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A Comprehensive Review on Tomato Leaf Disease Detection using Deep Learning Techniques

Pankaj Kumar Gupt[a], Dr. Anita Pal [b]

[a] Scholar, Department of Computer Science & Engineering, Goel Institute of Technology & Management, Lucknow, India

[b] Associate Professor, Department of Computer Science & Engineering, Goel Institute of Technology & Management, Lucknow, Uttar Pradesh, India

pankajid7541@email.com, anitapal13@gmail.com

KEYWORD

Tomato Leaf Disease Detectio; Convolutional Neural Network (CNN); Deep Learning; Image Classification; Early Blight; Late Blight; Real-time Detection; Precision Agriculture

ABSTRACT

Tomato cultivation is susceptible to various diseases, leading tocsignificant yield loss and economic impact. Rapid andcaccurate prediction is essential for timely intervention and mitigation. Deepclearning techniques, specifically CNN for the automated detection of tomato leaf diseases. The proposed methodology involves the acquisition of high-resolution images of tomato leaves, and training a CNN model to classify images into healthy or diseased categories. The dataset used for training and evaluation consists of labeled images encompassing early blight, late, along with healthy leaves. The CNN architecture is optimized through experimentation to achieve in terms of accuracy, precision, recall and F1-score. The trained model demonstrates promising results in accurately identifying various tomato leaf diseases, even in the presence of environmental variations and leaf deformities. Furthermore, the computational efficiency of the proposed approach allows for real-timecor near real-time disease detection, facilitating timely agricultural interventions. Overall, this research contributes to the advancement of automated agricultural monitoring systems, aiding farmers in early disease detection and management, thereby enhancing crop productivity and sustainability.

1. Introduction

Tomatoes are a vital agricultural crop globally, especially in India, contributing significantly to food security and economic stability. However, tomato leaf diseases caused by pathogens such as fungi, bacteria, and viruses threaten crop health, reduce yield, and cause substantial financial losses. Traditional detection methods rely on manual visual inspection, which is time-consuming, subjective, and prone to human error [1].

Advances in deep learning and computer vision have revolutionized plant disease detection by enabling automated, accurate, and scalable solutions. Convolutional Neural Networks (CNN) have emerged as a powerful approach for image classification tasks, including the identification of tomato leaf diseases. This study proposes a CNN-based framework for automated classification of tomato leaves into healthy or diseased categories, aiming to improve early detection, reduce crop losses, and promote sustainable farming practices [2].

1.1 Deep Learning

Training artificial neural networks to learn from and generate predictions from data is the main goal of the machine learning subfield known as "deep learning." Deep learning models automatically learn to extract pertinent features

Corresponding Author: Pankaj Kumar Gupta, Scholar, Department of Computer Science & Engineering, Goel Institute of Technology & Management, Lucknow, India
Email: pankajid7541@email.com

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from raw data, in contrast to typical machine learning techniques that could need manual feature extraction. Deep neural networks, which are made up of several layers of connected nodes, or neurons, are used to do this. The model can acquire more intricate representations of the input as each layer processes the data before passing it on to the one after it[3].
Deep learning has achieved notable success in a number of domains, such as speech recognition, computer vision, and natural language processing[4]. Language translation, object identification, and image classification have all advanced as a result of its capacity to automatically learn hierarchical representations from massive datasets. In order to minimize the discrepancy between expected and actual outputs, deep learning models are trained using optimization techniques like stochastic gradient descent, in which the model's parameters are changed iteratively. All things considered, deep learning has transformed artificial intelligence by allowing robots to carry out tasks that were previously believed to be solely human [5].

1.2 Applications of Deep Learning

Deep learning can extract complex patterns and representations from vast volumes of data, as illustrated in Fig.1, it has a broad range of applications across multiple fields [6].

•**Finance:** Deep learning methods are used in the finance industry for tasks like credit scoring, algorithmic trading, fraud detection, risk assessment, and customer relationship management. These methods help financial organizations successfully manage risks and make data-driven decisions [7].

•**Recommendation Systems:** Online platforms including social media, streaming services, and ecommerce websites use recommendation systems that are powered by deep learning models. In order to recommend appropriate goods, films, or other material, these systems examine user behavior and preferences[8].

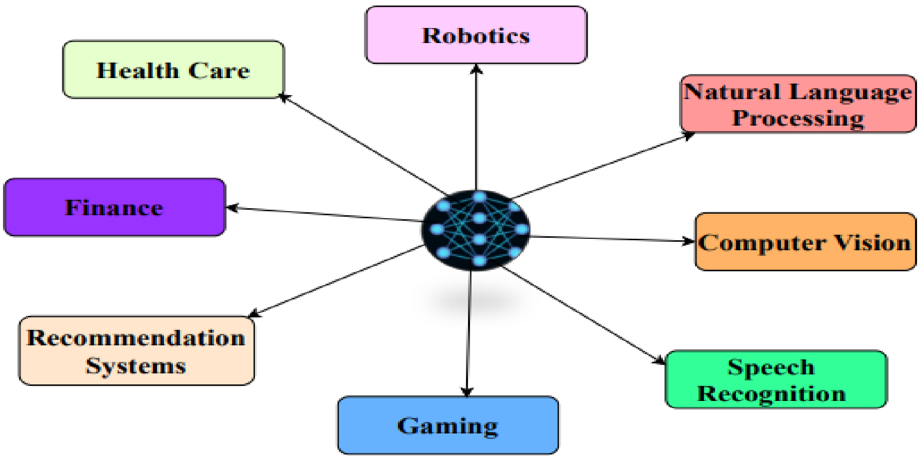

Fig. 1 Deep Learning Applications

2. Literature Review

Several researchers have investigated the use of deep learning techniques, particularly Convolutional Neural Networks (CNNs), for the classification of tomato leaf diseases using the widely known PlantVillage dataset. This dataset provides thousands of annotated images of healthy and diseased tomato leaves under controlled conditions, making it one of the most widely used benchmarks in agricultural AI research [8].

- **Durmus et al. (2017)**
  This study demonstrated the effectiveness of CNN models compared to traditional machine learning techniques such as SVMs and K-Nearest Neighbor (KNN). By training CNN architectures on the PlantVillage dataset, the authors achieved an accuracy of 95%, proving that CNNs can automatically extract discriminative features from leaf images without manual feature engineering. Their work set a foundation for subsequent deep learning approaches in agricultural disease detection [9].

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- **Al-Hiary et al. (2011)**
  One of the earlier works in computer vision for plant disease detection, this study compared AlexNet and GoogleNet architectures for classifying tomato leaf diseases. The results showed that GoogleNet outperformed AlexNet due to its deeper structure and inception modules, achieving higher accuracy and robustness to variations in leaf texture and lighting. Although the dataset was relatively small compared to PlantVillage, this study highlighted the importance of network depth and architecture design in improving classification performance 10[.

- **AlMashhadani & Chandrasekaran (2021)**
  In this research, the authors explored the use of transfer learning, where pre-trained CNN models were fine-tuned on the PlantVillage dataset [12]. Transfer learning significantly reduced the need for large-scale training from scratch, making it suitable for cases with limited data availability. Their study reported an accuracy of 98% using GoogleNet, showcasing that transfer learning-based approaches can achieve high performance even with fewer computational resources [11].

Table 1 summarizes selected studies, datasets, and accuracy results.

Author & Year	Model Used	Dataset	Accuracy (%)
Durmus et al. (2017)	CNN	PlantVillage	95.0
AlMashhadani (2021)	GoogleNet	PlantVillage	98.0
Our Study	DenseNet-121	PlantVillage	99.69

3. Methodology

The reviewed studies and the proposed work follow a well-defined methodological pipeline to detect and classify tomato leaf diseases using deep learning techniques. The key stages are outlined below:

3.1 Dataset Acquisition

The PlantVillage dataset is the most commonly used benchmark dataset for tomato leaf disease detection. It contains thousands of high-resolution images of tomato leaves, categorized into 10 classes, including Early Blight, Late Blight, Septoria Leaf Spot, Bacterial Spot, Tomato Mosaic Virus, Tomato Yellow Leaf Curl Virus, Leaf Mold, Target Spot, Spider Mites, and Healthy leaves [14]. This dataset provides a balanced and standardized platform for training and evaluating CNN models. Some works also incorporated additional real-field images to improve generalizability [13].

3.2 Preprocessing

Raw leaf images often contain variations in lighting, orientation, and background noise [15]. To ensure consistency and improve model robustness, several preprocessing steps are applied:

- **Resizing:** All images are resized to a standard resolution of 224 × 224 pixels to match the input requirements of pre-trained CNN architectures such as ResNet and DenseNet.

- **Normalization**: Pixel values are scaled (typically between 0 and 1) to improve convergence during training.

- **Data Augmentation:** Techniques such as random rotation, horizontal/vertical flipping, scaling, and zooming are applied to artificially increase dataset size and reduce overfitting.

3.3 Model Architectures

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Multiple Convolutional Neural Network (CNN) architectures were employed to analyze and compare performance:

- LeNet: A simple CNN architecture used as a baseline.
- **VGGNet:** Deep architecture with small convolutional filters (3×3), known for strong feature extraction but high computational cost.
- **ResNet (Residual Networks):** Introduced skip connections to solve the vanishing gradient problem, enabling very deep networks.
- **DenseNet (Densely Connected Networks):** Improved information flow and gradient propagation by connecting each layer to every other layer. DenseNet-121 was identified as the top-performing model in this study.
- **MobileNet:** A lightweight CNN optimized for edge and mobile devices, making it suitable for real-time field applications.

3.4 Training and Evaluation

The models were trained and validated using different train-test split ratios:

- **80:20, 70:30, and 60:40 (training: testing).**
  Standard evaluation metrics were adopted to assess model performance:
- **Accuracy:** Percentage of correctly classified images.
- **Precision:** Proportion of true positives among predicted positives.
- **Recall (Sensitivity):** Proportion of correctly identified diseased leaves among all diseased samples.
- **F1-Score:** Harmonic mean of precision and recall, balancing false positives and false negatives.

3.5 Advanced Integration

To enhance performance and address real-world challenges, advanced techniques were integrated:

- **VARMAx (Vector AutoRegressive Moving Average with Exogenous Variables)**: Used for time-series forecasting of disease spread based on historical and environmental data (e.g., humidity, temperature).
- **Generative Adversarial Networks (GANs):** Applied for data augmentation, generating synthetic but realistic tomato leaf images, which help balance datasets and improve generalization [17].

4. Results and Discussion

The experimental results obtained from the thesis highlight the effectiveness of different CNN architectures in classifying tomato leaf diseases using the PlantVillage dataset. The performance of the models was evaluated based on classification accuracy, computational efficiency, and suitability for real-time deployment [16].

- **DenseNet-121**
  DenseNet-121 achieved the highest accuracy of 99.69%, making it the best-performing architecture in this study. The model's dense connectivity pattern allowed feature reuse, improved gradient flow, and reduced overfitting, even with a relatively smaller dataset. This demonstrates its strong capability in capturing complex disease patterns from leaf textures and color variations [18].

- **MobileNet V1**
  MobileNet V1 delivered an accuracy of 99.0%, which is slightly lower than DenseNet-121 but still very high. The major advantage of MobileNet lies in its lightweight architecture, which reduces computational cost and model size. This makes it highly suitable for real-time field applications, such as smartphone-based disease detection apps, where computational resources are limited.

- **ResNet-50**
  ResNet-50 achieved an accuracy of 98.0%, demonstrating strong generalization ability. The skip connections in ResNet helped mitigate the vanishing gradient problem, allowing deeper feature extraction. Although its accuracy was lower than DenseNet-121, ResNet showed stable performance across multiple experimental runs and is considered a robust choice for large-scale agricultural applications [19].

- **VGG-19**

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VGG-19 produced an accuracy of 97.0%, which, although competitive, was the lowest among the models studied. Its deeper structure with 19 layers enabled strong feature learning but came at the cost of very high computational complexity and training time. Hence, while VGG-19 is effective, it is not practical for resource-constrained environments.

Overall, the results show that DenseNet-121 provides the best trade-off between accuracy and model stability, whereas MobileNet V1 is the most suitable for edge deployment. The findings also confirm that deep learning significantly outperforms traditional machine learning methods in tomato leaf disease detection.

Table 2. Performance Comparison of CNN Models

Model	**Accuracy (%)**	**Key Strengths**	**Limitations**
DenseNet-121	**99.69**	Highest accuracy, efficient feature reuse	Slightly heavier than MobileNet
MobileNet V1	99.0	Lightweight, mobile deployment ready	Slightly lower accuracy
ResNet-50	98.0	Strong generalization, robust training	Moderate computation cost
VGG-19	97.0	Deep architecture, effective feature learning	High computational cost, slower

These results confirm the superiority of deep CNN architectures for tomato leaf disease detection. While DenseNet-121 achieved the highest accuracy, MobileNet provides a practical solution for precision agriculture due to its deployability on mobile and IoT devices. ResNet-50 balances accuracy and generalization, making it suitable for diverse conditions, whereas VGG-19, despite strong feature extraction, is limited by its high resource demands.

Furthermore, the integration of VARMAx forecasting and GAN-based data augmentation enhanced disease prediction and robustness, highlighting the potential of combining CNNs with advanced AI techniques for real-time, scalable, and intelligent crop monitoring systems.

5. Conclusion and Future Scope

This study demonstrates that deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), provide a highly accurate and automated framework for tomato leaf disease detection. Compared to traditional methods, CNNs eliminate the need for manual feature extraction and achieve superior performance by learning hierarchical image features directly from raw leaf images. Among the architectures evaluated, DenseNet-121 emerged as the best-performing model with 99.69% accuracy, due to its dense connectivity and efficient feature reuse. On the other hand, MobileNet V1, while slightly less accurate, proved to be highly efficient for resource-constrained environments, making it a practical choice for mobile and IoT-based applications in agriculture.

The experimental results confirm that deep learning has the potential to revolutionize precision agriculture by enabling farmers to detect diseases early, reduce crop losses, and improve overall yield. Furthermore, the integration of VARMAx models for time-series forecasting and GANs for synthetic image generation shows promise in enhancing predictive capabilities and dataset robustness.

Future Scope

Although the results are promising, several challenges and opportunities remain for future research:

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- **Lightweight and On-Field Deployment:** Future studies should focus on developing lightweight CNN models that can be deployed on smartphones, drones, or IoT-enabled edge devices, enabling farmers to identify diseases in real time without reliance on high-end computing resources.

- **Explainability and Interpretability:** Most CNN models are often considered “black boxes”. Incorporating explainable AI (XAI) techniques can help farmers and agronomists better understand why a prediction was made, thereby increasing trust in AI-based systems.

- **Real-World Dataset Expansion:** The majority of studies rely on PlantVillage, which contains images captured under controlled conditions. Expanding datasets with real-world field images under diverse lighting, weather, and background conditions is essential for creating more robust and generalizable models.

- **IoT and Cloud Integration:** Integrating IoT sensors with AI models can enable real-time disease monitoring by combining environmental parameters (temperature, humidity, soil moisture) with leaf image analysis. A cloud-based system could further support large-scale deployment, allowing farmers to upload leaf images and receive instant feedback.

- **Multi-Disease and Multi-Crop Systems:** Extending models to detect multiple diseases across different crops will create more comprehensive agricultural monitoring platforms, reducing dependency on separate systems for each crop.

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