Real-Time Plant Disease Detection in Field Conditions using Deep Learning

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Abstract. Plant disease identification is essential to guarantee agricultural yields and food security. Conventional approaches depend on manual examination, which is labor-intensive and subject to human mistakes. Deep learning and computer vision advancements in the recent past have made it possible to automate plant disease classification, but the majority of models are not robust enough to handle field-conditioned images with varying lighting, occlusions, and cluttered backgrounds. This paper suggests a refined deep learning method with EfficientNetB3 and spatial attention for resilient disease detection in practical agricultural environments. The model is trained on the PlantDoc dataset with data augmentation methods to enhance generalization. Experimental results show better performance compared to baseline models with high classification accuracy at low computational costs. The new approach provides an efficient solution to real-time disease diagnosis, benefiting farmers through early intervention and protection of crops. . . .

Keywords: Plant disease detection, Deep learning, EfficientNetB3, Spatial attention

1 Introduction

Plant diseases pose a significant threat to global agriculture, leading to reduced crop yields and economic losses. Early and accurate disease detection is crucial for effective intervention and sustainable farming. Traditionally, plant disease identification has relied on manual inspection by farmers and agricultural experts, which is not only time-consuming but also prone to human error. With advancements in artificial intelligence, deep learning has emerged as a powerful tool for automating plant disease detection[11].The decline in agricultural productivity highlights the challenges caused by factors such as human error. Therefore, there is a growing need for an efficient solution that minimizes manual effort while ensuring accurate plant disease detection[2]. Convolutional neural networks (CNNs) have demonstrated remarkable success in image-based classification tasks, making them a suitable choice for identifying plant diseases from

leaf images[5]. However, real-world conditions, such as background clutter, and occlusions in field images, pose challenges for classification.
Field images used for plant disease detection exhibit high variability due to diverse environmental conditions, making it difficult for conventional deep learning models to achieve reliable performance[9]. Many publicly available datasets primarily consist of laboratory-captured images with uniform backgrounds, which do not accurately represent real-world agricultural settings. Additionally, dataset-related challenges such as class imbalance, where certain diseases have fewer samples than others, further complicate model training. Some plant diseases exhibit similar visual symptoms, increasing the risk of misclassification[12]. To address these issues, a feature extraction technique is essential to enhance model generalization and improve classification accuracy in uncontrolled environments. This study presents a deep learning-based approach using EfficientNet-B3 integrated with a spatial attention mechanism to improve plant disease classification in real-world conditions. The proposed model enhances feature extraction by directing attention to disease-affected regions while suppressing irrelevant background information. The combination of EfficientNet-B3's efficient feature extraction capability and spatial attention leads to improved classification performance compared to traditional CNN-based architectures. Experimental results demonstrate that the model outperforms existing approaches in terms of accuracy and robustness when tested on the PlantDoc dataset, which contains field images with diverse backgrounds. This research highlights the potential of integrating spatial attention mechanisms with state-of-the-art deep learning models for accurate and automated plant disease detection in real-world agricultural applications.

2 Literature Review

The literature review summarizes key research studies on plant disease detection using deep learning, focusing on datasets, methodologies, findings, and limitations. It provides insights into various approaches, including CNN-based architectures, attention mechanisms, and transfer learning techniques. By comparing different models and datasets, the review highlights advancements in accuracy, robustness, and real-world applicability. Additionally, it identifies existing challenges, such as dataset limitations, misclassification issues, and computational constraints, guiding future research directions.The literature review is summarized in Tabel 1.

3 Implementation

This work uses the PlantDoc dataset, which provides actual field photographs, to design a deep learning plant disease model. The scheme in this paper makes use of EfficientNet-B3 with the spatial attention technique for improving the extraction of features and classification rate.

Table 1. Summary of Literature Survey on Plant Disease Detection

Authors	Models Used	Dataset	Results and Findings	Limitations
Doutoum et al. [4]	CNN architectures (AlexNet, LeNet, InceptionV3, VGGNet, ResNet, GoogLeNet, DenseNet)	PlantVillage	ResNet achieved 99.2% for apple disease classification	Dataset imbalance, misclassification in visually similar diseases
Wang et al. [13]	VGG16, Inception-V3, ResNet50	PlantVillage	Achieved accuracy of 97%, followed by VGG16 (96%)	Misclassification in adjacent severity stages, limited training samples
Shivaprasad et al. [11]	CNN, VGG16, VGG19	9,127 plant leaf images (8 classes)	CNN achieved 97% accuracy; VGG16 excelled in precision	Overfitting risk, difficulty in overlapping disease detection
Moupojou et al. [9]	MobileNet, VGG16, InceptionV3, InceptionResNetV2	FieldPlant dataset (5,170 images)	Improved field dataset performance over PlantDoc	Needs additional disease class inclusion
Balafas et al. [3]	ResNet50, MobileNetV2, YOLOv5	PlantDoc	YOLOv5 achieved highest object detection accuracy	Struggles in uncontrolled environments
Asha Rani et al. [1]	EfficientNetV2B2, EfficientNetV2B3, InceptionResNetV2	Agri-ImageNet, Sunflower, Cauliflower datasets	EfficientNetV2 models had highest classification accuracy	Difficulty in classifying visually similar diseases
Lili Li et al. [7]	AlexNet, GoogLeNet, ResNet50, VGG16, InceptionV3, DenseNet	Real-world datasets	Accuracy exceeding 99% on controlled datasets	Limited diversity, difficulty in early disease detection
Shifa Aiman Bagban et al. [2]	SVM and CNN	Modified PlantVillage	CNN achieved 71.7% accuracy	Environmental constraints affect real-world use
SK Mahmudul Hassan et al. [5]	Novel CNN architecture	PlantVillage, Rice, Cassava Disease Datasets	99.39% on PlantVillage, 99.66% on Rice, 76.59% on Cassava dataset	Difficulty handling multiple leaves
Muhammad Umar et al. [12]	CNN, YOLOv7 with SimAM	Custom tomato leaf dataset	YOLOv7 achieved 98.8% accuracy	Struggles with visually similar diseases
Peng Jiang et al. [6]	INAR-SSD	Apple Leaf Disease Dataset (ALDD)	INAR-SSD achieved 78.80% mAP	Misclassification due to small lesion sizes
Emmanuel Moupojou et al. [8]	FAM and FCDD	PlantVillage, PlantDoc, FieldPlant datasets	Model improved classification accuracy by 10% on PlantDoc	Challenges differentiating dense greenery from leaves
Pedapudi Nagababu et al. [10]	CNN	Custom dataset with 30 classes	CNN achieved 98.59% accuracy	Needs better real-world adaptability

3.1 Dataset Description

The PlantDoc dataset is a publicly available collection of 2,598 field images of plant leaves affected by different diseases. It consists of 38 classes, covering multiple plant species (apple, bell pepper, blueberry, cherry, corn, grape, peach, potato, raspberry, soyabean, squash powder, straw berry, and tomato) and disease categories, making it a valuable resource for training and evaluating deep learning models[9]. The images are captured in real-world field conditions, exhibiting variations in lighting, background complexity, occlusions, and natural environmental factors such as shadows and overlapping leaves[9]. Unlike lab-captured datasets with uniform backgrounds, PlantDoc provides a challenging benchmark for models to generalize well in practical farming environments.No algorithms have been specifically tested on the PlantDoc dataset so far. However, numerous studies have utilized the PlantVillage dataset for plant disease detection research[3]. This dataset plays a crucial role in developing automated plant disease detection systems suitable for real-world agricultural applications.

3.2 Workflow

As shown in"Fig. 1" the workflow of plant disease detection using deep learning, specifically utilizing the PlantDoc dataset and the EfficientNetB3 model. The process begins with data collection, where images of plant leaves with various diseases are gathered from the PlantDoc dataset. These images undergo data preprocessing and augmentation, which includes resizing, normalization, and applying transformations such as rotation and flipping to enhance model robustness. The model is then trained using a labeled dataset, optimizing parameters to achieve accurate classification. Once trained, it performs disease analysis, identifying plant diseases based on input images. Additionally, a severity analysis step is included to determine the extent of infection in affected plants. Finally, the model generates predictions, providing information on disease type and severity, which can be used for decision-making in agriculture.

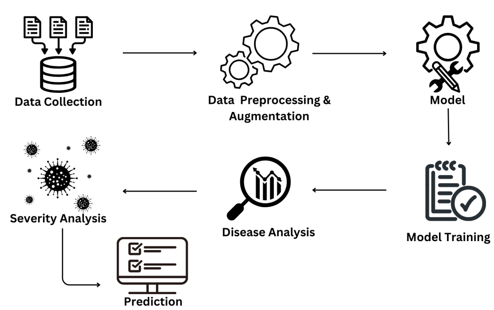

Fig. 1. Disease Detection Workflow

3.3 Data Pre-processing and augmentation

Data preprocessing and augmentation play a crucial role in improving the accuracy and robustness of plant disease detection models.By applying transformations to generate new data samples, these techniques help minimize overfitting and enable the model to learn more robust and generalized representations of the data[1]. In this study, images from the PlantDoc dataset are resized to 224×224 pixels to match the input size required by EfficientNet-B3. Normalization is applied using standard mean and standard deviation values to align with pre-trained ImageNet weights. To enhance model generalization, various augmentation techniques are used, including random horizontal flipping, random rotation, and random resized cropping. Color jittering is applied to introduce variations in brightness, contrast, saturation, and hue, making the model more adaptable to real-world lighting conditions. These augmentations help the model recognize diseases more effectively, even under challenging field conditions. Image processing techniques were applied to isolate each detected object in the image, and the background elements were manually separated from the identified leaves[8]. This approach ensures improved feature extraction, allowing the model to focus on disease-specific regions with the help of the spatial attention mechanism.

3.4 Model Architecture

The model architecture for plant disease detection system using the PlantDoc dataset and the EfficientNetB3 model with spatial attention. The process starts with input samples from the PlantDoc dataset, which are then passed through data preprocessing steps such as resizing, normalization, and noise reduction. After preprocessing, data augmentation techniques like rotation, flipping, and brightness adjustments are applied to enhance the dataset's diversity. The augmented images are fed into the EfficientNetB3 model, where they first pass through the stem layer, which extracts basic features. The data then moves through MobileNet (MB) convolutional blocks integrated with spatial attention to enhance the focus on disease-affected regions. The final feature extraction is performed in the fully connected layers, leading to an output classification of plant disease. Following classification, severity detection determines the intensity of the disease, and performance analysis evaluates the model before generating the final prediction "Fig. 2".

- EfficientNetB3 is a deep learning model known for its optimized architecture, balancing accuracy and computational efficiency. It scales depth, width, and resolution systematically using a compound coefficient, ensuring efficient feature extraction. Its MBConv blocks (Mobile Inverted Bottleneck Convolution) help preserve spatial information while reducing computational complexity, making it ideal for plant disease classification.
- Spatial attention enhances the model's ability to focus on the most critical regions of an image, ensuring that disease-affected areas receive more attention. Instead of treating all parts of an image equally, spatial attention

assigns higher weights to significant areas (e.g., leaf spots, discoloration) while suppressing irrelevant background noise. This leads to more precise disease identification.
- In this architecture, spatial attention is integrated within the MBConv blocks of EfficientNetB3. Specifically, after each MBConv block extracts features, the spatial attention mechanism is applied to highlight the most relevant regions before passing them to the next layer. This placement ensures that important spatial features are retained and refined, improving classification accuracy while maintaining efficiency.

3.5 Severity Detection

Severity detection in plant disease classification helps determine the extent of infection, which is essential for effective disease management. The function first processes the input image by applying necessary transformations and converting it into a format suitable for model prediction[13]. The trained EfficientNet-B3 model is then used to classify the disease, and the severity level is determined based on predefined severity categories. The severity index is calculated by mapping the predicted class to an appropriate severity level, ensuring accurate classification of mild, moderate, or severe infections. This approach allows farmers and researchers to take appropriate measures based on the severity of the disease, improving overall crop health management.

4 Results

The plant disease detection model, trained on the PlantDoc dataset using EfficientNet-B3 with spatial attention, achieved good classification accuracy and reliable severity prediction. The spatial attention mechanism improved feature extraction, leading to better identification of disease-affected regions.

- The model achieved 72.53% accuracy, outperforming baseline models without spatial attention.
- The overall precision was 72.98%, ensuring a lower false positive rate in disease classification.
- The recall value of 72.53% indicates the model effectively detects diseased samples with minimal false negatives.
- With an F1-score of 71.02%, the model maintains a balance between precision and recall, proving its robustness.

As shown in “Fig. 3” Detection of diseased mildew leaf, where in the model predicted the disease as Squash Powdery mildew leaf and also it predicted the severity as Moderate.

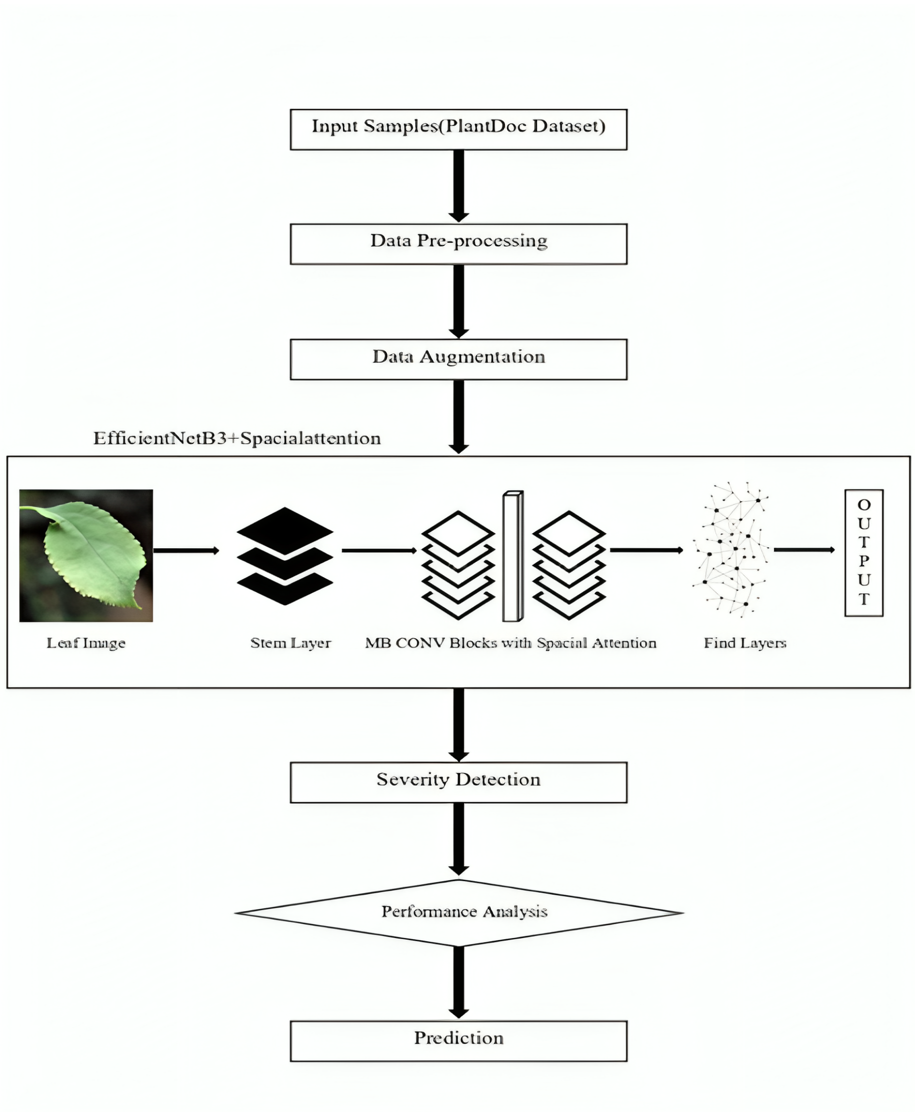

Fig. 2. Model Architecture

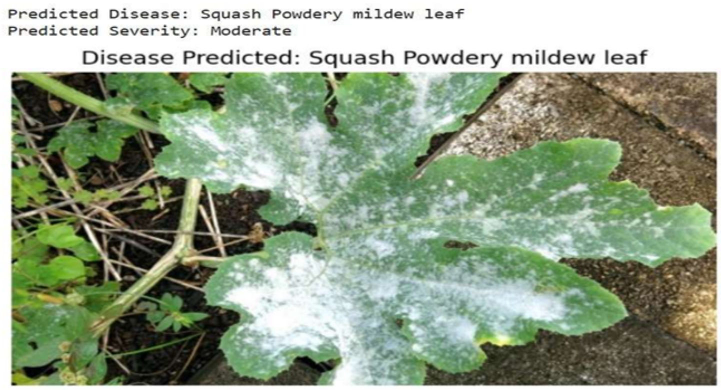

Fig. 3. Disease Detection

5 Future Enhancement and Discussions

The plant disease detection model integrates EfficientNet-B3 with spatial attention to enhance feature extraction, particularly in distinguishing disease-affected leaf regions from healthy areas. Using the PlantDoc dataset, the model effectively handles real-world variations, such as inconsistent illumination, leaf occlusions, and complex backgrounds, improving classification accuracy.

- Spatial attention highlights infection-specific regions in leaves, reducing false positives in diseases with similar symptoms, like early and late blight in tomatoes.
- The model mitigates the impact of shadowed or partially occluded leaves in PlantDoc images, maintaining high accuracy across diverse environments.
- EfficientNet-B3's compound scaling ensures accurate classification with fewer parameters, achieving an inference speed suitable for real-time mobile applications.

6 Conclusion

The proposed plant disease detection system, utilizing EfficientNet-B3 with spatial attention and trained on the PlantDoc dataset, demonstrates high accuracy in identifying and classifying plant diseases. The integration of spatial attention enhances the model's ability to focus on critical diseased regions, reducing misclassification, especially in visually similar conditions. The model effectively handles challenges such as occlusions, varying lighting conditions, and complex backgrounds present in real-world agricultural settings. Additionally, EfficientNet-B3's optimized architecture ensures a balance between computational efficiency and performance, making it suitable for real-time deployment on mobile and edge devices. This approach significantly contributes to precision agriculture by enabling early disease detection, which can help farmers take timely action to prevent crop losses. Future work can explore further improvements in model generalization across larger datasets and the integration of explainable AI techniques for better interpretability.

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