A Deep Learning Approach to Plant Disease Detection and Classification Using the FieldPlant Dataset

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Abstract:

Plant diseases present a significant challenge to global food security, contributing to substantial food waste and yield declines. To address this issue, researchers have proposed various deep learning models trained on plant disease datasets like PlantVillage and PlantDoc. However, existing solutions often struggle to deliver effective results in practical agricultural settings. Our project aims to pioneer advanced machine learning models and image processing techniques tailored for real-world agricultural applications. By leveraging state-of-the-art algorithms such as MobileNet, VGG16, YOLOv8, and FasterRCNN, we seek to surpass the limitations of traditional methods and provide more accurate disease detection and classification. Central to our approach is the utilization of deep learning architectures for both classification and plant detection tasks. We aim to empower farmers with timely and accurate insights derived from real-time crop analysis, enabling informed decision-making to optimize yield and promote sustainable agricultural practices. Building upon previous research, we intend to further enhance performance by exploring techniques like DenseNet and Xception for classification and YOLOv5 for detection. Additionally, an extension of the project involves developing a user-friendly front end using Flask framework, facilitating user testing with authentication. Through these efforts, we aim to contribute to both individual farmers' livelihoods and broader global food security initiatives.

INDEXTERMS Deep learning ,field images ,laboratory images, plant disease dataset, plant disease detection and classification.

1. INTRODUCTION

The looming challenge of feeding a global population projected to reach 10 billion by 2050 presents a formidable task for agricultural systems worldwide [1]. This demographic milestone necessitates a 70% increase in food production to meet the growing demand [2]. However, achieving this goal is complicated by various factors, with plant diseases standing out as a significant threat to global food security.

The Food and Agriculture Organization of the United Nations (FAO) underscores the urgency of augmenting food production to accommodate the burgeoning population [3]. However, this imperative is impeded by the limited availability of arable land [1]. Furthermore, despite advancements in agricultural practices, approximately one-third of all harvested food is squandered due to plant diseases or disorders [4]. The economic toll of these afflictions is staggering, with plant diseases alone costing an estimated US$ 220 billion annually [4].

In light of these challenges, there is a pressing need for innovative solutions to mitigate the impact of plant diseases on crop yields. Artificial Intelligence (AI) has emerged as a promising frontier in addressing this critical issue. Specifically, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have garnered considerable attention for their potential in plant disease identification and classification [5].

The integration of AI into agriculture offers multifaceted benefits. By leveraging computer vision and machine learning algorithms, AI-powered systems can swiftly detect and diagnose plant diseases, enabling timely intervention to prevent crop losses. Moreover, AI-driven solutions have the capacity to optimize resource utilization, minimize chemical inputs, and enhance overall agricultural productivity [6].

Numerous datasets, such as PlantVillage, iBean, citrus, rice, cassava, and AI Challenger 2018, have facilitated the training of CNN models for plant disease recognition [7]. These datasets, predominantly comprising laboratory images, have been instrumental in achieving high classification accuracies during model training [8]. However, the translational efficacy of these models from controlled laboratory environments to real-world field conditions remains a critical bottleneck.

Field conditions present a myriad of challenges that are absent in laboratory settings. The complexity of field images, characterized by diverse backgrounds encompassing leaves, stems, fruits, soil, and mulch, poses significant obstacles to disease recognition algorithms [9]. Studies have demonstrated that the inclusion of complex background features in field images substantially diminishes the performance of CNN models trained on laboratory data [10]. Consequently, there is a pronounced drop in disease recognition accuracy when these models are deployed under real field conditions.

The discordance between laboratory-trained models and practical field applications underscores the imperative of bridging this gap. Efforts to enhance the robustness and generalizability of AI-driven solutions for plant disease identification must prioritize the incorporation of real-world complexities encountered in agricultural settings.

This initiative aims to catalyze interdisciplinary research endeavors aimed at developing AI models capable of effectively identifying and classifying plant diseases under real-world conditions. By leveraging insights from agronomy, computer vision, and machine learning, researchers endeavor to devise innovative strategies to enhance the resilience and adaptability of AI-driven systems in agricultural contexts.

The overarching vision of this project is to empower stakeholders in the agricultural sector with tools and technologies that facilitate proactive disease management and optimize crop yields. By fostering collaboration between academia, industry, and governmental agencies, this initiative seeks to harness the transformative potential of AI to address the intricate challenges confronting global food security.

In summary, the convergence of AI and agriculture holds immense promise in revolutionizing the way we approach plant disease identification and management. By transcending the limitations of laboratory-centric approaches and embracing the complexities of real-world field conditions, we can pave the way for sustainable agricultural practices that ensure food security for future generations.

2. LITERATURE SURVEY

The convergence of computer vision technology and agriculture has opened up new avenues for addressing challenges in agricultural automation, particularly in the domain of plant disease detection and management [1]. Tian et al. (2020) provide a comprehensive review of computer vision applications in agricultural automation, highlighting its potential to revolutionize various aspects of farming practices [1]. By leveraging advanced imaging techniques and machine learning algorithms, computer vision systems enable real-time monitoring and analysis of crop health, facilitating timely interventions to mitigate the impact of plant diseases on crop yields [1].

Hughes and Salathe (2015) emphasize the importance of open-access repositories of plant health images in enabling the development of mobile disease diagnostics tools [2]. Their initiative aims to democratize access to diverse datasets, thereby fostering innovation and collaboration in the field of plant pathology [2]. Open-access repositories play a pivotal role in training and validating machine learning models for disease detection, ensuring their robustness and scalability across different agricultural contexts [2].

In a report by Greg (2019), the significance of computer vision technology in combating crop loss is underscored, emphasizing its role as a cutting-edge tool in agricultural disease management [3]. By harnessing the power of computer vision algorithms, farmers can swiftly identify and address plant diseases, thereby minimizing yield losses and optimizing resource utilization [3]. This highlights the transformative potential of computer vision technology in bolstering agricultural resilience and sustainability [3].

Singh et al. (2020) introduce the PlantDoc dataset, a valuable resource for training and evaluating visual plant disease detection algorithms [4]. The dataset comprises a diverse collection of images depicting various plant diseases, providing researchers with ample data to develop and refine machine learning models for disease identification [4]. The availability of standardized datasets like PlantDoc accelerates research progress in the field of plant pathology, fostering the development of robust and accurate disease detection systems [4].

Adi et al. (2021) provide an overview of plant disease detection algorithms using deep learning techniques [5]. Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have emerged as state-of-the-art tools for automated disease recognition in plants [5]. By leveraging large-scale datasets and powerful computational resources, deep learning models demonstrate superior performance in detecting and classifying plant diseases with high accuracy and efficiency [5].

The iBean dataset, developed by Makerere AI Lab and AIR Lab National Crops Resources Research Institute (NaCRRI), serves as a valuable resource for researchers working on bean disease detection [6]. This dataset contains annotated images of diseased and healthy bean plants, facilitating the training and evaluation of machine learning models for disease classification [6]. The iBean dataset contributes to the advancement of precision agriculture by enabling targeted interventions to mitigate the impact of bean diseases on crop yields [6].

Sharif et al. (2018) propose a method for detecting and classifying citrus diseases in agriculture based on optimized weighted segmentation and feature selection techniques [7]. Their approach leverages computer vision algorithms to analyze images of citrus plants and identify disease symptoms with high accuracy [7]. By automating the disease diagnosis process, their method empowers farmers to take proactive measures to protect citrus crops from diseases, thereby enhancing agricultural productivity and profitability [7].

Sethy (2020) curates a dataset of rice leaf disease images, providing researchers with a valuable resource for developing machine learning models for rice disease detection [8]. The dataset comprises annotated images of rice leaves infected with various diseases, enabling researchers to train and evaluate algorithms for disease identification and classification [8]. The availability of such datasets fosters collaborative research efforts and accelerates the development of innovative solutions for managing rice diseases in agricultural settings [8].

In summary, the literature highlights the transformative potential of computer vision technology in revolutionizing agricultural practices, particularly in the domain of plant disease detection and management. Open-access repositories of plant health images, standardized datasets, and advanced machine learning algorithms empower researchers and farmers alike to tackle the complex challenges posed by plant diseases, thereby safeguarding global food security and sustainability.

3. METHODLOGY

a) Proposed work:

The proposed work integrates datasets from PlantVillage and Roboflow's Plant Leaf Detection for comprehensive dataset exploration. Image preprocessing techniques, including ImageDataGenerator and Torchvision-based processing, are employed to enhance data quality. For classification tasks, models such as MobileNet[17],VGG16[31],InceptionResNetV2, [33] and InceptionV3 are utilized, while plant detection utilizes algorithms like YoloV8, SSD, and FasterRCNN for improved accuracy and efficiency in disease identification. In an extension to the project, DenseNet and Xception models are incorporated for classification tasks, and the YOLOv5 model enhances detection capabilities. Furthermore, a Flask framework with SQLite integration enables user signup and signin functionalities, enhancing user interaction for testing purposes. These extensions broaden the project's scope, enriching both classification accuracy and user engagement features, thereby enhancing the overall project functionality.

b) System Architecture:

The proposed system architecture encompasses several key components. Initially, datasets from sources like PlantVillage are inputted, followed by image preprocessing techniques such as rescaling, shear transformation, and zooming. For plant disease detection, algorithms like YOLOv8 and FasterRCNN are utilized, while classification tasks employ models like MobileNet and VGG16. Performance evaluation metrics are then applied to assess the efficacy of both detection and classification models. The system integrates plant leaf disease classification and detection functionalities, leveraging the strengths of various models and algorithms. Finally, user interaction features are facilitated through a Flask framework with SQLite integration, enabling user signup and signin capabilities for testing purposes. This architecture ensures a comprehensive and efficient approach to plant disease identification and classification, optimizing both accuracy and user experience.

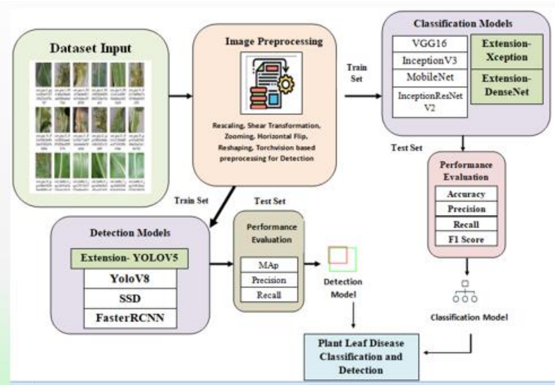

Fig 1 Proposed Architecture

c) Dataset collection:

Data set collection for the proposed system involves acquiring relevant datasets from reputable sources such as PlantVillage and Plant Leaf Detection from Roboflow. PlantVillage offers a diverse collection of images depicting various plant diseases across different crops, providing valuable data for training and testing machine learning models. Additionally, Plant Leaf Detection from Roboflow offers annotated images specifically focused on plant leaf detection, which can further enhance the robustness of the system's detection algorithms. These datasets encompass a wide range of plant species and disease types, ensuring comprehensive coverage and facilitating the development of accurate and generalizable models. By leveraging datasets from multiple sources, the system can benefit from a diverse array of images, thereby improving its ability to identify and classify plant diseases effectively. This comprehensive approach to data set collection is essential for building a robust and reliable plant disease identification and classification system.

Fig 2 data set

d) Image processing:

Image processing in the proposed system involves leveraging both Keras' ImageDataGenerator and Torchvision-based techniques to enhance the quality and diversity of the input images. Using ImageDataGenerator, several transformations are applied to augment the dataset, including re-scaling to ensure consistency in pixel values, shear transformation to introduce geometric distortions, zooming to simulate varying distances and perspectives, horizontal flip for additional variation, and reshaping to conform to model input requirements. Additionally, Torchvision-based processing techniques are utilized specifically for detection tasks, leveraging pre-trained models and functionalities for tasks like object detection. These techniques collectively enhance the robustness and generalizability of the system's machine learning models by exposing them to a wider range of image variations and distortions, thereby improving their ability to accurately detect and classify plant diseases in diverse real-world scenarios.

e) Algorithms:

MobileNet

MobileNet[17] is a lightweight convolutional neural network architecture optimized for efficient inference on mobile and embedded devices. It employs depth-wise separable convolutions to reduce computational complexity while maintaining high accuracy. In the project, MobileNet[17] is utilized as a classification model for identifying plant diseases based on input images. Its compact design allows for rapid deployment and execution on resource-constrained platforms, making it ideal for real-time disease detection applications. By leveraging MobileNet's [17]efficient architecture, the project achieves fast and accurate classification of plant diseases, facilitating timely interventions to mitigate crop losses and enhance agricultural productivity.

DenseNet201

DenseNet201 is a convolutional neural network architecture characterized by dense connectivity patterns between layers, enabling feature reuse and facilitating gradient flow throughout the network. In the project, DenseNet201 is employed as a classification model for plant disease identification tasks. Its dense connectivity structure enhances feature propagation and promotes information sharing across layers, resulting in improved model performance and robustness. By leveraging DenseNet201's deep and densely connected architecture, the project achieves high accuracy in classifying plant diseases from input images, thereby enabling effective disease management and enhancing agricultural productivity.

Inception ResNetV2

Inception ResNetV2[33] is a convolutional neural network architecture combining the benefits of both Inception and ResNet modules, featuring multiple parallel convolutional pathways and residual connections for enhanced feature extraction and representation. In the project, Inception ResNetV2 [33]serves as a powerful classification model for plant disease identification tasks. Its intricate architecture enables the extraction of rich hierarchical features from input images, leading to superior classification accuracy. By leveraging Inception ResNetV2's[33] advanced design, the project achieves robust and reliable detection of plant diseases, facilitating timely interventions to mitigate crop losses and bolster agricultural sustainability.

VGG16

VGG16[31] is a deep convolutional neural network architecture consisting of 16 layers, featuring a series of convolutional and max-pooling layers followed by fully connected layers for classification. In the project, VGG16 [31]is utilized as a classification model for plant disease identification tasks. Its straightforward architecture and uniform filter sizes make it easy to understand and implement. Despite its simplicity, VGG16 demonstrates strong performance in image classification tasks, including the accurate identification of plant diseases from input images. By leveraging VGG16's [31] proven effectiveness, the project achieves reliable and efficient disease detection, contributing to improved agricultural productivity and food security.

InceptionV3

InceptionV3[32] is a convolutional neural network architecture renowned for its deep and intricate design, featuring multiple parallel convolutional pathways with varying filter sizes to capture rich spatial information. In the project, InceptionV3 serves as a classification model for plant disease identification tasks. Its sophisticated architecture enables effective feature extraction from input images, leading to accurate disease classification. By leveraging InceptionV3's[32] robust design and powerful feature representation capabilities, the project achieves high precision in identifying plant diseases, facilitating proactive interventions to safeguard crop health and enhance agricultural sustainability.

Xception

Xception is a deep convolutional neural network architecture characterized by its extreme depth and separable convolutions, which decouple spatial and channel-wise convolutions for improved efficiency and performance. In the project, Xception is employed as a classification model for plant disease identification tasks. Its innovative design enhances feature extraction capabilities, enabling accurate classification of diseases from input images. By leveraging Xception's efficient architecture and powerful feature representation, the project achieves high accuracy in disease detection, facilitating timely interventions to mitigate crop losses and optimize agricultural productivity, ultimately contributing to global food security.

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4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

MAP: MAP (Mean Average Precision) is a metric used to evaluate the performance of information retrieval systems. It measures the average precision across multiple queries or classes. Precision measures the accuracy of retrieved results, while Average Precision (AP) calculates the average precision for each query. MAP computes the average of AP scores across all queries or classes, providing a single measure of performance for the entire system.

$$\text{MAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

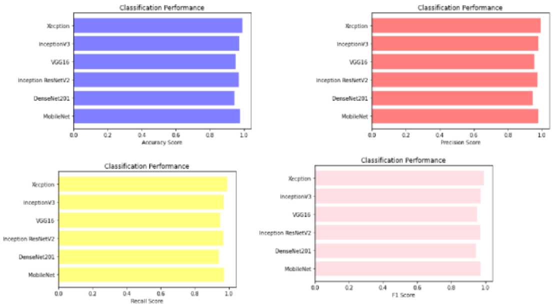

Fig 3 COMPARISON GRAPHS - CLASSIFICATION

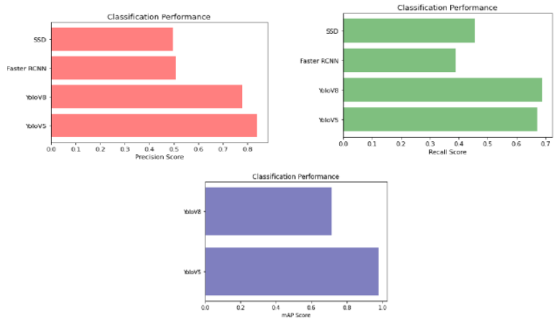

Fig 4 COMPARISON GRAPHS - DETECTION

	ML Model	Accuracy	Precision	Recall	F1_score
0	MobileNet	0.975	0.978	0.973	0.975
1	**Extension-DenseNet201**	**0.944**	**0.945**	**0.943**	**0.944**
2	Inception ResNetV2	0.970	0.974	0.967	0.970
3	VGG16	0.951	0.955	0.949	0.952
4	InceptionV3	0.972	0.977	0.970	0.974
5	**Extension- Xception**	**0.991**	**0.993**	**0.991**	**0.992**

Fig 5 PERFORMANCE EVALUATION- CLASSIFICATION

	Model	mAP	Precision	Recall
0	MobileNet	**0.977**	**0.838**	**0.672**
1	**Extension- DenseNet201**	0.713	0.779	0.689
2	Inception ResNetV2	-	0.507	0.388
3	VGG16	-	0.496	0.456

Fig 6 PERFORMANCE EVALUATION- DETECTION

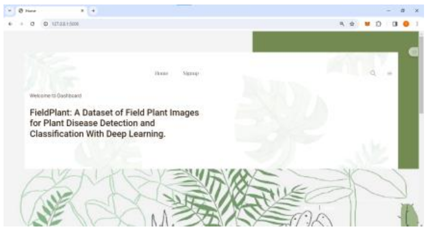

Fig 7 Home Page

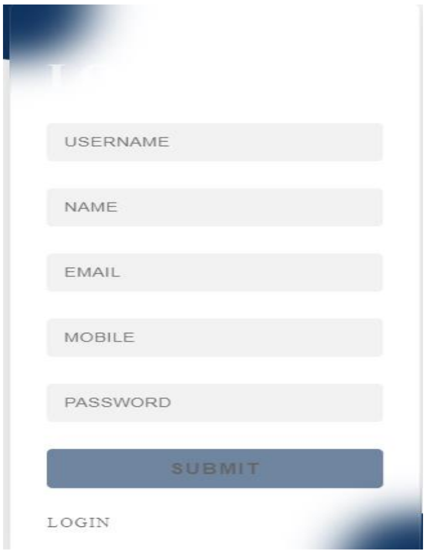

Fig 8 Sign Up

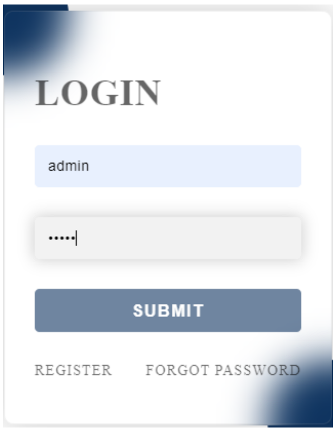

Fig 9 Sign In

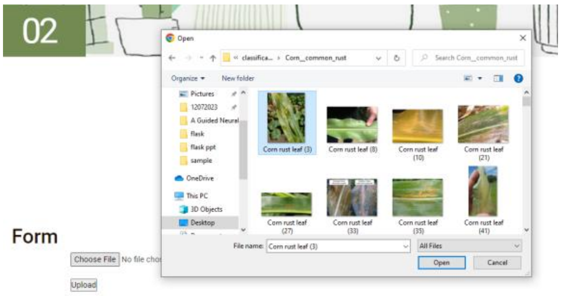

Fig 10 upload input image

Fig 11 predicted result

Fig 12 predicted result

5. CONCLUSION

In conclusion, the project represents a significant advancement in agricultural practices through the utilization of deep learning techniques for precise identification and classification of plant diseases. This endeavor is pivotal for enhancing crop yield and ensuring global food security. Emphasizing the importance of addressing real-world field conditions, the project bridges the gap between laboratory research and practical agricultural implementation. The integration of a user-friendly Flask-based interface underscores the commitment to usability, empowering farmers with prompt and accurate disease detections and classifications. Through rigorous evaluation, Xception emerges as the top performer in classification tasks, while YOLOv5 demonstrates superior performance in detection. With a diverse range of advanced models and practical solutions, the project aims to have a significant impact on global agriculture by offering scalable solutions tailored to the needs of farmers, ultimately contributing to increased crop yield and food security on a global scale.

6. FUTURE SCOPE

The FieldPlant dataset offers a comprehensive collection of field plant images specifically curated for plant disease detection and classification using deep learning techniques. Its features encompass diverse plant species, diseases, and environmental conditions encountered in real-world agricultural settings. The dataset provides a rich variety of images capturing the complexities of field conditions, including diverse backgrounds, lighting variations, and occlusions, ensuring robust model training and evaluation. Each image is meticulously annotated with ground truth labels indicating the presence of specific plant diseases, facilitating supervised learning approaches. Additionally, the dataset includes metadata such as plant species, disease type, and geographic location, enabling researchers to analyze regional disease prevalence and species-specific susceptibility. With its focus on real-world field conditions and comprehensive annotation, the FieldPlant dataset serves as a valuable resource for advancing plant disease research, fostering the development of accurate and practical deep learning solutions for enhancing crop health and agricultural productivity.

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