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An Effective Review on Classification and Detection of Fruit Leaf Diseases using Machine Learning and Deep Learning Techniques

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Abstract: ***The effective detection of leaf diseases in fruit crops is vital for optimizing agricultural productivity and mitigating economic losses. Recent advancements in Machine learning (ML) and Deep learning (DL) have revolutionized the field of plant pathology, offering innovative solutions for accurate and efficient disease detection. This review paper provides a comprehensive overview of ML and DL techniques applied for classifying and detecting fruit leaf diseases. We systematically evaluate various methods, including classical ML algorithms like Support Vector Machines and Random Forests, and state - of - the - art DL models such as Convolutional Neural Networks, Recurrent Neural Networks, and Transfer Learning. The paper highlights key factors influencing model performance, such as dataset quality, Image Resolution, Pre - processing methods, and Feature Extraction techniques. We also explore the challenges and limitations associated with these technologies, including the need for large annotated datasets, computational demands, and deployment in real - world agricultural settings. By synthesizing current research trends and technological advancements, this review aims to provide a clear understanding of the capabilities and limitations of ML and DL approaches for leaf disease detection and classification to propose directions for future research and development in this field.***

Keywords: Machine Learning, Deep Learning, Fruit diseases, Convolutional Neural Networks, Transfer Learning

1. Introduction

Agricultural productivity plays a pivotal role in ensuring global food security and economic stability. However, crop diseases, particularly those affecting plant leaves, pose significant challenges by reducing yield quality and quantity [1]. Early and accurate detection of leaf diseases is crucial to mitigating their impact and enhancing agricultural output. Traditional methods for identifying plant diseases often rely on manual inspection by experts, which is not only time - intensive but also susceptible to human error.

Recent advancements in artificial intelligence, particularly in machine learning (ML) and deep learning (DL), have opened new avenues for automating the detection and classification of leaf diseases [2]. These technologies leverage powerful computational models capable of processing large volumes of image data to identify patterns and anomalies indicative of diseases. Machine learning techniques, such as support vector machines (SVMs) and k - nearest neighbors (k - NN), have been employed for disease classification based on handcrafted features [3]. Meanwhile, deep learning algorithms, particularly convolutional neural networks (CNNs), have demonstrated superior performance by automatically extracting features from raw image data without the need for manual intervention. Fig 1 illustrates the general process in fruit plant leaf disease detection and classification tasks.

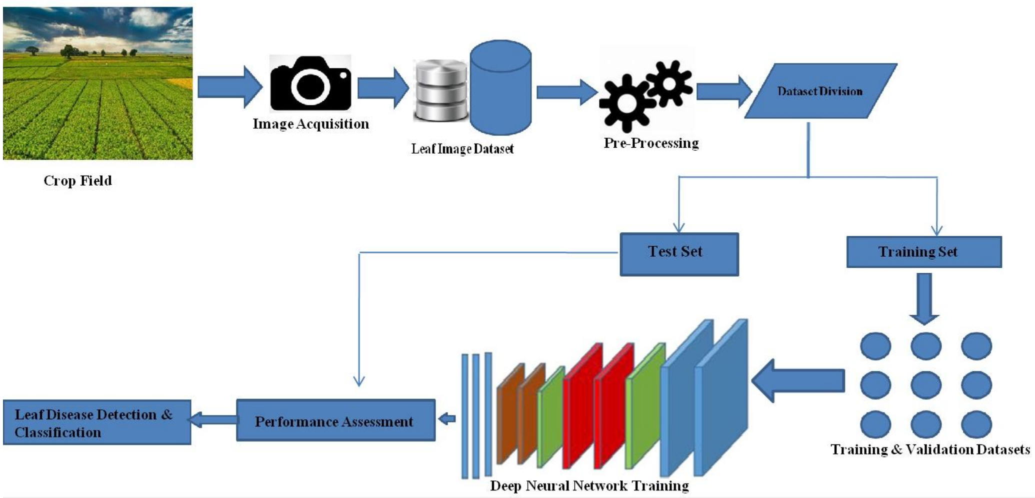

Figure 1: Process in Fruit Plant Leaf Disease Detection and Classification Systems

Good outcomes have been reported in the literature; however, the variety of utilized datasets remains limited [4]. Large datasets are crucial for training CNNs effectively. Unfortunately, researchers have not yet compiled diverse and extensive datasets for fruit leaf disease detection. Currently, transfer learning (TL) provides a promising approach to improve the robustness of CNN methods for fruit leaf disease detection. TL enables the use of pre - trained CNNs by fine - tuning them with smaller datasets whose distribution differs from the larger datasets previously used to train the network from scratch. Specifically, pre - trained CNN models on large databases like ImageNet can be fine - tuned for fruit leaf disease detection tasks [5]. Thus, the combination of transfer learning and deep learning (DL) offers a viable solution to address the issue of limited data on fruit leaf diseases.

This survey paper aims to comprehensively study existing research on fruit leaf disease detection and classification using machine learning (ML) and deep learning (DL) algorithms. We begin by discussing the importance of early disease detection in fruit plants and the challenges associated with traditional methods. Subsequently, we review the limitations and requirements of current crop disease recognition systems. Moreover, we analyze and summarize the existing studies that utilize ML and DL approaches for detecting and classifying fruit leaf diseases (FLD).

2. Background Information

Traditionally, human vision - based methods have been employed for fruit leaf disease detection. However, these methods are time - consuming, expensive, and reliant on the expertise of specialists or individuals to assess performance. In contrast, automated fruit leaf disease detection systems streamline the diagnostic process, enabling farmers to make accurate and timely decisions regarding plant health. These advancements can help improve fruit crop yields and optimize resource utilization [6]. The application of ML and DL algorithms for fruit leaf disease detection is a field that has not yet been explored extensively. Despite the potential benefits, these methods have not gained significant attention. Disease outbreaks in fruit crops highlight the importance of further research in this domain to mitigate losses and improve yields. The adoption of these techniques offers the potential for significantly greater accuracy and efficiency in disease diagnosis for fruit crops.

2.1. Need for Automatic Fruit Leaf Disease Detection and Classification

- **Improved Crop Health**: Early detection of leaf diseases ensures timely treatment, maintaining plant health and productivity.
- **Prevent Economic Losses**: Disease outbreaks can lead to significant financial losses; detecting them early minimizes damage [7].
- **Enhance Fruit Yield and Quality**: Healthy leaves are essential for photosynthesis, which directly affects the size, quality, and quantity of fruits.
- **Efficient Use of Resources**: Early diagnosis helps optimize the use of fertilizers, water, and pesticides, reducing waste and production costs.
- **Minimize Pesticide Overuse**: By identifying specific diseases, farmers can use targeted treatments, promoting safer and eco - friendly farming practices [8].
- **Prevent Disease Spread**: Timely detection stops diseases from spreading to other plants, protecting entire orchards.
- **Support Sustainable Agriculture**: Monitoring and managing diseases effectively promotes long - term sustainability in fruit farming.
- **Reduce Labor and Time**: Automated or efficient disease detection methods save farmers time spent on manual inspection.
- **Meet Market Demands**: Disease - free fruits are essential to meet consumer expectations and international market standards [9].
- **Adapt to Climate Challenges**: As changing climates make crops more vulnerable to diseases, early detection is critical for maintaining productivity.

2.2. Challenges Associated with Automatic Fruit Leaf Disease Detection and Classification

There are numerous challenges related to the detection of fruit leaf diseases, such as:

- **Diversity of fruit diseases:** Fruit crops are affected by a wide range of diseases caused by various pathogens, including viruses, bacteria, and fungi. These diseases can impact different parts of the plant and present a variety of symptoms, making it complex to accurately diagnose and differentiate between diseases.
- **Limited access to technology:** Many farmers in remote and rural areas may lack access to the resources and technologies required for accurate disease detection [10]. This limitation makes it challenging to effectively protect their fruit crops and manage diseases.
- **Lack of standardized methodologies:** Currently, there are no universally accepted or standardized methods for detecting fruit leaf diseases. This inconsistency hinders the ability to diagnose diseases effectively across different regions and makes it difficult to compare the performance of detection techniques [11].
- **Balancing accuracy and computational efficiency:** Developing a disease detection method that is both highly accurate and computationally efficient remains a challenge. Many existing approaches are either computationally intensive or impractical for real - time applications.
- **Difficulties in data collection:** Collecting large and diverse datasets for training and testing automated diagnosis methods is a significant challenge [12]. Factors such as varying lighting conditions, environmental factors, and inconsistent imaging can affect the quality of the datasets, making it harder to develop reliable models.

2.3. Overview of CNN Model for Fruit Leaf Disease Detection

Deep Learning (DL), a prominent Machine Learning (ML) approach, has been widely studied in recent years. It is a multi - layered framework used to extract and define features from large datasets [22]. CNN (Convolutional Neural Network), a specialized DL architecture, comprises various layers designed for specific tasks, including convolutional, pooling, activation, flattening, and fully connected (FC) layers [13].

These layers work together to analyze and classify fruit leaf disease images effectively.

- **Convolutional Layer:** The convolutional layer is pivotal in extracting features from input data. This layer applies filters to the input images to transform them into a feature space using weighted sum aggregation. The first convolutional layer is directly linked to the image dataset, performing low - level feature extraction, such as detecting edges, colors, and basic textures, which are essential for identifying disease symptoms on fruit leaves [14].
- **Activation Layer (Nonlinearity Layer):** The activation layer applies a non - linear function to all pixels in the image to introduce non - linearity into the model. The ReLU (Rectified Linear Unit) activation function is now commonly used instead of traditional sigmoid or hyperbolic tangent functions due to its efficiency. This layer ensures that the network captures complex patterns related to fruit leaf diseases.
- **Pooling (Down - Sampling) Layer:** A critical component of the CNN architecture, the pooling layer reduces the number of parameters and computational complexity in the network. This layer has two main advantages: reducing computation in subsequent layers and constraining the network's ability to overfit. Common pooling techniques include max pooling, average pooling, and sum pooling. Pooling helps preserve key features of the fruit leaf images while simplifying the representation.
- **Flatten Layer:** The flattening layer prepares the input data for the final classification layers. As neural networks require a 1D array format for input, this layer transforms matrix - type data from previous layers into a 1D array [15]. In this process, all image pixels are organized into a single line, making it suitable for further processing.
- **Fully Connected (FC) Layers:** The FC layers depend on the output of all preceding layers. These layers vary in number based on the CNN architecture. Nodes in these layers retain features extracted from earlier steps, and the learning process involves adjusting weights and biases [16]. This layer is responsible for final processing, where it classifies fruit leaf disease images based on the extracted features, enabling accurate diagnosis. By leveraging these CNN components, fruit leaf disease detection systems can effectively analyze complex patterns, extract meaningful features, and classify diseases with high precision.

3. Review of existing Fruit Leaf disease Detection and Classification using Machine Learning Techniques

In [17], the author conducts a comparative analysis of three models: Support Vector Machines (SVM), K - Nearest Neighbor (KNN), and Convolutional Neural Networks (CNN), for leaf disease detection. The study examines the performance of these models in detecting eight different leaf diseases using the soybean leaf disease dataset. Among the models, CNN achieved the highest accuracy of 96%, significantly outperforming the KNN and SVM models, which attained accuracies of 64% and 76%, respectively. This demonstrates the superior capability of CNNs in effectively identifying and classifying leaf diseases.

In [18], the author proposed a CNN - based approach for detecting plant diseases, which was evaluated using sample images to analyze the temporal complexity and infected regions. The model was tested on three specific disease cases: Corn Common Rust, Tomato Bacterial Spot, and Potato Early Blight. Using the CNN algorithm, the model achieved an accuracy of 95.55% for detecting Tomato Bacterial Spot, 96.72% for Corn Common Rust, and 97.63% for Potato Early Blight. This approach demonstrates potential for aiding in the accurate diagnosis and effective treatment of plant diseases.

In [19], the author introduces a computer vision approach utilizing an optimized Capsule Neural Network (CapsNet) to detect and classify ten tomato leaf diseases using standard image datasets. To address overfitting, data augmentation and pre - processing techniques were applied during the training phase. CapsNet was selected over traditional CNNs due to its enhanced ability to capture spatial relationships and positional information within images. The proposed CapsNet model achieved an impressive accuracy of 96.39% with minimal loss, using a 0.00001 Adam optimizer. A comparison with state - of - the - art methods demonstrated the effectiveness of CapsNet in accurately identifying and classifying tomato leaf diseases based on the shape, color, and location of disease spots. These results highlight the potential of CapsNet as a robust alternative to CNNs for advancing disease detection and classification in plant pathology research.

In [20], the author proposed an automated system for detecting diseases in crops, highlighting its significant role in agriculture by enabling early disease detection. The system was developed by constructing a stepwise disease detection model using images of healthy and diseased plants, along with a CNN algorithm based on five pre - trained models. The disease detection framework follows a three - step classification process: crop classification, disease detection, and disease classification. To enhance the model's versatility and applicability, an 'unknown' category was included to handle cases beyond the trained data. During validation tests, the system demonstrated high accuracy, classifying crops and disease types with an impressive accuracy of 97.09%.

Author [21], highlights advancements in computer vision and machine learning for efficient and accurate leaf disease detection using high - resolution imaging, deep learning models, and sophisticated image processing techniques. By leveraging diverse datasets, expert annotations, and data augmentation, the study ensures robust model training and reliability through methods like K - fold validation. The proposed model outperforms traditional algorithms with high accuracy, demonstrating its effectiveness in real - time leaf health monitoring and precision agriculture, emphasizing technology's transformative role in optimizing crop resilience and agricultural practices.

Author [22] investigates the detection of disorders in tomato leaves to help farmers identify diseases based on early symptoms. In the study, tomato leaf samples were resized to 256 × 256 pixels, and their quality was enhanced using Histogram Equalization. K - means clustering was employed to partition the dataspace into Voronoi cells, while contour tracing was used to extract the boundaries of the leaf samples.

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Multiple feature extraction methods, including Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Grey Level Co - occurrence Matrix (GLCM), were applied to obtain informative features from the leaf samples. The extracted features were then classified using machine learning techniques such as Support Vector Machine (SVM), Convolutional Neural Network (CNN), and K - Nearest Neighbor (KNN). The proposed model achieved accuracy rates of 88% with SVM, 97% with KNN, and 99.6% with CNN on tomato leaf disorder samples.

Author [23] proposed a novel segmentation technique based on an extended fuzzy set form of neutrosophic logic to evaluate regions of interest in leaf images. The segmented neutrosophic image is characterized by three membership components: true, false, and intermediate regions. Using these segmented regions, a new feature subset is derived by analyzing texture, color, histogram, and disease - affected regions to classify leaves as either diseased or healthy. To assess the effectiveness of the combined feature set, nine different classifiers were employed, with the random forest classifier outperforming the others. The proposed system was validated on 400 cases (200 healthy and 200 diseased leaves) and demonstrated high efficacy, achieving an impressive classification accuracy of 98.4%. This technique shows promise as a powerful tool for accurate leaf disease identification.

Author [24] proposed a hybrid model for plant disease detection by combining multiple Deep Learning (DL) techniques. The approach utilized a UNET - based DL framework for disease detection and classification. Feature extraction was performed using the convolutional neural layer, while the pooling layer optimized these features. Finally, a dense layer was used to classify the test objects. Both synthetic and real - time plant datasets were employed for evaluation. Extensive experimental analysis included the implementation of two ML classifiers (SVM and PCA) and two DL classifiers (CNN and a modified CNN or mCNN). The mCNN model combined VGG16 and its backbone architecture for classification and integrated the YOLOv3 model for data pre - processing. The mCNN achieved an impressive 96.80% accuracy in detection and classification on a heterogeneous dataset, outperforming traditional classifiers and other DL models.

Author [25] investigated the impact of unexpected weather on agricultural output and the effectiveness of AI - based machine learning and deep learning algorithms for detecting apple leaf diseases. Through a bibliometric analysis of 109 publications from the Scopus database (2011–2022), the study explored research trends, citation patterns, collaborations, and publishing practices. Tools like VOS viewer and Bibliophagy identified key journals, authors, and topics, while citation and co - citation analysis revealed patterns and trends in apple disease detection research.

In the proposed work of [26], apple leaves with different backgrounds were segmented. The process begins with enhancing the leaves using the Brightness - Preserving Dynamic Fuzzy Histogram Equalization technique, followed by the extraction of the diseased leaf areas using a novel extraction algorithm. A real - time plant leaf database was used to validate the approach. The results demonstrate that the proposed methodology outperforms existing segmentation algorithms. From the segmented apple leaves, color and texture features are extracted and classified as Marsonina coronaria or apple scab using various machine learning classifiers. The best accuracy of 96.4% was achieved using the K - Nearest Neighbor classifier. Table 1 provides a detailed Review of Present Fruit Plant Leaf Disease Detection and Classification using Machine Learning and Deep Learning Techniques.

4. Review of existing Fruit Leaf disease Detection and Classification using Deep Learning Techniques

In the study [27], the author created an expert - annotated apple disease dataset comprising around 9, 000 high - quality RGB images, covering all major foliar diseases and symptoms. The proposed apple disease detection system utilizes deep learning for efficient and accurate identification of symptoms. The system operates in two stages: the first stage uses a lightweight, custom - built classification model to categorize input images as diseased, healthy, or damaged. If a disease is detected, the second stage (detection stage) begins, where the system performs the detection and localization of symptoms on diseased leaf images.

In the study [28], the author introduced a hybrid deep learning framework for real - time detection of multiple diseases on a single guava leaf in several stages. First, a Guava Infected Patches Modified MobileNetV2 and U - Net (GIP - MU - NET) model was proposed to segment infected guava patches, using a modified MobileNetV2 as the encoder and the up - sampling layers of the U - Net model as the decoder. Next, the Guava Leaf Segmentation Model (GLSM) was introduced to differentiate between healthy and infected leaves. Finally, the Guava Multiple Leaf Diseases Detection (GMLDD) model, based on YOLOv5, was used to identify various diseases on the guava leaf.

In study [29], the author focused on detecting and classifying leaf diseases in Grapes and Mango using a dataset of 8, 438 images of both diseased and healthy leaves, sourced from the Plant Village dataset and local collections. A deep convolutional neural network (CNN) was trained to identify the presence or absence of diseases. The pre - trained AlexNet CNN architecture was used for automatic feature extraction and classification. Developed using MATLAB, the system achieved detection accuracies of 99% for Grape leaves and 89% for Mango leaves. Additionally, an Android app named "JIT CROPFIX" was created to implement the system on smartphones.

In the study [30], the author identified CNN - based detectors suitable for agricultural engineering, including CenterNet, YOLOv4, Faster - RCNN, DetectoRS, Cascade - RCNN, FoveaBox, and Deformable DETR. These models were implemented and fine - tuned to detect citrus leaf diseases using the CCL'20 dataset. A comprehensive performance and computational analysis was conducted to assess how effectively these models diagnose different stages of citrus leaf diseases.

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In the study [31], Deep Learning (DL) was employed to detect powdery mildew (PM), a persistent fungal disease in strawberries, aiming to reduce unnecessary fungicide use and the reliance on field scouts. The study optimized and evaluated several well - known models, including AlexNet, SqueezeNet, GoogLeNet, ResNet - 50, SqueezeNet - MOD1, and SqueezeNet - MOD2. To prevent overfitting and account for the varying shapes and orientations of leaves in the field, data augmentation was performed on a dataset of 1, 450 healthy and infected leaf images.

In the study [32], a convolutional neural network (CNN) model with 19 convolutional layers was proposed for the effective and accurate classification of Marsonina Coronaria and Apple Scab diseases in apple leaves. The researchers collected a dataset of 50, 000 leaf images from apple farms in Himachal Pradesh (H. P.) and Uttarakhand (India). To improve accuracy, an augmentation technique was applied to the dataset, increasing the number of images available for training the model.

In the study [33], the authors developed a plant disease recognition model to detect diseases in apple leaves and predict the percentage of leaf area affected. The model uses leaf image classification and convolutional neural network algorithms, achieving an accuracy of 97.5%.

In study [34], an ensemble of pre - trained models—DenseNet121, EfficientNetB7, and EfficientNet was used to classify apple tree leaves into categories such as healthy, apple scab, apple cedar rust, and multiple diseases based on their images. The research incorporated various image augmentation techniques to expand the dataset, which ultimately led to improved model accuracy.

In study [35], the author introduced a new hybrid deep learning architecture called "CTPlantNet. " This architecture combines convolutional neural network (CNN) models with a vision transformer model to effectively classify plant foliar diseases, advancing the methods used for disease classification in plant pathology research.

In the study [36], the author employed the Capsule Neural Network (CapsNet) architecture and enhanced its learning capacity by adding extra convolutional layers. This modification aimed to improve the model's ability to classify apple diseases, including apple rust, apple scab, healthy leaves, and leaves affected by multiple diseases.

In the study [37], the author introduced a deep evidence fusion framework that combines multi - saliency maps in the Hue Saturation Value (HSV) color space with belief Cauchy–Schwarz divergence. The study also proposed a new evidence fusion method based on belief Cauchy–Schwarz, bridging the gap between evidence theory and apple leaf disease classification. Fig.2 depicts the sample Fruit leaf images which are used in the existing works.

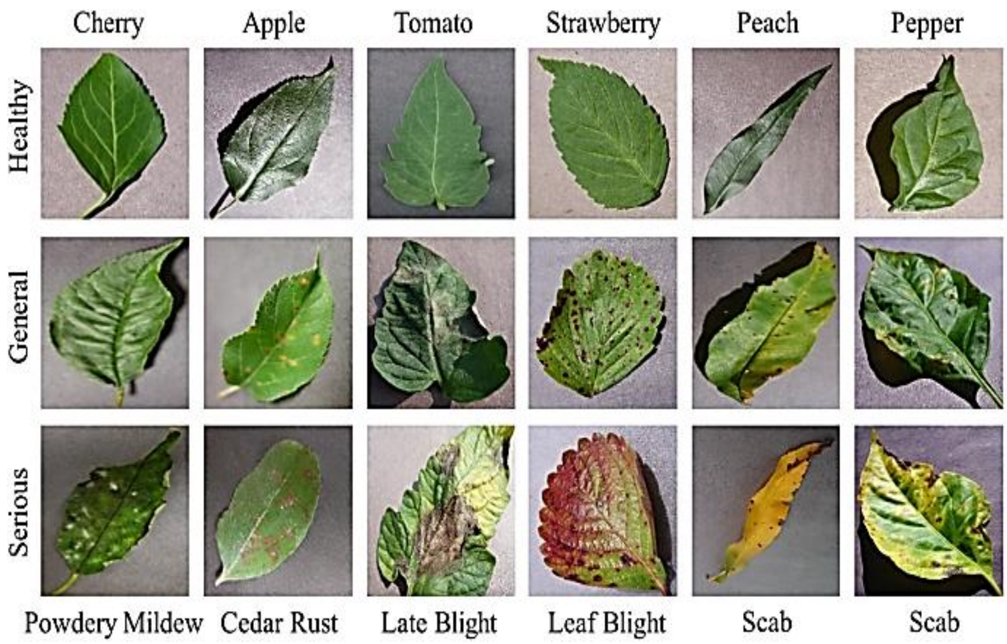

Figure 2: Sample Fruit Leaf Images

Table 1: Review of Present Fruit Plant Leaf Disease Detection and Classification

References	Crops/ Leaves Used	Techniques used	Accuracy (%)
Machine Learning Techniques			
[17]	Soyabean Plant leaves	SVM, KNN, CNN	96.00%
[18]	Tomato Leaves	CNN	96.72%
[19]	Tomato Leaves	Capsule Neural Network (CapsNet)	96.39%
[20]	Plant Leaves	CNN	97.09%
[21]	Plant Leaves	KNN, SVM, CNN	93.00%
[22]	Tomato Leaves	DWT, PCA, SVM, GLCM, KNN, CNN	99.06%
[23]	Plant Leaves	Random Forest	98.04%
[24]	Plant Leaves	SVM, PCA	96.80%

[25]	Apple Leaves	AI - based machine learning	98.05%
[26]	Apple Leaves	KNN	96.04%
Deep Learning Techniques			
[27]	Apple Leaves	lightweight, custom - built classification model	98.07%
[28]	Guava Leaves	MobileNetV2 and U - Net	97.00%
[29]	Grapes and Mango Leaves	AlexNet CNN	99.00%
[30]	Citrus Leaves	CenterNet, YOLOv4, Faster - RCNN, DetectoRS, Cascade - RCNN, FoveaBox, and Deformable DETR.	99.03%
[31]	Strawberry Leaves	AlexNet, SqueezeNet, GoogLeNet, ResNet - 50, SqueezeNet - MOD1, & SqueezeNet - MOD2.	97.08%
[32]	Apple Leaves	19 CNN Layers	98.75%
[33]	Apple Leaves	CNN, DL Methods	97.05%
[34]	Apple Leaves	DenseNet121, EfficientNetB7, and EfficientNet	99.07%
[35]	Apple Leaves	CTPlantNet	98.09%
[36]	Apple Leaves	Capsule Neural Network (CapsNet)	98.97%
[37]	Apple Leaves	Hue Saturation Value (HSV)	98.01%

5. Conclusion

Over the past decade, fruit leaf disease detection systems have seen remarkable advancements through machine learning (ML) and deep learning (DL), offering significantly improved accuracy and efficiency compared to traditional methods. ML models such as SVM, k - NN, and random forests have been extensively studied, while DL models, particularly CNNs and transfer learning, have shown exceptional performance on large datasets for identifying fruit leaf diseases. However, challenges such as heterogeneous symptoms, inconsistent data quality, and computational resource limitations remain. Addressing these issues through further research and development is essential to achieving practical and scalable solutions. These technologies enable farmers to quickly and accurately diagnose diseases through automated systems, leading to improved cultivation practices, higher yields, and reduced losses. By integrating these techniques into real - world agricultural practices, such as mobile applications, IoT systems, or smart farming platforms, they can further enhance efficiency. As automated detection systems continue to evolve, they have the potential to revolutionize fruit agriculture, making it more sustainable, efficient, and resilient to disease outbreaks.

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