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Performance Comparison of CNN Models for Tomato Disease Detection using Image-Based Data in both Controlled and Real-World Conditions

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Abstract

Tomato plants are integral to worldwide agricultural production, yet they remain vulnerable to numerous diseases stemming from fungi, bacteria, and viruses. Prompt and precise identification of these ailments is vital for maintaining crop productivity and safeguarding food supplies. This paper consolidates insights from revolutionary machine learning (ML) and deep learning (DL) methodologies, particularly convolutional neural networks (CNNs), for identifying tomato plant diseases. Employing datasets like Plant Village and authentic field specimens, we evaluate model performance across diverse scenarios. Findings indicate that CNNs attain over 99% accuracy in controlled environments but face considerable obstacles in practical field applications because in many real-world applications the data can vary greatly due to environmental factors such as lighting conditions, weather, and seasonal changes. This paper explores three CNN architectures DenseNet, ResNet50 and VGG16 while offering approaches to improve model adaptability and expandability for RealWorld implementation.

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Introduction

Tomatoes (Solanum lycopersicum) are considered one of the most extensively cultivated crops globally, contributing significantly to agricultural output and economic value because of its demand throughout the year. Food and Agriculture Organization[1] (FAO) data indicates that global tomato yield exceeds 180 million tons per annum, with India occupying the position of second largest producer. Notwithstanding their economic significance, tomato plants exhibit susceptibility to diseases that can substantially impact yields, with annual losses estimated between 20% and 40%.

Conventional approaches to disease detection, such as visual assessment or laboratory analysis,

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necessitate skilled professionals and considerable time. These methodologies are also susceptible to human error due to environmental variations and the similar symptomatology exhibited by different diseases.[2] In rural or resource limited regions, the paucity of experts and diagnostic facilities further complicates timely disease management.

The revolutionary Machine Learning (ML) and Deep Learning (DL) has transformed agricultural practices,[3] particularly in automating plant disease detection and classification. Among these techniques, Convolutional Neural Networks (CNNs) are particularly noteworthy for their capacity to learn hierarchical features directly from image data, obviating the need for manual feature extraction. However, while DL models excel under controlled conditions, their practical implementation faces challenges, including data diversity and scalability. This objective of this paper is to provide a comprehensive examination of tomato disease detection techniques, with a focus on CNN based models, their efficacy, and approaches to overcome real-world obstacles. CNNs breaks down images into hierarchical layers of features and outperform traditional methods like manual feature extraction, rely on predefined rules or human expertise to detect specific features (e.g., leaf spots or discoloration).

Tomato disease detection has garnered significant attention due to its impact on agricultural productivity. Recent advancements leverage deep learning and image processing techniques to enhance detection accuracy and efficiency. Various methodologies have been proposed,[4] each addressing specific challenges in identifying diseases in tomato plants. Several studies utilize CNNs for automated disease detection, effectively learning complex patterns from tomato leaf images. Parallel CNN[5] approach has also used in literature to reduce the training time. For instance, a CNN-based model achieved over 90% accuracy in classifying diseases like leaf mold and target spot (Sonawane, 2023) (R., 2024). During disease detection,[6,7] researcher has also emphasis on the feature extraction techniques which incorporate self-attention mechanisms and dynamic activation functions to improve feature extraction, resulting in a mean Average Precision (mAP). Many researcher has used image processing methods[8,9] to enhance visual features of tomato plants, allowing for precise identification of diseases like early and late blight. This approach aids in distinguishing between various disease types through unique feature signatures. Bootstrapping approach[10] and deep CNN[11,12] are extensively used in agriculture domain for identification of diseases for different plants.[13]

Materials and Methods

The study utilized a combination of publicly available and custom collected datasets like Plant Village Dataset and real world dataset as refered in Table 1. Plant village dataset contains over 14,500 annotated images of tomato leaves, representing both healthy and diseased samples. It includes classes such as bacterial spot, early blight, late blight, and septoria leaf spot.

RealWorld dataset contains 5000 field images which were collected under varying environmental conditions to simulate real-world diversity. These images featured heterogeneous lighting, complex backgrounds, and varied resolutions. Table 1 shows the brief summary of dataset used under consideration.

Table 1: Dataset Information

Dataset	Number of Images	Classes	Conditions
Plant Village Dataset	14,500	10	Controlled
RealWorld Dataset	5,000	6	Uncontrolled

In this paper, the advanced techniques for tomato disease detection which makes use of machine learning and deep learning approaches are explained. Preprocessing is critical for ensuring model robustness. During preprocessing resizing, normalization and augmentation are carried out on dataset. All images were standardized to 224×224×3 pixels to align with the input requirements of convolutional neural network[14] architectures. Pixel values were scaled to the range [0, 1] to enhance computational efficiency. Techniques such as cropping, rotation, flipping and zooming are applied at data augmentation stage to artificially expand the dataset and address class imbalances. The main goal of data augmentation is to increase the diversity of the training data important when the dataset is limited or have imbalanced distribution, as it helps reduce the risk of overfitting and allows the model to learn more robust and varied patterns. In this paper three different approaches are applied and tested as explained in following section.

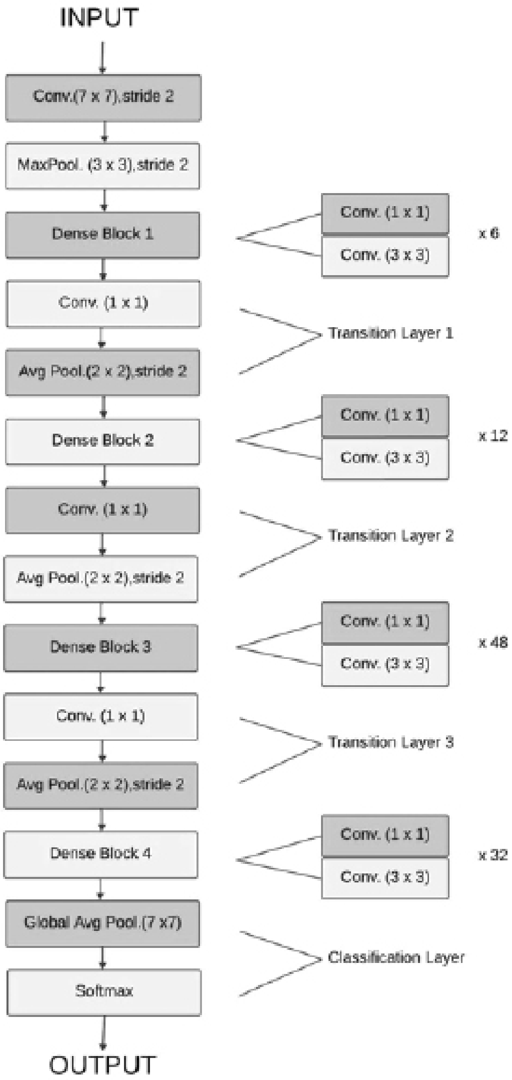

Fig 1: DenseNet Model

Approach1

DenseNet

The model combines a pre-trained DenseNet201 architecture with a CNN classifier, chosen for its superior accuracy compared to other models. DenseNet architecture[15] is applied here to achieved the best accuracy due to its densely connected layers that optimize feature reuse. DenseNet201 extracts features which are processed by the convolutional neural network for classification. The model's performance is evaluated using test and validation sets. The initial stage involves data pre-processing, followed by data augmentation as second stage.

The third stage introduced the DenseNet201 that leverages transfer learning. DenseNet 201 without human intervention extract features and apply the weights pre-trained on the ImageNet dataset, thereby reducing computational demands. DenseNet201's structure enables the development of uncomplicated models. It also allows for feature reuse across layers, enhancing parameter efficiency and enabling greater diversity in successive layers, thus improving performance. In a feed forward approach every layer is connected to successive layer and creates a direct pathway for information to flow throughout the network. Moreover, DenseNet201 incorporates a pooling layer and bottleneck structure, which minimizes model complexity and parameter count, increasing efficiency. Every layer in the DenseNet201 network performs a nonlinear transformation to capture complex patterns. Each layer comprising of convolution (Conv), pooling, rectified linear units (ReLU), and batch normalization (BN). DenseNet201 employs a unique approach where all layers are connected in such as way that the output of one layer is used as input of successive layers. This dense connectivity pattern results in a total of N(N+1)/2 connections in an N-layer network, significantly increasing the flow of information and improving the model's ability to reuse features from earlier layers. In this paper, the DenseNet201 structure consists of more than 700 layers and more than 20 million parameters. The input layer is configured to accept images with dimensions of 224 x 224 x 3. The DenseNet201 structure is illustrated in Fig.1.

During the fourth stage, the classification layers are eliminated, and six new layers are introduced for the classification task. The initial layer and second layer consists of 1024 neurons and 512 neuron respectively. Both layers utilizing a ReLu activation function. A dropout layer is implemented as the third layer, with a dropout rate of 0.2 to mitigate the effect of overfitting. The fourth layer incorporates a global average pooling layer for reduction in feature maps. The fifth layer is comprising 128 neurons and ReLu function. A second dropout layer is also introduced with a 0.2 dropout rate serves as the sixth layer. The final layer consists of only 10 neurons and a Softmax function, which outputs the 10 classes of tomato diseases. The subsequent section provides a detailed examination of the proposed model's results and compares them to other models.

Approach 2

ResNet50

In place of DenseNet, ResNet is implemented which is known for its residual learning framework, which mitigates the vanishing gradient problem. First two phases are remain same i.e. preprocessing and augmentation where after data collection, a cleaning process is implemented to remove faulty images from the dataset. Images are resized to 224 × 224 pixels, which optimizes machine load during training and yields optimal results. The images are then labeled using a one-hot encoding system and converted into a NumPy array for faster computation. ResNet has several variants based on CNN principles but with varying layer counts. In the third phase, a deep ResNet50[16] model which comprises of convolutional layers(CONV), identity block(IB), convolutional block (Conv Block), and the fully connected as shown in fig. 2. ResNet50 refers to the 50-layer neural network variant where convolutional layers are responsible for extracts various features from input images while the IB and Conv block are responsible for processing and transforming these features to train the model. The final phase utilizes a fully connected layer for classification. The accuracy of a deep CNN model is heavily influenced by dataset quality.

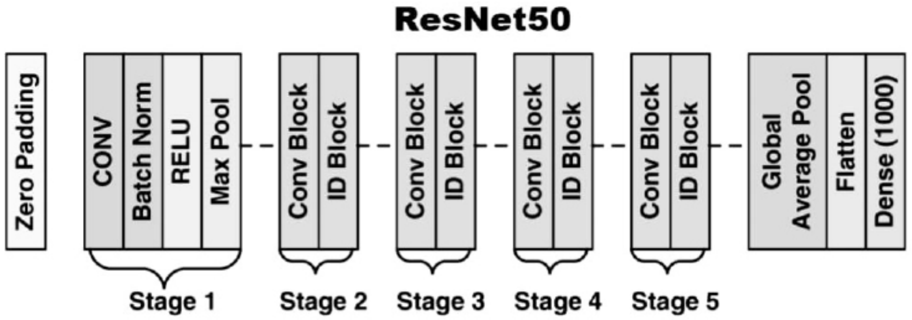

Fig. 2: Composition of ResNet50

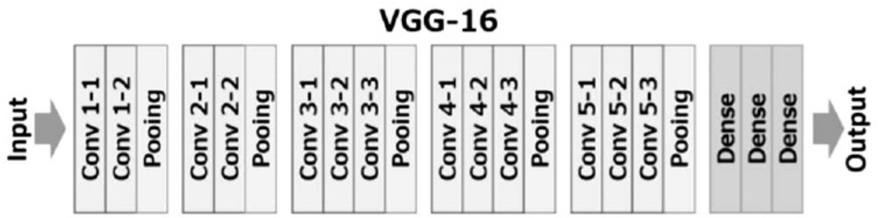

Fig. 3: Composition of VGG 16

Approach 3

VGG16

VGG-16 is a widely adopted CNN architecture acronym as "VGG" stands for Visual Geometry Group. VGG architecture[17] is particularly renowned for its effectiveness with ImageNet, an extensive project used for visual object recognition. This model is highly regarded in the field of image classification within deep learning due to its exceptional utility. In VGG16 "16" indicates the number of layers in the neural network which comprises of 13 convolutional Layers, 5 pooling layer and 3 dense layers as shown in fig. 3.

Experimental Results

The three models were evaluated using the following metrics

Accuracy

Percentage of correctly classified samples.

Precision, Recall, F1Score

Metrics for class wise performance analysis.

Confusion Matrix

Visualized misclassifications across disease classes.

DenseNet achieved the highest overall accuracy of 99.9% under controlled conditions, significantly outperforming other architectures as shown in table 2. However, when tested on real-world datasets, all models exhibited a performance drop, highlighting challenges in generalization. Models may not generalize well to diverse environments, leading to reduced accuracy and robustness.

While comparing the training time of these models VGG16 takes less training time as compare to other two approaches as shown in table 3.

Table 2: Model Performance Accuracy

Model	Controlled Environment					Real World Environment					Drop (%)
	TP	FP	FN	TN	Acc. (%)	TP	FP	FN	TN	Acc. (%)	
DenseNet	13997	11	10	482	99.9	2132	866	760	1242	67.5	32.4
ResNet50	13685	170	190	455	97.6	2105	1003	783	1109	64.3	33.3
VGG16	13385	340	465	310	94.5	2002	1106	883	1009	60.2	34.3

Table 3: Model Training Time

Model	Training Time (hrs.)	Parameter Count (millions)	Notable Features
DenseNet	8.5	28	Dense connections
ResNet50	7.2	23	Residual blocks
VGG16	6.8	138	Sequential architecture

Discussion

A common deep learning issue which was observed is increase in training and test error rates as layer count increase. Among CNN architectures[18,19] particularly DenseNet and ResNet, excelled in capturing complex features, reducing the need for manual preprocessing. Their scalability and adaptability to different image datasets make them suitable for agricultural applications. Some of the challenges associated with CNN architecture are overreliance on controlled datasets hampers real-world performance which results in dataset bias, Training CNNs requires significant computational resources like GPU etc. and Real-time processing on low power devices remains a challenge during field deployment. As deep learning is evolving need to have advance techniques for improvements to the current methodology especially for real time validation and suggest areas for further investigation, such as expanding the dataset or exploring new feature extraction techniques.

Conclusion

This paper underscores the potential of deep learning in automating tomato disease detection. In this paper three different approaches of deep learning are applied and tested on controlled environment and realtime environment. DenseNet, ResNet50 and VGG16 demonstrated near perfect accuracies in controlled settings, though significant challenges persist in adapting these models for real-world use. While the advancements in CNN models for tomato disease detection are promising, challenges remain in achieving consistent performance across varying environmental conditions and image qualities. Further research is needed to enhance model robustness and reduce false positives in complex agricultural settings. Future work should focus on expanding datasets to include diverse environmental conditions, developing lightweight models for mobile and IoT devices, enhancing interpretability to build farmer centric solutions. By addressing these gaps, deep learning technologies can revolutionize agricultural disease management, improving productivity and ensuring global food security.

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Ethics Statement
This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Informed Consent Statement
As part of our commitment to ethical research practices, all participants involved in data collection for this project provided informed consent.

Author Contributions
- **Meenakshi Thalor:** Initiated the research work by outlining, mentioning objectives and prepared the system architecture. Contributed in customized data collection using camera and in documentation of paper.
- **Yash Chavhan:** Implementation of system starting from data collection to classification task.
- **Sanjay Mate:** Performed the validation of model by using different evaluation measures like precision, recall and f score.

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