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Fleldplant Disease Detection and Classification using YOLOv11

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ABSTRACT: Indeed, precise and timely detection of diseases in plants is one of the most vital elements in maximizing crops to uphold global food security. Traditional methods are often time-consuming, subjective, and sometimes require expert knowledge. This project involves the use of a Deep Learning framework for automatic Field Plant Disease Detection and Classification, making use of the advanced YOLOv11 object detection model. Namely, YOLOv11 is utilized because of its superior balance of detection speed and accuracy in comparison with earlier models. This makes it ideal for real-time applications on the field. The plant image dataset is proposed to be collected, preprocessed, and annotated, involving different crops and common diseases in a large dataset.

The YOLOv11 architecture is trained to simultaneously locate the disease regions (bounding boxes) on leaves, stems, or fruits and classify the specific type of disease. This may involve techniques for improving model robustness, such as data augmentation and transfer learning, which should enable better generalization across diverse environmental conditions. Such performances will then be checked using metrics such as Mean Average Precision and the speed of inferences: Frames Per Second.

The system will be reliable, efficient, and scalable for farmers and agricultural experts. Implementation challenges include model size optimization for mobile deployment and continuous retraining on new disease strains, but the integration of YOLOv11 has great potential to revolutionize precision agriculture and smart farming by providing the ability for instantaneous disease management.

KEYWORDS: Plant Disease Detection, Deep Learning, YOLOv11, Object Detection, Classification, Precision Agriculture.

I. INTRODUCTION

Agriculture remains a fundamental pillar of global food security and economic stability. However, plant diseases caused by fungi, bacteria, viruses, and pests significantly threaten crop productivity and quality, with annual global losses estimated between **10%** and **16%**. Traditionally, disease diagnosis relies on manual visual inspection, which is subjective, time-consuming, and prone to error.

Recent advancements in computer vision and deep learning have transformed automated plant disease diagnostics. Among these, the **You Only Look Once (YOLO)** series has emerged as a pivotal method for real-time object detection. The latest iteration, **YOLOv11**, introduces a more efficient architecture designed to optimize both speed and accuracy.

A. Maintaining the Integrity of the Specifications

The IEEEtran class file is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. This document follows these deliberate specifications to ensure it can be integrated into the conference proceedings.

B. Innovations in YOLOv11 for Agricultural Use

YOLOv11 features several architectural innovations that enhance its performance in complex agricultural environments:

- **C3K2 Block**: Optimizes feature extraction by using smaller 3×3 kernels, which are computationally.
- **C2PSA Block**: Introduces spatial attention mechanisms that improve the model's focus on critical regions, such as small or partially occluded disease spots on leaves.
- **SPPF (Spatial Pyramid Pooling Fast)**: Enhances the network's ability to capture objects of different sizes by pooling features at varying scales.
- **YOLO**: You Only Look Once.
- **mAP**: mean Average Precision.
- **CNN**: Convolutional Neural Network.
- **FPS**: Frames Per Second.

III. UNITS

Use SI (MKS) as primary units. English units may be used as secondary units in parentheses. Avoid combining SI and CGS units, as this often leads to confusion when equations do not balance dimensionally.

- Spell out units when they appear in text: ". . . a few henries", not ". . . a few H".
- Use a zero before decimal points: "0.25", not ".25".

C. Objectives and Contributions

This study leverages YOLOv11 to detect and classify plant diseases with high precision and real-time efficiency. By training on diverse datasets, such as those containing healthy and infected leaf images, the system can accurately differentiate between various plant infections. The main contributions of this work include: Food, raw materials, and work for billions of people are given by agriculture, which is crucial to the world economy. According to recent statistics, worldwide agricultural production, including plant and fruit production, has continuously expanded over the years, sustaining growing populations and rising food need . However, the industry confronts sub spatial hurdles due to plant diseases, which can significantly The associate editor coordinating the review of this manuscript and approving it for publication was Adrian Stern . VOLUME 13, 2025 damage crop yields and quality. Plant diseases are estimated by the Food and Agriculture Organization (FAO) to contribute for 20–40% of crop production losses worldwide each year, resulting in billions of dollars in damages to the economy and compromising food security . For instance, the wheat rust disease alone is responsible for annual global losses of approximately $3 billion , while the potato blight has caused crop failures in key producing regions, including the infamous Irish Potato Famine, which resulted in the death of over a million people . In more recent years, the bacterial wilt disease in bananas has decimated plantations in

- Implementation of a real-time detection pipeline tailored for field-ready decision support.
- Analysis of feature extraction precision using YOLOv11's advanced attention mechanisms.
- Evaluation of the model's performance in terms of **mean Average Precision (mAP)** and inference speed.

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, ac, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

II. ABBREVIATIONS AND ACRONYMS

IV. EQUATIONS

Number equations consecutively. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Be sure that symbols are defined before or immediately following the equation.

The precision (P) and recall (R) used to evaluate YOLOv11 are defined as:

P = {TP}{TP + FP}

R = {TP}{TP + FN}

Where TP represents true positives, FP represents false positives, and FN represents false negatives. Use "(1)", not "Eq. (1)" or "equation", except at the beginning of a sentence: "Equation is . . .".

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III. PROPOSED METHODOLOGY

A. Dataset Preparation

Before styling the paper, write and save the content as a separate text file. The dataset for this study consists of high-resolution images of various plant species, including both healthy and diseased leaves. All images are resized to $640 times 640$ pixels to match the input requirements of the YOLOv11 architecture.

B. YOLOv11 Architecture for Disease Detection

The YOLOv11 model is selected for its superior balance of speed and accuracy. It utilizes a backbone for feature extraction and a head for predicting bounding boxes and class probabilities simultaneously.

- **Feature Extraction**: The model employs advanced C3K2 blocks to capture intricate patterns in leaf lesions.
- **Data Augmentation**: To prevent over fitting, we apply mosaic augmentation and random scaling during the training phase.

C. Training and Optimization

The model is trained using the AdamW optimizer with an initial learning rate of 0.01. We monitor the loss function components, including box loss, class loss, and DFL (Distribution Focal Loss), to ensure convergence.
Define abbreviations and acronyms the first time they are used in
the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, ac, and dc do not have to be

IV. FIGURES AND TABLES

Place figures and tables at the top and bottom of columns. A placing them in the middle of columns. Figure captions should be below the figures; table heads should appear above the tables.

TABLE I. PERFORMANCE METRICS OF YOLOV11
Model Variant | mAP@50 | Inference Time (ms) YOLOv11n | YOLOv11s

TABLE 1. Summary of the recent works on plant disease detection using deep learning approaches.

SI. No.	Authors	Models	Dataset	Accuracy (%)
1	Huang et al. [13]	FC-SNDPN		97.59
2	Baser et al. [14]	TomConv		98.19
3	Arafath et al. [15]	Deep CNN		99.00
4	Roy et al. [20]	PCA+DeepNet	TDDS	99.60
5	Zhang et al. [22]	B-ARNet		97.12
6	Sunil et al. [23]	MFFN		99.88
7	Indira et al. [16]	CNN		97.33
9	Arshad et al. [19]	PLDNet		98.66
10	Rashid et al. [24]	YOLOv5		99.75
11	Khaparde et al. [25]	CNN		91.41
12	Mahum et al. [26]	DenseNet201		97.20
13	Goyal et al. [27]	TL+SVM		99.42
14	Das et al. [17]	VGG19	PPDS	97.00
15	Mahesh et al. [28]	YOLOv3		90.00
16	Begum et al. [21]	GSAtt-CMNetV3		97.87
17	Kapoor et al. [18]	VGGNet		99.38
19	Chao et al. [36]	DCNN		98.82
20	Ghosh et al. [37]	ANN		94.79
21	Fatima et al. [29]	GoogleNet		99.79
22	Hasan et al. [30]	DWT	AGDS	98.63
23	Rehman et al. [31]	MASK RCNN		96.60
24	Ji et al. [32]	UnitedModel		98.57
25	Rao et al. [33]	CNN		99.00

V. METHODOLOGY

This study introduces a novel deep multistacking integrated model for plant leaf disease detection, leveraging the strengths of fine-tuning TL models, multistacking feature generation, and an ensemble meta classifier. The methodol ogy comprises several key components: 1) Fine-Tuning TL Models: The fine-tuning process involves specialized pipelines for image preprocessing and augmentation, along with modifications to the TL models. Fine- tuning layers are incorporated to build models specifically adapted for detecting plant diseases. 2) Multistacking Feature Generation: This step generates features based on the ArgMax of the prediction probabilities from the fine-tuned TL models. These features are then used to train an ensemble XGBoost meta classifier, forming a hybrid model that excels in both performance and computational efficiency. 3) Ensemble Meta Classifier: By utilizing the XGBoost algorithm as the

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meta classifier, the model integrates the strengths of various fine- tunedTLmodels,resulting in higher accuracy and reduced prediction times compared to existing methods.

The proposed architecture is illustrated in Figure 1, showcasing the comprehensive integration of fine-tuning, multistacking, and ensemble classification to enhance plant disease detection.

A. DATASET DESCRIPTION

In our experiment, we have used three datasets to cross-check the performance and prove the robustness of our hybrid model. These datasets are part of the Plant Village dataset collection, which is a well-known repository for plant disease images. This dataset predominantly contains images captured under controlled conditions to ensure consistent quality and eliminate potential noise factors caused by variations in natural lighting. Controlled settings allow for accurate disease annotation and facilitate the development of reliable models. The datasets used are: Tomato Disease Dataset (TDDS): This collection includes photos of tomato plants that are both healthy and unhealthy. It is essential for differentiating and recognizing the various illnesses that impact tomato plants. With a total of 18,160 images, the TDDS contains a wide range of classes,including Tomato Late Blight, Tomato Healthy, Tomato Early Blight, Tomato Septoria Leaf Spot, Tomato Yellow Leaf Curl Virus, Tomato Bacterial Spot, Tomato Target Spot, Tomato Mosaic Virus, Tomato Leaf Mold, and Tomato Spider Mites (Two- spotted spider mite). Potato Pepper Dataset (PPDS): Images of both healthy and unhealthy potato and bell pepper plants are included in this dataset. Its function is to identify and classify illnesses in crops of potatoes and bell peppers. With 4,627 photos, the classifications in this collection are Potato Healthy, Potato Late Blight, Potato Early Blight, Pepper(Bell)Bacterial Spot, and Potato Healthy. The construction of powerful disease recognition models is aided by the diverse set of images in PPDS, which aids in comprehending the disease signs in bell pepper and potato plants. Apple Grape Dataset (AGDS): Images of both healthy and diseased apple and grape plants are included in this dataset. It is critical for identifying and categorizing illnesses in grape and apple plants. With a total of 7,233 photos, the AGDS includes classes including Apple Cedar Apple Rust, Apple Healthy, Apple Apple Scab, Apple Black Rot, Grape Healthy, Grape Leaf Blight (Isariopsis Leaf Spot), Grape Black Rot, and Grape Esca (Black Measles). By utilizing these three datasets, we aim to ensure that our hybrid model performs well across a variety of crops and disease types, demonstrating its effectiveness and robustness in plant disease detection and classification. Table 2 shows the Distribution of Plant Disease Datasets.

B. IMAGE PREPROCESSING

The process of enhancing a picture's format and quality prior to feeding it into a deep learning model is known as image preprocessing. By standardizing the input data and emphasizing key traits, these methods aid in enhancing the model's accuracy and performance.

"Eq. (1)" or "equation (1)", except at the beginning of a sentence: "Equation (1) is . . ."

A. LATEX-Specific Advice

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B. Some Common Mistakes

- The word "data" is plural, not singular.
- The subscript for the permeability of vacuum $\mu 0$, and other common scientific constants, is zero with subscript formatting, not a lowercase letter "o".
- In American English, commas, semicolons, periods, ques- tion and exclamation marks are located within quotation marks only when a complete thought or name is cited, such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
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- Be aware of the different meanings of the homophones "affect" and "effect", "complement" and "compliment", "discreet" and "discrete", "principal" and "principle".
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- The abbreviation "i.e." means "that is", and the abbreviation "e.g." means "for example".

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C. Authors and Affiliations

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Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References and, for these, the correct style to use is "Heading 5". Use "figure caption" for your Figure captions, and "table head" for your table title. Run-in heads, such as "Abstract", will require you to apply a style (in this case, italic) in addition to the style provided by the drop down menu to differentiate the head from the text.

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E. Figures and Tables

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TABLE I Table Type Styles a Sample of a Table footnote.

Table Head	**Table Column Head**		
	Table column subhead	***Subhead***	***Subhead***
copy	More table copy[a]		

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Capitalize only the first word in a paper title, except for proper nouns and element symbols.

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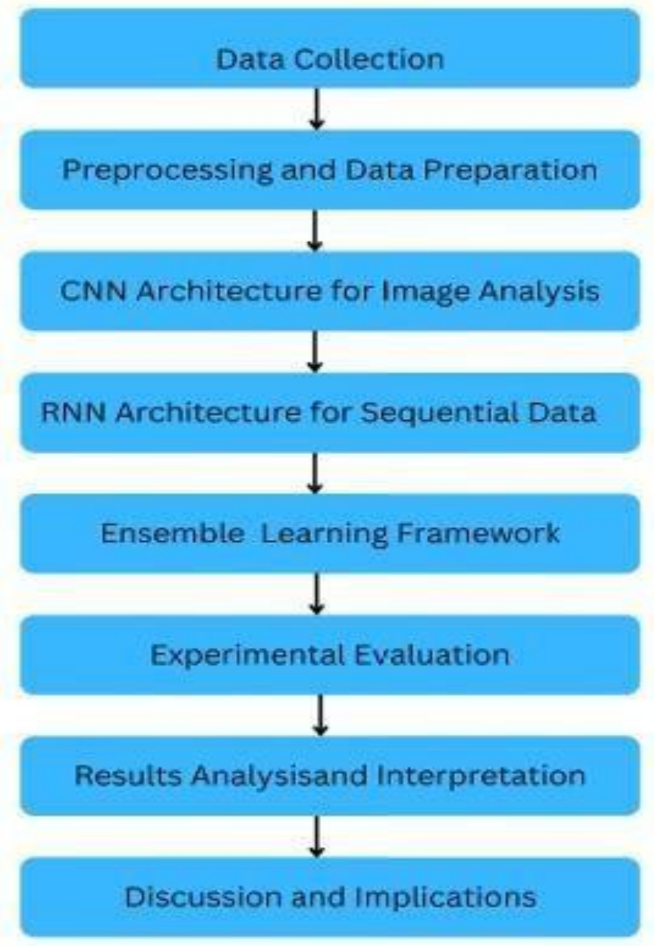

Fig. 1. Example of a figure caption.

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