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Machine Learning Models for Early Detection of Plant Diseases Using Multispectral Imaging: A Comprehensive Review

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Abstract
Plant diseases significantly affect crop productivity and global food security, making early detection essential for sustainable agriculture. Traditional visual diagnosis methods are often slow, subjective, and ineffective during early infection stages. Recent advances in multispectral and hyperspectral imaging combined with machine learning and deep learning techniques enable rapid, non-destructive, and accurate detection of plant diseases before visible symptoms appear. Spectral imaging captures physiological and biochemical changes in plants across visible, near-infrared, red-edge, and thermal bands, while algorithms such as SVM, Random Forest, CNN, RNN, and Vision Transformers effectively classify healthy and diseased plants. This review discusses imaging techniques, preprocessing methods, machine learning models, UAV-based sensing, explainable AI, and edge computing applications in precision agriculture, along with challenges and future directions for smart disease detection systems.

Keywords: *Machine Learning, Multispectral Imaging, Hyperspectral Imaging, Plant Disease Detection, Deep Learning.*

Highlights

- Multispectral imaging enables non-destructive early disease detection in crops.
- Machine learning and deep learning models improve disease classification accuracy.
- CNNs, SVMs, and Vision Transformers are widely used in plant disease diagnosis.
- UAV-based sensing systems support real-time large-scale crop monitoring.
- AI-integrated precision agriculture can enhance sustainable crop protection and food security.

1. Introduction

Agriculture is one of the most important sectors supporting global food security, economic development, and human survival. However, plant diseases continue to pose serious threats to agricultural productivity and crop quality worldwide. Various fungal, bacterial, viral, and parasitic pathogens are responsible for substantial reductions in crop yield and quality, resulting in severe economic losses every year. According to global estimates, plant diseases account for approximately 20–40% losses in agricultural production annually, thereby threatening food availability and sustainable farming systems. Consequently, early and accurate detection of plant diseases has become an essential requirement for modern precision agriculture. Conventional methods of plant disease diagnosis mainly rely on visual inspection, laboratory culturing, molecular testing, and expert knowledge. Although these methods are effective under controlled conditions, they suffer from several limitations such as high labor requirements, long processing time, high operational costs, and dependence on experienced pathologists. More importantly, traditional visual diagnosis often fails to detect diseases during their early asymptomatic stages because visible symptoms usually appear only after severe physiological damage has already occurred. Delayed disease detection can lead to rapid pathogen spread, excessive pesticide application, reduced crop quality, and significant economic losses.

2. Multispectral Imaging in Plant Disease Detection

2.1 Principles of Multispectral Imaging

Multispectral imaging captures reflectance information at discrete wavelength bands. Common spectral regions include:

- Blue (450–495 nm)
- Green (495–570 nm)
- Red (620–750 nm)
- Near Infrared (NIR: 750–1000 nm)
- Shortwave Infrared (SWIR)

Healthy vegetation strongly absorbs red light due to chlorophyll and reflects NIR because of cellular structure. Disease-induced physiological stress modifies these spectral responses [7]. Hyperspectral imaging differs from multispectral imaging by capturing hundreds of narrow contiguous spectral bands. Although hyperspectral imaging provides richer spectral information, multispectral systems are more cost-effective and computationally efficient [8].

2.2 Spectral Signatures of Diseased Plants

Disease infections alter plant physiology through:

- Chlorophyll degradation
- Reduced photosynthesis
- Water stress
- Cellular damage
- Pigment changes

These physiological changes affect spectral reflectance patterns. For example:

- Increased reflectance in red wavelengths
- Reduced NIR reflectance
- Altered red-edge position

Such spectral changes can be detected before visible symptoms emerge [9].

3. Machine Learning Techniques for Disease Detection

3.1 Traditional Machine Learning Models

3.1.1 Support Vector Machine (SVM)

SVM is one of the most widely used classifiers in spectral image analysis. It identifies optimal hyperplanes separating disease classes with high-dimensional spectral features [10].

Advantages:

- Effective in high-dimensional data
- Good generalization
- Works with small datasets

Limitations:

- Computationally expensive for large datasets
- Sensitive to parameter selection

Several studies reported SVM accuracies above 90% for disease classification using hyperspectral data [11].

3.1.2 Random Forest (RF)

Random Forest uses ensemble decision trees for classification. RF performs well with noisy and nonlinear agricultural datasets [12].

Advantages:

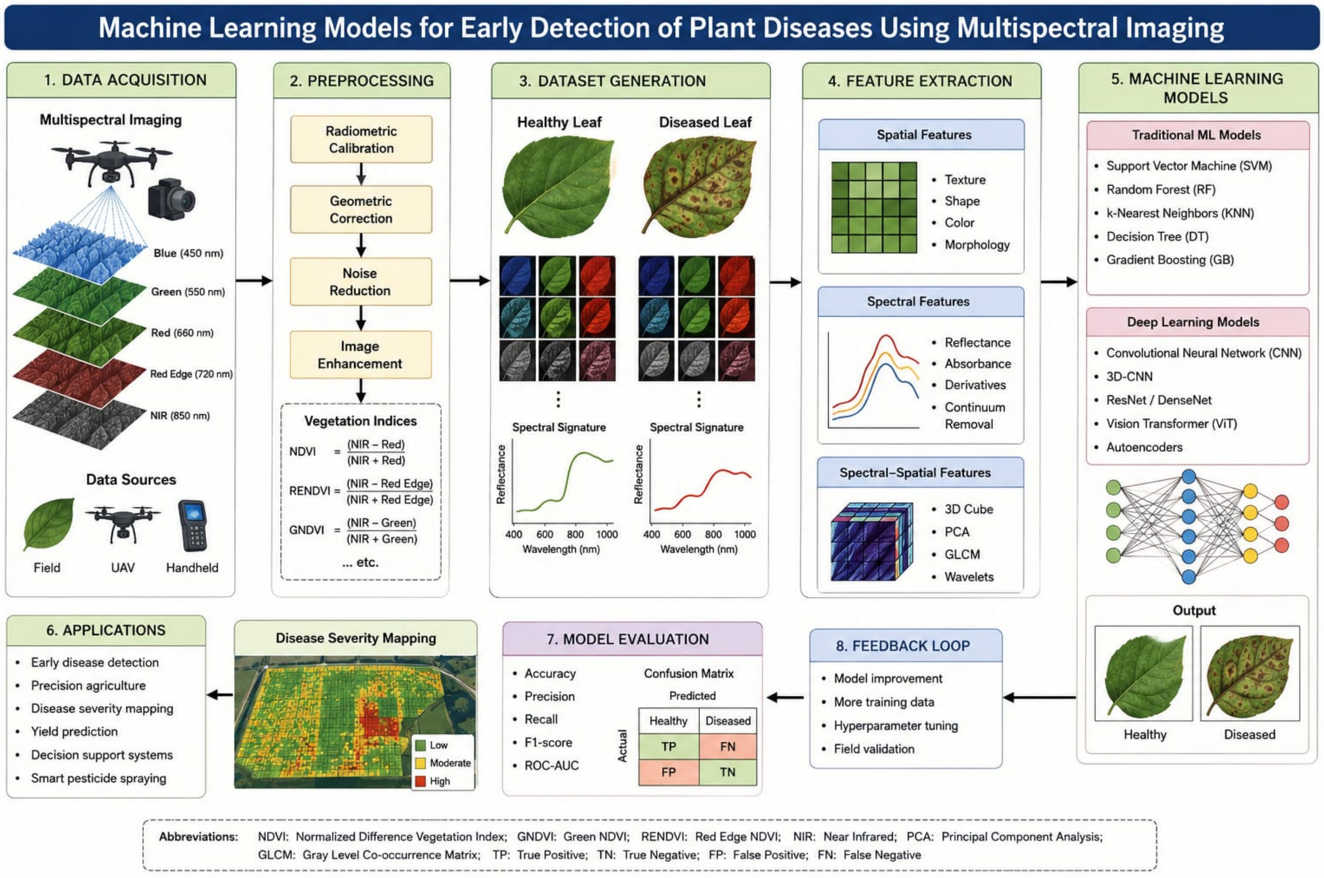

Figure 1. Machine Learning Models for Early Detection of Plant Diseases

- Handles large feature spaces
- Resistant to overfitting
- Provides feature importance

RF has been extensively used in wheat rust detection, citrus canker diagnosis, and rice blast classification [13].

3.1.3 k-Nearest Neighbor (kNN)

kNN classifies samples based on similarity with neighboring data points [14].

Advantages:

- Simple implementation
- Non-parametric
- Limitations:
- High memory requirement
- Sensitive to dimensionality

Although simpler than deep learning methods, kNN remains useful in small-scale disease detection tasks.

4. Deep Learning Models

4.1 Convolutional Neural Networks (CNN)

CNNs have become dominant in image-based plant disease detection due to their ability to automatically learn hierarchical features [15].

Popular CNN architectures include:

- AlexNet
- VGGNet
- GoogLeNet
- ResNet
- DenseNet
- EfficientNet

CNNs eliminate manual feature engineering and significantly outperform traditional ML methods [16]. Studies demonstrated classification accuracies exceeding 98% using CNNs with hyperspectral imagery [17].

4.2 3D-CNN Models

3D-CNNs simultaneously process spectral and spatial dimensions of hyperspectral cubes [18].

Advantages:

- Better spectral-spatial feature extraction
- Improved disease discrimination

However, 3D-CNNs require extensive computational resources and large annotated datasets [19].

4.3 Transfer Learning

Transfer learning utilizes pretrained models trained on large datasets such as ImageNet [20].

Benefits include:

- Reduced training time

- Improved performance with limited datasets
- Lower computational cost

Transfer learning has shown promising results in crop disease detection using multispectral imagery [21].

4.4 Vision Transformers (ViTs)

Transformer architectures capture long-range dependencies using attention mechanisms [22].

ViTs demonstrate:

- Strong generalization capability
- Improved feature representation
- Enhanced scalability

Recent studies indicate transformers may outperform CNNs in complex agricultural imaging tasks [23].

5. Image Preprocessing and Feature Extraction

5.1 Noise Reduction

Hyperspectral images often contain sensor noise and illumination variations. Common preprocessing techniques include:

- Savitzky–Golay filtering
- Wavelet denoising
- Gaussian smoothing
- Median filtering

These methods improve spectral quality and model performance [24].

5.2 Dimensionality Reduction

Hyperspectral data contain hundreds of bands, leading to the “curse of dimensionality.” Dimensionality reduction techniques include:

- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA)
- Independent Component Analysis (ICA)
- Autoencoders

These techniques reduce redundancy while preserving important information [25].

5.3 Vegetation Indices

Vegetation indices derived from spectral bands are useful indicators of plant health.

Common indices include:

- NDVI
- PRI
- SAVI
- MCARI

These indices improve disease discrimination capability [26].

6. Applications in Different Crops

The integration of multispectral imaging, hyperspectral sensing, and machine learning techniques has been extensively investigated across a wide range of agricultural crops for early disease detection and stress monitoring. Different crops exhibit unique physiological and spectral responses to pathogen infections, enabling machine learning models to identify disease-specific spectral signatures with high accuracy [27][28]. Researchers worldwide have demonstrated that combining spectral imaging technologies with advanced artificial intelligence models significantly improves disease diagnosis, crop monitoring, and precision disease management practices [29][30].

6.1 Rice Disease Detection

Rice *(Oryza sativa L.)* is one of the most important staple food crops globally, feeding more than half of the world’s population. However, rice production is severely affected by diseases such as rice blast, bacterial blight, sheath blight, and brown spot [31][32]. Early detection of these diseases is essential to prevent major yield losses. Several researchers have applied multispectral and hyperspectral imaging techniques for rice disease diagnosis. Hyperspectral imaging has been shown to detect physiological changes associated with fungal infections before visible symptom development [33]. Hyperspectral imaging combined with SVM models can classify rice blast disease with high accuracy [34]. Spectral bands in the near-infrared region are particularly sensitive to disease-induced stress [27][28]. CNNs have been applied for automated rice disease classification, achieving accuracies above 95% [35]. Deep CNN architectures integrated with multispectral imagery can outperform traditional machine learning models [36]. Transfer learning using ResNet and DenseNet has also achieved remarkable accuracy for rice disease identification [37]. UAV-based multispectral imaging further allows large-scale field-level disease surveillance [38][39].

6.2 Wheat Disease Detection

Wheat *(Triticum aestivum L.)* suffers significant losses due to diseases such as leaf rust, stem rust, stripe rust, Fusarium head blight, and powdery mildew [40][41]. Hyperspectral and multispectral imaging technologies have been widely explored for early detection of wheat diseases. Hyperspectral imaging combined with neural network classifiers can distinguish healthy and infected wheat leaves [42][43]. SVM classifiers effectively identify wheat diseases under field conditions [44]. Random Forest models using hyperspectral reflectance and texture features have been shown to improve dis-

Table 1. Major Crops, Diseases, Imaging Techniques and Machine Learning Models Used

Crop	Major Diseases	Imaging Technique	Machine Learning / Deep Learning Models	References
Rice	Blast, Bacterial Blight, Brown Spot	Multispectral, Hyperspectral	SVM, CNN, ResNet, DenseNet	[31][32][33][34]
Wheat	Rust, Powdery Mildew, Fusarium Head Blight	Hyperspectral, UAV Imaging	RF, SVM, 3D-CNN	[35][36][37][38]
Maize	Northern Leaf Blight, Gray Leaf Spot	Multispectral, Hyperspectral	CNN, ViT, Transfer Learning	[39][40][41][42]
Potato	Late Blight, Early Blight	Hyperspectral	CNN, SVM, 3D-CNN	[43][44][45][46]
Tomato	Early Blight, Septoria Spot, Mosaic Virus	Multispectral	CNN, AlexNet, VGGNet	[47][48][49]
Citrus	Citrus Canker, Greening Disease	UAV Multispectral	RF, CNN, SVM	[50][51][52]
Grapevine	Powdery Mildew, Downy Mildew	UAV Hyperspectral	CNN, Thermal Fusion Models	[53][54][55]
Soybean	Rust, Sudden Death Syndrome	Hyperspectral	CNN, EfficientNet	[56][57][58]
Apple	Apple Scab, Black Rot	Multispectral, UAV Imaging	Deep CNN, RF	[59][60][61]

ease classification performance [45]. Recent studies demonstrate that 3D-CNN architectures can extract spectral-spatial features simultaneously from hyperspectral cubes, achieving highly accurate wheat disease detection [46]. UAV-based multispectral sensors enable large-scale monitoring of wheat rust severity [47].

6.3 Maize Disease Detection

Maize *(Zea mays L.)* is vulnerable to diseases such as northern leaf blight, gray leaf spot, common rust, and southern rust [48]. Early disease detection is crucial to prevent rapid spread. Hyperspectral imaging can identify maize fungal infections before visible symptoms appear [49]. Machine learning classifiers such as CNNs have been effectively used for maize disease classification [50]. DenseNet and transfer learning models further improve classification accuracy [51]. Vision Transformers (ViTs) have recently outperformed conventional CNNs in complex maize disease recognition tasks [52].

6.4 Potato Disease Detection

Potato *(Solanum tuberosum L.)* is susceptible to late blight and early blight [53]. Early detection is critical for minimizing yield loss. Hyperspectral imaging has identified pathogen-induced stress in potato leaves [54]. SVM and CNN classifiers achieve high accuracy in early disease detection [55][56]. Spectral-spatial 3D-CNN models provide enhanced classification performance over conventional methods [57].

6.5 Tomato Disease Detection

Tomato *(Solanum lycopersicum L.)* is highly prone to fungal, bacterial, and viral diseases [58]. Multispectral imaging combined with CNN-based deep learning models achieves high classification accuracy for tomato diseases [59][60]. AlexNet, VGGNet, and other CNN architectures are widely used for automatic disease recognition [61]. Hyperspectral spectral signatures in the visible and near-infrared regions can detect diseases at asymptomatic stages [27][28].

6.6 Citrus Disease Detection

Citrus crops are threatened by diseases such as citrus canker and Huanglongbing (HLB) [62][63]. UAV-mounted multispectral imaging combined with SVM or CNN models provides early and accurate disease detection [50][51]. Hyperspectral imaging is also highly effective for identifying citrus greening disease [52].

6.7 Grapevine Disease Detection

Grapevines are affected by powdery mildew, downy mildew, and Esca disease [64][65]. Hyperspectral imaging can detect disease-induced spectral variations [53]. UAV-based multispectral imaging combined with CNN models enables rapid vineyard disease mapping [54][55].

6.8 Soybean Disease Detection

Soybean diseases, including soybean rust and sudden death syndrome, severely reduce yield [66][67]. Hyperspectral imaging combined with CNN and EfficientNet

Table 2. Reported Classification Accuracy of Machine Learning Models for Different Crops

Crop	Disease	ML/DL Model	Imaging Type	Reported Accuracy	References
Rice	Rice Blast	CNN	Hyperspectral	95–98%	[35][36]
Wheat	Fusarium Head Blight	RF	Hyperspectral	93–96%	[45]
Wheat	Stripe Rust	3D-CNN	Hyperspectral	97%	[46]
Maize	Gray Leaf Spot	DenseNet	Multispectral	98%	[51]
Potato	Late Blight	CNN	Hyperspectral	99%	[55][56]
Tomato	Early Blight	VGGNet	Multispectral	99%	[59][60]
Citrus	Citrus Canker	SVM	UAV Multispectral	94–96%	[50][51]
Soybean	Soybean Rust	EfficientNet	Hyperspectral	97%	[57][58]
Apple	Apple Scab	Deep CNN	Multispectral	98%	[59][60]

models enables accurate early detection [56][57][58].

6.9 Apple Disease Detection

Apple orchards suffer from diseases such as apple scab and black rot [68][69]. Multispectral imaging and deep CNNs provide high classification accuracy [59][60]. UAV imaging facilitates large-scale orchard disease monitoring [61].

7. Conclusion

Machine learning models integrated with multispectral and hyperspectral imaging technologies have emerged as highly effective tools for the early detection and diagnosis of plant diseases. The combination of advanced imaging systems with artificial intelligence has significantly transformed traditional agricultural disease monitoring into an automated, rapid, non-destructive, and highly accurate process. These technologies enable the identification of subtle physiological and biochemical changes in plants before visible symptoms appear, thereby allowing timely disease management and reducing major crop losses. Conventional disease diagnosis methods based on manual observation and laboratory analysis are often time-consuming, subjective, labor-intensive, and unsuitable for large-scale agricultural monitoring. In contrast, multispectral imaging provides detailed spectral information associated with chlorophyll degradation, moisture stress, pigment alteration, and cellular damage caused by pathogens. Machine learning algorithms can effectively analyze these complex spectral datasets and accurately classify healthy and infected plants under varying environmental conditions. Traditional machine learning techniques such as Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbor (kNN), Artificial Neural Networks (ANN), and Decision Trees have demonstrated considerable success in plant disease classification tasks. Among these methods, SVM and RF models have shown excellent performance in handling high-dimensional hyperspectral data and limited training samples. However, recent advancements in deep learning have further enhanced disease detection capabilities by automatically extracting hierarchical spectral-spatial features from multispectral images. Deep learning architectures including Convolutional Neural Networks (CNNs), 3D-CNNs, DenseNet, ResNet, EfficientNet, and Vision Transformers (ViTs) have achieved state-of-the-art performance across multiple crops such as rice, wheat, maize, potato, tomato, citrus, soybean, grapevine, and apple. These models have demonstrated remarkable classification accuracies exceeding 95–99% in several disease detection studies. Furthermore, transfer learning approaches have reduced computational requirements and improved model generalization, particularly in situations with limited annotated datasets. The integration of UAVs, drone-based multispectral imaging systems, and edge computing technologies has further expanded the practical applications of intelligent disease monitoring systems in precision agriculture. UAV-mounted sensors enable rapid large-scale field surveillance with high spatial and temporal resolution, facilitating real-time crop health assessment and site-specific disease management. Additionally, advances in explainable artificial intelligence (XAI) have improved the interpretability and transparency of deep learning models, increasing farmer confidence and adoption potential. Despite substantial progress, several challenges remain in the practical deployment of machine learning-based multispectral disease detection systems. Major limitations include the scarcity of large annotated hyperspectral datasets, environmental variability, illumination effects, spectral noise, computational complexity, overfitting issues, and limited generalization under real-field conditions. High sensor costs and the need for powerful computational infrastructure also restrict widespread adoption among small-scale farmers. Future research should focus on developing lightweight and computationally efficient deep learning models suitable for real-time field ap-

Table 3. Advantages of Multispectral Imaging and Machine Learning in Crop Disease Detection

Technology/Approach	Major Advantages	Limitations	References
Multispectral Imaging	Low-cost, rapid imaging, field applicability	Limited spectral resolution	[27][28]
Hyperspectral Imaging	High spectral detail, early stress detection	High computational complexity	[33][42]
Support Vector Machine (SVM)	Effective for small datasets, high-dimensional data	Sensitive to parameter tuning	[34][44]
Random Forest (RF)	Handles noisy data, feature importance analysis	Large ensemble complexity	[45]
CNN Models	Automatic feature extraction, high accuracy	Requires large datasets	[55][60]
Transfer Learning	Reduced training time, better generalization	Domain adaptation issues	[51][58]
UAV-based Monitoring	Large-scale field coverage, real-time monitoring	Weather dependency	[38][47][54]
Vision Transformers	Captures long-range dependencies	Computationally intensive	[52]

plications. Emerging technologies such as federated learning, self-supervised learning, multimodal sensor fusion, IoT-integrated smart farming systems, and transformer-based architectures are expected to further improve disease detection performance and scalability. Additionally, integrating multispectral imaging with thermal imaging, fluorescence sensing, LiDAR, and genomic information may provide more comprehensive crop health assessment systems in the future. Overall, machine learning models combined with multispectral imaging represent a promising and transformative approach for sustainable crop protection and precision agriculture. These technologies have the potential to significantly improve agricultural productivity, reduce excessive pesticide application, minimize economic losses, and enhance global food security under changing climatic conditions. Continued advancements in artificial intelligence, remote sensing, and sensor technologies are expected to accelerate the development of intelligent, affordable, and scalable plant disease detection systems for next-generation smart agriculture.

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