

Classification of tomato leaf images for detection of plant disease: A Comprehensive Review

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Abstract

Tomatoes are one of the most extensively cultivated vegetable crops in India, and they benefit from the country's tropical climate. However, various environmental factors, including fluctuating climatic conditions and plant diseases, significantly impact its growth and yield. Among these challenges, plant diseases pose a major threat, leading to substantial economic losses. Traditional methods for disease detection in tomato plants have proven inefficient due to their delayed diagnosis and limited accuracy. Early identification of diseases can help mitigate crop losses and improve yield quality. To address this issue, advanced computer vision and deep learning techniques offer promising solutions for early and accurate disease detection. This study provides a detailed analysis of different machine learning-based approaches for tomato leaf disease classification, highlighting their advantages and limitations. Additionally, the paper proposes a hybrid deep-learning model CNN, RNN, YOLOv8 are designed to enhance early detection accuracy and improve disease management strategies in tomato cultivation.

Keywords: Tomato; Plant Leaf Disease Detection; Machine Learning; Deep Learning

1. Introduction

1.1. Convolutional Neural Network

A Convolutional Neural Network (CNN) is a specialized deep learning model designed for image processing and pattern recognition tasks. It excels in applications like image classification, object detection, and medical image analysis by automatically learning important features from raw data. Inspired by how the human brain processes visual information, CNNs extract patterns from images in a hierarchical manner. The initial layers capture basic features like edges and corners, while deeper layers recognize more complex structures such as textures and objects. Unlike traditional machine learning approaches that require handcrafted features, CNNs autonomously learn feature representations, making them highly effective for large datasets.

A CNN is composed of multiple essential layers, including convolutional, activation, pooling, and fully connected layers. The convolutional layer applies multiple small filters (kernels) to the input image to generate feature maps that highlight significant patterns. To introduce non-linearity and enable complex learning, the ReLU activation function is used. The pooling layer, commonly using max pooling, helps reduce the spatial size of feature maps, thereby improving computational efficiency while retaining important information. After passing through multiple convolutional and pooling layers, the extracted features are flattened and fed into the fully connected layer, which classifies the image. The

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final classification output is handled by either a softmax function for multi-class problems or a sigmoid activation for binary classification.

Over the years, CNN architectures have undergone significant advancements, leading to more efficient and accurate models. LeNet-5 was one of the earliest CNNs, designed primarily for recognizing handwritten digits. The introduction of AlexNet in 2012 marked a breakthrough in deep learning by using deeper layers and ReLU activation to achieve superior performance. Later architectures, such as VGGNet, ResNet, and EfficientNet, introduced concepts like deeper networks, skip connections, and optimized convolutions to further enhance model accuracy. CNNs are now widely used in applications such as facial recognition, medical imaging, self-driving cars, and plant disease detection.

In the domain of tomato leaf disease detection, CNNs are instrumental in identifying and classifying diseased leaves based on their unique visual characteristics. Pretrained models like MobileNetV2, ResNet, and EfficientNet serve as feature extractors, improving classification accuracy and reducing training time. By employing transfer learning, these models can be fine-tuned to work with specific datasets, making them highly adaptable to various agricultural challenges. As technology continues to advance, CNNs are expected to play an even greater role in precision farming, enabling early disease diagnosis and ensuring better crop health and yield.

Plant diseases pose a significant challenge in the agricultural sector, hindering crop growth and leading to substantial financial losses for farmers. Among the various crops grown in India, tomatoes are a crucial staple, cultivated extensively across the country. Studies indicate that tomato plants are vulnerable to over 20 different diseases, which negatively impact both yield and quality. These diseases contribute to significant economic setbacks for cultivators, affecting market supply and profitability. As a result, early detection and effective disease management strategies have become essential to safeguarding tomato production and ensuring sustainable agricultural practices.[12].

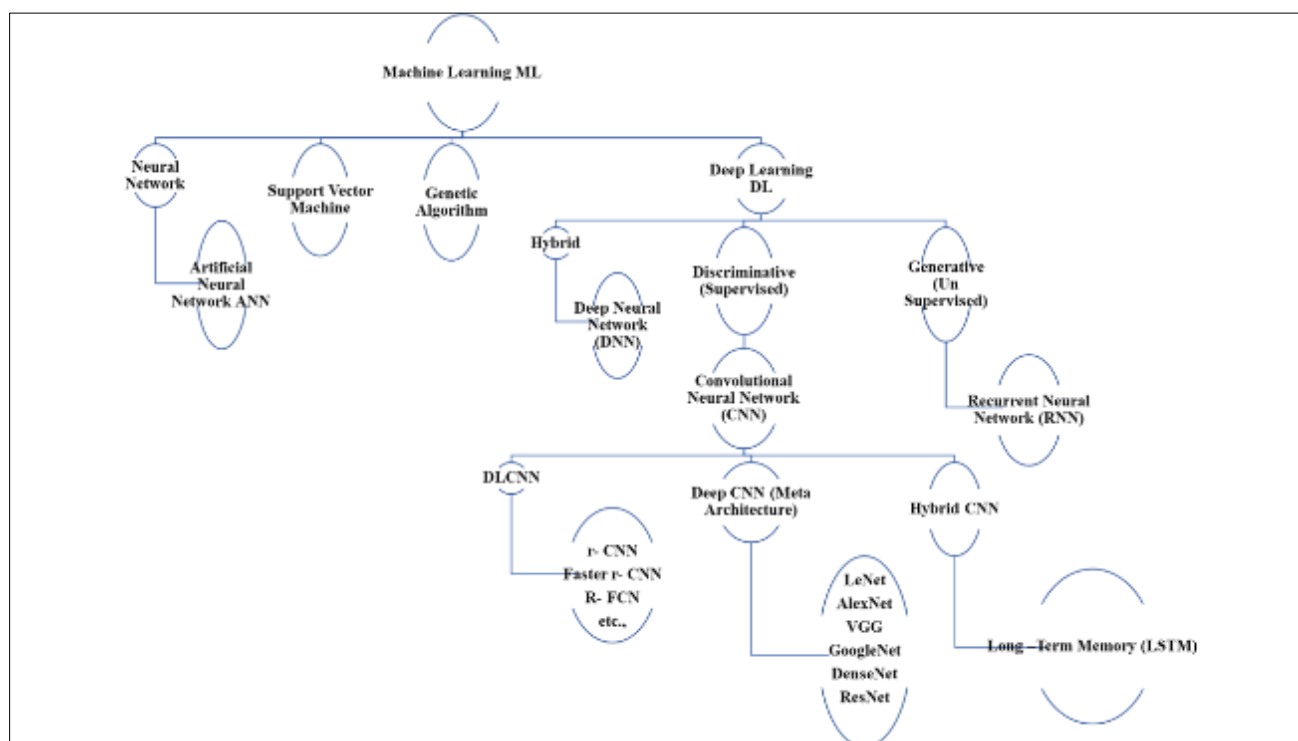


Figure 1 Machine Learning concepts

Tomato plants are highly susceptible to various diseases that can impact their leaves, roots, stems, and fruits, ultimately affecting their overall growth and productivity. Changes in leaf structure and coloration due to infections often result in stunted growth, tissue damage, and, in severe cases, complete plant deterioration. Common tomato leaf diseases include early blight, spider mites, leaf mold, target spot, mosaic virus, and yellow curl virus. These infections not only reduce crop yield but also compromise the quality of the produce, making early diagnosis and effective disease management crucial for sustainable tomato cultivation.[13]

Recognizing and diagnosing tomato leaf diseases solely through visual inspection by agricultural experts is a challenging and less precise method, which is also limited to specific regions. Farmers and agricultural professionals often lack direct access to such experts, and seeking their assistance for crop inspection involves significant costs and requires considerable time. However, recent advancements in computing technology have led to the development of AI and machine learning, enabling automated detection of tomato leaf diseases. These computerized techniques facilitate efficient monitoring of large-scale tomato crops.[14]

The advancement of computer technology has significantly improved plant protection practices within agriculture. The progression of machine learning, as illustrated in Fig.1, highlights its various developmental stages up to the present. These ML-driven approaches have led to substantial progress across multiple domains, introducing innovative solutions and concepts. Initially, digital image processing techniques were employed for plant disease classification in early disease detection methods.

The latest approach utilizes deep learning with neural networks, which enhances classification accuracy by automatically extracting multiple features at different stages. [15]. Fig. 1: shows a well-known object detection and segmentation architectures such as R-CNN, Mask R-CNN, FCN, and SSD were designed to improve detection accuracy, though they required significant processing time to achieve optimal results. [16]. Further advancements in deep CNN led to the development of hybrid architectures, enhancing the performance and accuracy of convolutional neural networks. CNNs are widely used in applications such as object detection, recognition, segmentation, and classification, demonstrating exceptional performance when provided with adequately labeled data. Moreover, advancements in CNN have led to the integration of hybrid models like Long Short-Term Memory (LSTM). Some key benefits of CNN include automatic feature extraction, hierarchical learning, and multitasking capabilities.

1.2. Review of Detection Methods for Plant Leaf Diseases

Rakesh Sharma et al, proposed a Tomato leaf disease detection method, using CNN and Res Net 50 with different dataset. CNN provides a best accuracy among Res Net 50. [1]. Mohit Agarwal et al, proposed a leaf disease detection using CNN with VGG16 Inception V3 and MobileNet. It provides a more accuracy between 76% to 100%.[2]. Rishad Khan et al, suggested a tomato leaf disease detection using image processing techniques like SVM – Based with GLCM and SIFT features. It provides better recognition results. [3]. Yong Wang et al, introduced an attention mechanism & multi scale feature fusion method for tomato leaf disease detection with CBAM, BirepGFPN, YOLOv6 algorithms with the accuracy of 93.8%. [4]. Md. Iqbal et al, reviewed a deep convolutional neural network. This model gives the highest accuracy of 98.27% in VGG-19, 94.98% in MobileNet-V2 and 99.53% in ResNet-50.[5]. Anjan Debnath et al, proposed a efficient NetV2B2 with AI. The suggested this model gives the 5-fold cross-validation method achieved 99.02% to 98.96% accuracy. [6]. Bodruzzaman Khan et al, presented Bayesian optimized multimodal with deep hybrid learning approach. This proposed model, achieved the highest classification performance among the seven hybrid models. This accuracy values is 98.527% [7].

M. Sharmila et al, outlined the kernel extreme learning machine model with firefly optimization method. The accuracy is 94.42% [8]. Marriam Nawaz et al, proposed robust deep learning model for leaf disease localization and classification gives 92% accuracy. [9]. Vengaiah et al, offered VARMAx- CNN-GAN integration model. The proposed work, has proven effective in attaining optimized results with 93.24% accuracy. [10]. Stanley Glenn E, et al. introduced the YOLOv9 for the localization of seven distinct tomato leaf diseases using annotated image datasets. They suggested YOLOv9 model achieves an impressive mAP of 96.4%, precision of 96%, and recall of 94.8%, demonstrating its effectiveness in early and accurate disease detection. [19]. Stanley Glenn E, et al. reviewed the YOLOv8, integrated with RoboFlow, is utilized for detecting nine common tomato leaf diseases in the Philippines. The model achieves an average precision of 99% on validation and test accuracy. [20]. Arshleen Kaur et al. developed an ensemble model combining LSTM and CNN was proposed for the classification of ten different types of tomato leaf diseases The model achieved a remarkable accuracy of 99.8%. [23]. Md. Afif Al Mamun, et al. reviewed deep learning-driven plant disease detection, emphasizing the feasibility of CNN-based models for early and accurate tomato leaf disease identification with an accuracy of 98.77%. [26]. Samkeliso S Dube, et al. developed a tomato leaf disease detection system utilizing convolutional neural networks (CNN) in a web-based application for real-time disease classification this model, achieving an accuracy of 93%. [27]. Somya Srivastav, et al. reviewed a deep learning-based approach using an enhanced CNN model with MobileNet architecture for real-time tomato leaf disease detection with 95.79% accuracy. [28].

Jyoti Agarwal, et al. designed CNN-based models, for accurate plant disease identification, achieving high classification accuracy. It integrated hybrid approaches, such as LSTM-CNN and EfficientNet-VGG16, and object detection models like YOLO for real-time disease detection. It receives 93% of accurate result. [30]. Shaik Johny Basha, et al. It reviews various deep learning and machine learning approaches applied to tomato leaf disease identification, offering insights into

automated solutions. The study aims to support the agricultural research community in leveraging technology for timely disease management and improved crop yield.[31]. Jiahe Yang, outlined the challenge of early tomato leaf disease detection by leveraging a balanced dataset created through web crawling and data augmentation. It evaluates the performance of various CNN architectures, including AlexNet, GoogleNet, VGG16, MobileNetV2, and ResNet50, introducing a novel loss function, BCCE, to enhance classification accuracy. The results demonstrate that MobileNetV2 with BCCE outperforms other models, achieving 98.01% accuracy. [32]

Jiang et al. introduced a real-time apple leaf disease detection method using an improved CNN model. A detection rate of 78.80% accuracy. [11].

Arshleen Kaur et al. reviewed the hybrid model combining VGG16 and CNN for precise detection of diseases in orange leaves. The model achieves a high testing accuracy of 98.43% at 50 epochs, demonstrating improved reliability in disease identification.[17]. Jyothi Joshi, et al. reviewed a hybrid model combining EfficientNet B3 and VGG16 for classifying orange leaf diseases into healthy, sooty mold sick, and citrus canker sick. With an overall accuracy of 97.87%. [21]. Maye Uddin Mojumdar, et al. suggested an automated orange disease detection system was developed using K-means clustering for segmentation and GLCM for feature extraction, followed by SVM-based classification. This method achieved an accuracy of 82.3%. [24].

Nosin Ibna Mahbub et al, presented the Lightweight Convolutional Neural Network (LCNN) to classify seven distinct mango leaf diseases along with healthy leaves. This deep learning models, achieving a 98% testing accuracy. [18]. Sachin Jain, et al. introduced a hybrid deep learning model that integrates SVM with Stochastic Gradient Descent (SGD) to enhance mango leaf disease classification. The Mango Leaves 2021 Dataset was used to train the model, achieving a classification accuracy of 97.7%. [22]. Eshika Jain, et al. designed a CNN-based automated system capable of classifying mango leaf diseases into seven categories, including both healthy and diseased leaves, with an accuracy target of 95%.[25].

Haridas D. Gadade, et al. Proposed convolutional neural networks (CNNs) for classifying and detecting leaf diseases in crops such as mango, tomato, and orange. Several researchers have proposed lightweight models and hybrid approaches to enhance classification accuracy. For instance, lightweight CNNs (LCNN) and hybrid architectures, such as EfficientNet-VGG16 and LSTM-CNN models, have demonstrated high classification accuracy, ranging from 97% to 99.8% in different datasets. [29]

Viswanathan Arjunan and Surya Prabha Deena, reviewed the role of Artificial Intelligence (AI) in detecting and managing plant parasitic nematode (PPN) infestations in sugarcane farming, a critical issue affecting yield and farmers' livelihoods. By leveraging machine learning algorithms, remote sensing, and data analytics, AI offers a promising solution for early detection, tracking, and prevention of nematode-related damage. The study emphasizes the integration of AI with traditional agricultural methods to enhance crop productivity and resistance, ultimately benefiting India's sugarcane industry. [36]

2. Conclusion

Based on the findings from the survey, it is evident that Convolutional Neural Network (CNN) methods are predominantly utilized for detecting plant leaf diseases. The accuracy of detection has shown notable improvement with the implementation of Deep CNN techniques, and the classification speed has significantly increased when integrated with Object Detection models. These advancements suggest that CNN alone may not be sufficient to achieve optimal accuracy and efficiency, necessitating the incorporation of an additional model for enhanced performance.

The analysis further reveals that while current models yield satisfactory results, they exhibit limitations in detecting diseases at an early stage. To address this challenge, we propose a hybrid model combining CNN, Recurrent Neural Network (RNN), and YOLOv8. This integrated approach is expected to enhance early-stage detection of tomato leaf diseases, ensuring timely intervention and improved crop health.

The input image first undergoes preprocessing and segmentation to eliminate noise and enhance the accuracy of feature extraction. Once preprocessing is complete, relevant features are extracted from the image. These extracted features, along with dataset values, are then used to train an RNN model. Following this, image reconstruction is performed. The output generated from the trained RNN is then fed into a hybrid CNN-RNN and YOLO classifier. This classifier processes the input and makes predictions, ultimately delivering the expected results.

Compliance with ethical standards

Disclosure of conflict of interest

The Authors declare that there is no conflicts of interest.

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