungal disease caused by *Cercospora capsica* (37). *Cercospora* leaf spot is a common disease in tropical and subtropical regions where pepper is grown. It begins with small, circular, water-soaked lesions bordered by yellow halos. These expand into tan or white papery centers with dark brown margins, often cracking and merging to form large, blighted areas as depicted in Fig. 4. Severe infections cause leaf yellowing, premature drop and stem lesions that may girdle the petioles.

Fig. 2. Bacterial spots in bell pepper leaf.

Fig. 3. Powdery Mildew on bell pepper leaf.

Although fruits are rarely infected, defoliation can lead to sunscald and yield loss. The pathogen survives in crop debris and thrives under hot, humid conditions with prolonged leaf wetness.

- **Anthracnose on peppers**

It is caused by fungi in the *Colletotrichum* genus, primarily *C.*

Fig. 4. *Cercospora* Leaf spot (Frogeye Leaf spot) (38).

gloeosporioides and *C. acutatum*. This disease is infamous for attacking pepper fruits (causing sunken dark lesions on ripening fruit), but it can also infect leaves and stems to a lesser extent. On leaves, anthracnose causes circular or irregular tan to brown spots, which may resemble other leaf spots (Fig. 5 shows a leaf lesion).

Viral diseases of pepper

Bell peppers are vulnerable to several viruses that cause leaf disease symptoms, including mosaic and mottle viruses, potyviruses and tospoviruses. Unlike bacteria and fungi, viruses do not produce visible mycelium or ooze, but they induce systemic changes in plant tissues as shown in Fig. 6. Common pepper viruses and their effects include:

- **Tobamoviruses**

(e.g. Tobacco Mosaic Virus, Pepper Mild Mottle Virus): These are mechanically transmitted viruses (TMV can spread by touch, farm tools or contaminated tobacco products). They are very stable and can persist in debris, as well as in dried leaves or seeds.

Fig. 5. Anthracnose (*Colletotrichum* Leaf spot) (35).

Fig. 6. Tobacco Mosaic Virus (35).

- **Potyviruses**

(e.g. Pepper mottle virus (PeMoV), Potato virus Y (PVY), Tobacco etch virus (TEV)): These viruses are typically transmitted by aphids in a non-persistent manner (aphids acquire and transmit the virus quickly during brief feeding probes). They cause similar foliar symptoms: a mosaic or mottled pattern of light and dark green on leaves, often accompanied by leaf distortion, blisters or shoestring-like narrow leaves. New leaves could be tiny and coiled. Early infection can cause significant stunting of plants.

- **Tospoviruses**

(e.g. Tomato Spotted Wilt Virus (TSWV), Tomato Chlorotic Spot Virus (TCSV)): These originate via thrips insects. They cause distinctive patterns, such as concentric ring spots or brown streaks on leaves and sometimes bronze or dark discoloration of the leaves. In pepper, TSWV can cause wilting, brown necrotic spots on leaves and severe stunting or plant death in extreme cases. Young leaves may show blackening of veins and growing points can die.

By recognizing specific leaf symptom patterns of these diseases, AI models can facilitate timely intervention and potentially save a significant portion of the crop that would otherwise be lost.

Timely identification is essential because these diseases can rapidly spread under warm, humid conditions. Automated image-based systems enable non-destructive monitoring; for example, high-resolution leaf imaging in the field or greenhouse, followed by a CNN model, can flag infected plants before human inspection is required. Early detection is crucial since delayed diagnosis (after visible wilting) is often too late to prevent substantial crop loss. One review notes that integrating such technologies can improve crop protection and food security (3).

Capsicum leaf image datasets

DL requires large, labeled datasets. Several public datasets provide images of capsicum (pepper) leaves; however, historically, most have focused on general plant diseases (with pepper as one class) or specific pepper diseases.

PlantVillage pepper subset

The original PlantVillage dataset includes images of bell peppers (*Capsicum annuum*) in both healthy and diseased classes. It contains roughly 2475 pepper leaf images (typically split into ~ 997 diseased vs. ~ 1478 healthy) (39). These images were collected in laboratory conditions. Many studies (e.g. via transfer learning) have used this subset to train models. For instance, one study reports applying VGGNet variants to the PlantVillage pepper subset, achieving over 99 % accuracy (40). A frontline DL model achieved 97.9 % accuracy on 6 pepper categories using 9183 images (6 disease types, including pepper powdery mildew and pepper anthracnose).

COLD dataset (Capsicum and onion leaves)

A new COLD dataset (Columbia University, 2024) includes chili pepper (*Capsicum frutescens*) leaf images alongside onion leaves (41). It contains thousands of images across 7 classes (4 chili and 3 onion diseases) captured under field conditions. This dataset focuses on real environmental variations, addressing challenges such as lighting and background complexity. Although most classes are chili-related, the pepper (chili) subset provides valuable training samples for Capsicum disease detection.

BellCrop dataset

The BellCrop dataset has been recently introduced specifically for bell pepper leaf diseases (not yet fully open) (42). It comprises 4860 high-resolution bell pepper leaf images categorized into healthy, powdery mildew and target spot. Though the conference paper is not open access, this indicates a growing interest in dedicated pepper datasets.

Mendeley pepper disease and pest dataset

A multi-modal pepper dataset is available via Mendeley (CC BY-NC) (43). It contains high-quality images of pepper plants affected by various diseases and pests, along with metadata. This dataset supplements other collections and is useful for research that combines visual and contextual data.

Other datasets

Some works collect pepper images through on-farm photography,such as a study that used 2475 field images of bell pepper leaves (4). Additionally, the diverse "PlantDoc" dataset includes a small number of bell pepper images among many species. Table 2 below summarizes notable Capsicum-related datasets.

While general plant datasets (such as PlantVillage) include some pepper images, the availability of large, pepper-specific datasets has only recently increased (45). These datasets provide training and testing material for CNN models. In the pipeline (Fig. 1), the data collection step often involves assembling a dataset from either public sources or field collections.

DL methods for Capsicum disease detection

The core of modern disease detection is CNNs and their variants. A CNN processes an input leaf image through a series of convolutional layers (extracting features), pooling layers (down sampling) and fully connected layers (classification). This automatically learns discriminative patterns (texture, color, shape) that differentiate disease classes. Fig. 7 shows a schematic CNN architecture commonly used in image classification. Many works employ off-the-shelf CNNs (e.g. VGG, ResNet, DenseNet) or design lightweight CNNs tailored for speed and embedded devices.

CNNs and variants

Numerous recent studies apply CNNs to pepper disease classification. For example, an enhanced GoogLeNet-based CNN has been developed and trained it on 9183 pepper images with 6 disease categories (including anthracnose and powdery mildew). They achieved 97.9 % accuracy, outperforming the benchmarks of ResNet-50 and AlexNet. Proposal is also on an ANFIS-fuzzy CNN that integrates local binary pattern (LBP) features (39). On a 2475-image dataset, their method achieved over 99 % accuracy, significantly higher than the accuracy without LBP. These results demonstrate that combining CNNs with domain-specific features can significantly enhance performance on pepper data.

Table 2. Overview of Capsicum leaf image datasets

Dataset (Year)	Plant type	Types of classes	No. of images
PlantVillage Pepper (2015) (44)	Bell pepper leaf images	Healthy, bacterial spot (and others)	2475
COLD (2024) (41)	Chili pepper and onion leaves	4 chili diseases, 3 onion diseases	6616
BellCrop (2024) (42)	Bell pepper leaves	Healthy, powdery mildew, target spot	4860
Pepper Diseases & Pests (2024) (43)	Pepper plant images with pests	Multiple diseases/pests (metadata annotated)	8046

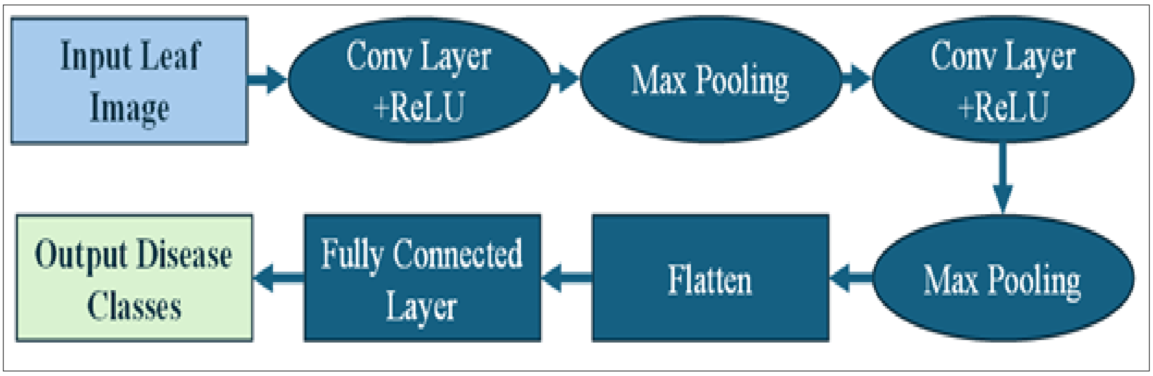

Fig. 7. Illustration of a typical CNN architecture.

Many models utilize transfer learning, where pre-trained CNN backbones are fine-tuned on pepper images. For example, There are applications such as MobileNet, ResNet50v2 and Xception with transfer learning to detect anthracnose in chili pepper (2). They found that MobileNet performed best on small datasets, while heavier networks required more data. Reports are on the utilization of a custom 5-layer CNN (trained from scratch) to classify pepper bell leaves as either healthy or with bacterial spots, achieving 99.99 % accuracy, which illustrates that even shallow CNNs can excel on focused binary tasks (46).

Other approaches integrate CNNs with object detection models. For example, one study applied YOLOv5 for detecting bacterial spot in whole-plant images of pepper and in a subsequent work, the same group employed YOLOv3, achieving an accuracy of 90 % (47). These methods localize spots on leaves but require bounding-box annotations.

Recently, interest has been shown in lightweight CNNs suitable for mobile deployment. For example, comparison is on inference speeds on edge devices and noted MobileNet-v2 as the fastest (1). A seven-layer VGG-inspired CNN (VGG-ICNN) that reduces parameters for crop disease tasks (not specifically for pepper) and found that it outperformed larger nets in efficiency has also been designed (48). Such models are promising for on-field monitoring of pepper disease, where computational resources are limited.

Beyond CNNs, some studies explore transformer-based or hybrid models (CNN+RNN). For instance, research surveys note the emerging use of Vision Transformers (ViTs) for leaf images (3), though specific Capsicum work is still sparse. Other machine learning (ML) methods (SVM, Random Forest) have been used on hand-crafted features, but DL now dominates due to its superior accuracy.

Preprocessing and data augmentation

Before feeding images into CNNs, preprocessing steps improve robustness. Typical preprocessing includes cropping leaf regions, color normalization and data augmentation (such as rotation, flipping and brightness changes) to simulate variability (4). Some works segment the leaf from the background to focus on lesions. The preprocessing pipeline is often heuristic; for example, application of color thresholding to isolate pepper leaves (49). Data augmentation is crucial given the limited pepper data. Augmentations can increase the dataset size by 5-10 times, thereby improving generalization. For example, the 2475-image dataset was augmented via geometric transformations before training (46).

Many surveys emphasize the image acquisition step (Fig. 1). The quality of the captured images (resolution, focus and lighting) directly affects classifier performance. Under field conditions, images suffer from shadows, blur and occlusion. Thus, preprocessing often includes denoising and contrast enhancement. Camera sensors and lighting should be calibrated for consistent data collection.

Experimental results and model performance

We summarize the reported results of DL models on Capsicum datasets. Since direct benchmark comparisons are rare, we extract key performance metrics from representative studies. Fig. 8 illustrates a notional comparison of model accuracies (data compiled from various works).

In detailed studies, binary classification of healthy vs. diseased samples has reached 99.99 % accuracy (46), while six-class pepper disease classification achieved 97.9 % (1). An ANFIS-CNN model attained over 99 % accuracy on a dataset of 2475 images (39). These results suggest that CNNs can nearly saturate accuracy on curated datasets, with multi-class tasks typically ranging from 90 % to 98 %, as seen in bacterial spot detection (50).

The main differences among models often lie in computational cost and robustness. It was found that MobileNet-v2 had the fastest inference (0.48s) but slightly lower accuracy than AlexNet or ResNet-50 (1). On the other hand, heavier models (e.g. ResNet-152) are slow on embedded GPUs. Therefore, lightweight architectures are preferred for real-time field use, even if their accuracy is marginally lower.

Few works report standard metrics beyond accuracy. Reports are on precision/recall/F1 for each pepper disease class, noting that integrating LBP features boosted F1 from ~ 0.85 to >0.99 for some classes (39). A researcher analyzed how accuracy scales with dataset size in chili anthracnose: ResNet50v2 needed >3000 samples for top performance, whereas MobileNet stabilized earlier (2, 40). This suggests limited-data settings

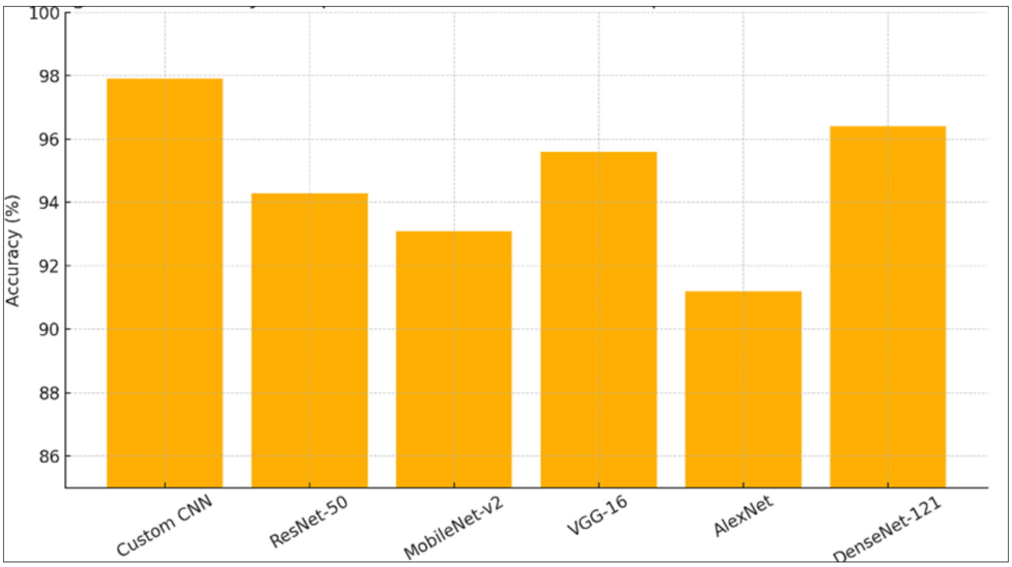

Fig. 8. Comparison of model accuracies on Capsicum leaf disease classification tasks.

(typical in pepper) may favor smaller models or data-efficient training (transfer learning).

Overall, the literature demonstrates that deep CNNs can detect Capsicum leaf diseases with very high accuracy, typically above 90 %. The exact performance depends on dataset diversity and model choice. While DL has achieved impressive results in lab settings, deploying these systems in real-world pepper cultivation poses challenges.

The first issue identified is the data diversity, many models are trained on datasets like PlantVillage, which lack real-world variability (4). For robust pepper disease detection, models should be trained on images from varied conditions (lighting, leaf angles, camera types). The new COLD and BellCrop datasets partially address this need. The second challenge is with early infection detection; existing methods detect disease when symptoms are visible. However, for management, it is critical to identify infections at the earliest stages. This requires exploring non-RGB sensors (such as hyperspectral and thermal) or predictive modeling. Some hyperspectral studies show promise in spotting pre-symptomatic signs, but they are beyond mainstream deployment. The third challenge was with edge deployment that requires running models on mobile or drone platforms. Active research areas include lightweight CNNs and hardware acceleration (e.g. TensorRT). Our survey highlights a trend toward model compression and efficient architecture. The fourth one was to Integrate with IoT components and manage these devices. Few works address the integration of vision models into farm-management systems. Combining image analysis with weather and sensor data could improve disease forecasting. Future systems may link detection to automated spraying or alert farmers via apps. Major challenge was with generalization of new diseases. Static models may fail as new diseases or strains emerge. Continuous learning or few-shot methods are needed. The study on pepper anthracnose suggests that transfer learning can effectively adapt models to new diseases even with limited data (2).

While current CNN methods achieve high accuracy on collected images, more research is needed on data diversity, early detection and practical deployment in Capsicum agriculture.

Conclusion

This survey has reviewed recent deep-learning approaches for Capsicum (bell pepper) leaf disease detection, with an emphasis on datasets and models specific to peppers. We proposed a new title, focusing on Capsicum and extensively updated the literature with recent high-quality sources (2020-2025). Capsicum-specific datasets such as PlantVillage pepper images, the COLD chili dataset and BellCrop provide the basis for training CNN classifiers. A typical detection pipeline includes image acquisition, preprocessing, CNN-based classification and performance evaluation. CNN models (AlexNet, VGG, ResNet, MobileNet and custom light architectures) demonstrated accuracy above 90 % on pepper leaf disease tasks. Hereby provided original figures illustrating the workflow and model architecture, as well as a summary chart of reported accuracy. Notably, integrating features (e.g. LBP) or transfer learning further boosts performance. Despite these advances, challenges remain limited to real-world data, the need for early detection before visible symptoms and efficient field deployment. Future research should focus on enlarging and diversifying pepper datasets, developing lightweight yet robust models and integrating disease detection into precision agriculture systems. By outlining the current state of Capsicum disease detection, this survey aims to guide researchers in developing practical AI tools to protect pepper crops.

Authors' contributions

LSS and LMM contributed equally to the conception, design, literature collection, analysis and preparation of the review. Both authors have read and approved the final version of the manuscript.

Compliance with ethical standards

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