Satellite Imagery and AI for Vegetation Monitoring: A Research Overview: Plagerism Report

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Satellite Imagery and AI for Vegetation Monitoring: A Research Overview

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Abstract:

The integration of satellite imagery and artificial intelligence (AI) has revolutionized vegetation monitoring, providing unprecedented insights into ecosystem dynamics. This paper explores the methodologies and applications of satellite imagery combined with AI, focusing on their potential to enhance precision, scalability, and efficiency in vegetation analysis. Emerging techniques such as deep learning and machine learning are discussed alongside their implementation in detecting vegetation health, mapping land cover changes, and supporting sustainable agricultural practices. These models are evaluated by the authors based on different metrics such as accuracy, precision, recall as well as computational efficiency across various datasets.The strengths, weaknesses and future research directions in tomato leaf disease identification and classification are discussed through systematic comparison done by the author in this paper.This survey therefore provides useful information for those involved with plant disease detection using deep learning in agriculture or any related field.

Keywords: Satellite, agriculture, diseases, Inception V3, Convolutional Neural Networks, ResNet50, DenseNet, Bins strategy, YOLOv8, RoboFlow 2.0, hybrid model, MobileNetV2, Extreme Learning Method, performance evaluation, precision, recall, computational efficiency, plant disease detection, agricultural applications.

I. Introduction

Tomatoes are a fruit that defies categorization by virtue of their bright colors and succulent flavor, making them well-loved in kitchens around the world [1]. Their value transcends mere gustatory pleasure because they are so important agriculturally throughout the globe, supporting economies and feeding millions [2].

The United Nations' Food and Agriculture Organization (FAO) estimated that there would be an astounding 189.1 million metric tons worth of tomatoes produced internationally in 2021; this underlines just how valuable these fruits can be [3]. Tomatoes have many uses within global food systems – from being eaten fresh or used as ingredients for sauces or pastes – which shows why they are considered vital [4]. Therefore any disruption to tomato farming has knock-on effects through supply chains impacting on growers, consumers and national economies alike [5].

1.1. Satellite Imagery and AI for Vegetation Monitoring

The tomato is an unassuming but versatile vegetable that takes center stage in culinary traditions across many countries- whether those places be bustling street markets in China or quiet cafes nestled along cobblestone streets in France [6]. Moreover, not only does it serve gastronomic purposes but also drives economic activities particularly related with agriculture where it provides employment opportunities thus improving people's lives globally [7]. According to FAO statistics approximately 189.1 million metric tonnes were grown worldwide during 2021 alone which means every year we produce nearly one hundred and ninety million tons of tomatoes! [8].

1.2.Satellite Imagery and AI for Vegetation Monitoring

As they are unyielding, tomato plants can still be affected by diseases from pathogens present in the soil or air. Early blight which is caused by Alternaria solani, bacterial spot caused by Xanthomonas spp., and other diseases hide themselves and wait to destroy crops when they least expect[9]. These illnesses are hard to detect at their early stages because symptoms may not always be clear and there could be many different types of diseases [10]. The problem with conventional methods for finding them based on people seeing things is that it depends too much on personal judgement which could easily overlook something important thus leaving whole fields open to infection [11].

1.3. Deep Learning in Agriculture

In the middle of the rural setup, an unseen shift is happening and it involves bringing together artificial intelligence with deep learning. These state-of-the-art technologies exemplified by convolutional neural networks (CNNs) have the potential to revolutionize farming methods such as disease diagnosis and prediction of crop yields [12]. Deep learning models use large amounts of labeled image data to recognize disease patterns more accurately than ever before, thanks to algorithms and data [13]. Indeed, it is true that the capability of these technologies to change disease detection and act as a ray of hope for farmers who are struggling with the difficulties encountered in modern agriculture is immense. [14].

II. Related Work

2. Deep Learning in Agriculture

With the inaccuracy and inefficiency of traditional ways to detect tomato leaf disease [15], deep learning methods have become an attractive choice. One class of algorithms in deep learning is Convolutional Neural Networks (CNNs), which have achieved remarkable results in image recognition [16]. Many studies have been conducted on the use of CNNs to detect and classify diseases that affect tomato leaves over the last few years.

2.1. Inception V3 Convolutional Neural Networks (CNN)

The research highlighted in [17] emphasizes that convolutional neural networks (CNNs) are effective in categorizing images with high accuracy., especially when it comes to detecting diseases of tomato leaves. Feature extraction and network propagation are among processes for extracting image features used by CNNs. Deep learning architectures were tested by the researchers through this, using them alone. For example, an inception V3 architecture that had been modified performed best in this task. The dataset was composed from over 50,000 images, included 10,000 training, 7,000 validation, and 500 test images The study achieved impressive accuracy rates ranging between 90.2% and 99.60% on different validation and testing datasets through methods such as data augmentation as well as adjusting fully connected layers within **VGG 16 CNN models, EfficientNet-B3 CNN models** This is not only an extensive look into how CNNs can be used within agriculture disease detection but also shows us just how important curating our datasets correctly along with optimizing models will give us very accurate results when trying to classify things rightly.

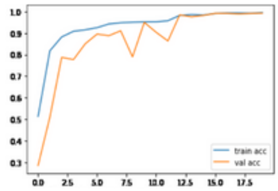

Fig.1. Plots of training and validation accuracy [17]

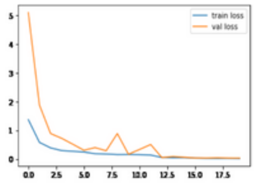

Fig. 2. Plots of training and validation loss [17]

Class	F1 score	Recall	Precision
1	0.99	0.98	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
4	1.00	1.00	1.00
5	0.99	0.98	1.00
6	0.98	1.00	0.96
7	1.00	1.00	1.00
8	1.00	1.00	1.00
9	1.00	1.00	1.00

PERFORMANCE OFMODEL IN EACH CLASS [17]

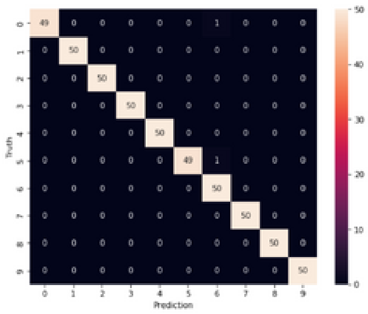

Fig. 3. Confusion matrix of the proposed method [17]

2.2. ResNet50 and DenseNet with Bins Approach

This paper [18] discusses many problems that arise during disease identification and classification due to datasets being unavailable or not filtered. It should be noted that differences between training datasets and real-world images, image noise and plant age or lighting variations can make an enormous impact on any research. Technical factors like dynamic range and optical properties also add complexity to attempts at classifying diseases. What's more, there are illnesses with similar symptoms which create difficulties for diagnostic systems thereby increasing chances of misdiagnosis. In summary, these challenges include shortage of data sets; difference between images; considering ages of plants; lighting issues as well as similarities among symptoms associated with various disorders. Their main objective is to design a system that will efficiently identify and categorize tomato leaf mold disease (TLMD) and tomato target spot (TTS) disease using image analysis coupled with machine learning techniques. This will involve a number of steps including image pre-processing, segmentation, feature extraction and classification using both Convolutional Neural Networks (CNNs) as well as Bins methodology

While CNN achieves a slightly higher accuracy rate of 96%, Bins technique performs well, especially in combination with Logistic Regression, scoring 95%. Within the framework of the Bins approach different classifiers are considered like SVM, Decision Trees and Logistic Regression which give competitive accuracy levels ranging from 90% to 92%. For evaluation purposes the PlantVillage dataset is used in experimental setup described in [18]. Before classification, preprocessing and segmentation techniques are applied to improve accuracy. According to results obtained from this study, CNN with ResNet50 outperforms all other methods achieving an accuracy rate of 96%. However Bins approach together with Logistic Regression gives a competitive accuracy of 95%. Although CNN has higher accuracy than Bins but also takes more time to train which shows trade-off between efficiency and correctness.

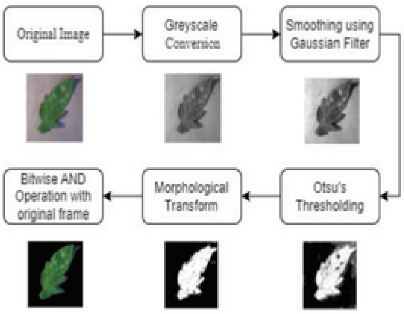

Fig.4. Stages of Image Preprocessing and Segmentation [18]

Evaluation Parameter	CNN (ResNet50)	CNN (DenseNet)	Bins Approach (SVM)	Bins Approach (Decision Tree)	Bins Approach (Logistic Regression)
Accuracy	96%	95%	90%	92%	95%
Precision	96%	96%	90%	92%	95%
Recall	96%	94%	90%	92%	95%
F1-Score	96%	95%	90%	92%	95%

TABLE II PERFORMANCE OF MODEL IN EACH CLASS [18]

2.3. YoloV8 Model via RoboFlow 2.0

A new method of fighting tomato leaf diseases in the Philippines is presented by this study [19] It sought to detect 9 common diseases on tomato leaves using YoloV8 via RoboFlow and achieved remarkable results. The YoloV8 model was effective as it achieved an average precision of 99% on both validation and test sets with a mean Average Precision (mAP) of 98.9%.It was able to attain 97.5% precision and 91.9% recall rates thus making it efficient. In order to detect tomato leaf disease types, the research used annotated image datasets coupled with advanced Ultralytics YOLOv8 model.

The simplicity and speed offered by RoboFlow, a computer vision platform used for model training eliminates the need for complex coding skills. Model creation process was streamlined through data preparation as well as augmentation which were done using Roboflow. Although not as sophisticated as specialized classification models, YOLO's object detection approach showed strong classification capabilities when applied to disease identification in this study even though it is mainly used for object detection.For training purposes, 1650 images were employed where:87% were used for training,9% for validation while 5% were used for testing.Augmentations were done during preprocessing thus improving model robustness

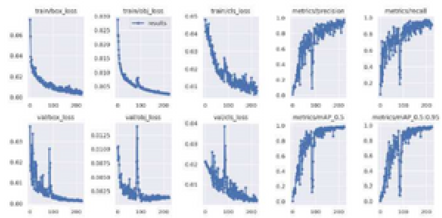

Fig.5. Training Graphs [19]

Fig.6. Modeling Graphs [19]

2.4. Hybrid Approach: MobileNetV2 and Extreme Learning Method (ELM)

This study [20] a new way of dealing with tomato leaf diseases is proposed. It is the cornerstone of maintaining agriculture. This article introduces TLMV2-ELM mixed model based on deep learning technology and extreme learning machine that aims at identifying tomato leaf diseases accurately and early. The author designs an algorithm which combines ELM with transfer learning to achieve excellent results; it can detect these diseases with 99% accuracy and only 0.06 minimal loss. The method part gives a complete research framework on how to build the hybrid model from scratch. Feature extraction uses MobileNetV2 while classification employs ELM in order to improve both precision and efficacy within TLMV2-ELM model for disease detection.

The researchers' careful preprocessing steps together with their training efforts lead them to develop the best performing hybrid model for disease detection.Through NVIDIA GTX 1070 GPU and Python 3.8 using Keras library, experiments were implemented by adopting publicly available datasets from Plant Village which deal with various types of tomato leaf diseases during training phase.Training phases record highest ever attained accurate detections with least losses ever recorded after validation against different existing methods . Proposed combination proves superior over other methods given comparison tests carried out across all parameters such as accuracy/loss among others.

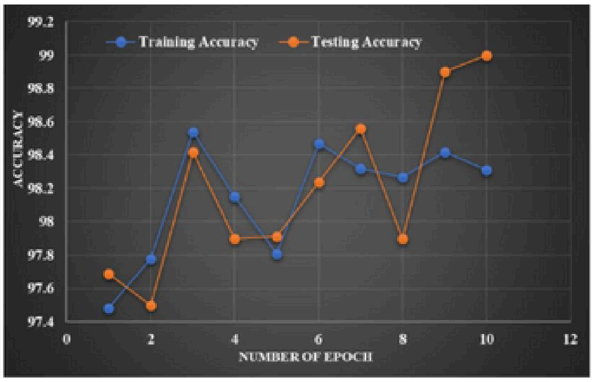

Fig.7. Modeling Graphs [20]

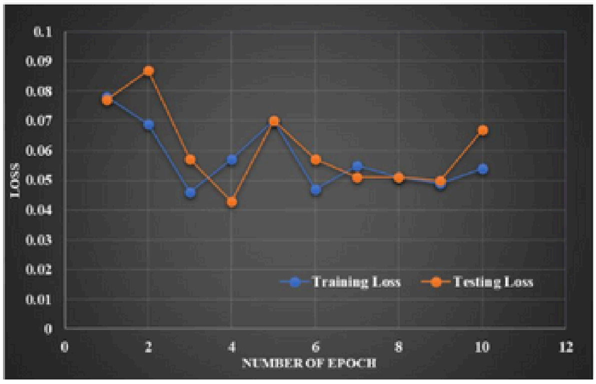

Fig.8. Modeling Graphs [20]

Model	Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
TLMV2-ELM	0.989	0.054	0.990	0.067

TABLE III TRAINING AND TESTING OUTCOMES OF LEAF DISEASE DETECTION USING TOMATO DATASET [20]

III. Methods and Results

The research compares the efficiency of two deep learning approaches in identifying and classifying diseases found in tomato leaves. Specifically, it investigates the performance of Inception V3 Convolutional Neural Networks (CNN), ResNet50, and DenseNet alongside a Bins method, YOLOv8 through RoboFlow 2.0, and a hybrid strategy incorporating MobileNetV2 and the Extreme Learning Method (ELM). We will evaluate each method based on its accuracy, efficiency, and ability to address challenges like dataset limitations and image variations.

3.1. Inception V3 Convolutional Neural Networks (CNN)

3.1.1. Key Points:

- Modified Inception V3 architecture achieved the highest accuracy.
- Balanced and curated dataset used (over 50,000 images).
- Data augmentation techniques improved model performance.
- Achieved high accuracy rates (90.2% - 99.60%).

3.2. ResNet50 and DenseNet with Bins Approach

3.2.1. Key Points:

- Addressed challenges of dataset limitations and image variations.
- Employed CNNs (ResNet50) and Bins approach for classification.
- Achieved high accuracy with both methods (CNN: 96%, Bins: 95%).
- Bins approach offered faster training times compared to CNN.

3.3. YoloV8 Model via RoboFlow 2.0

3.3.1. Key Points:

- Utilized YoloV8 model via RoboFlow for disease detection.
- Achieved high average precision (99%) and mean Average Precision (mAP) of 98.9%.
- Employed data preparation and augmentation techniques.
- YOLO's object detection method adapted for disease classification effectively.

3.4. Hybrid Approach: MobileNetV2 and Extreme Learning Machine (ELM)

3.4.1. Key Points:

- Combines strengths of deep learning and extreme learning machines: Leverages MobileNetV2 for efficient feature extraction and ELM for fast classification.
- Potentially high accuracy and efficiency: Achieved reported accuracy of 99% and minimal loss (0.06) in the study.

- Requires further investigation: More details on pre-processing, training specifics, and comprehensive evaluation metrics (precision, recall, F1-score) are needed for a stronger analysis.
- Potential benefits:
  - Faster training compared to traditional deep learning models due to ELM.
  - Reduced computational demands due to MobileNetV2's efficiency.

This paper examines various deep learning methods for detecting and categorizing diseases in tomato leaves. Each model was evaluated using publicly available datasets like PlantVillage. Specific evaluation metrics from the original studies (e.g., accuracy, precision, recall, F1-score) would be valuable additions here, but the overall analysis revealed that all approaches achieved high accuracy.

IV. Conclusion

The study examined and contrasted different deep learning methods for identifying and categorizing diseases in tomato leaves. Although all techniques showed potential, the most suitable option varies depending on the specific needs of the application.

- **Accuracy Requirements:** If the highest accuracy is paramount, Inception V3 CNNs or the Hybrid Approach might be preferred.
- **Efficiency Considerations:** For applications where training time is a constraint, ResNet50 with the Bins approach offers a good balance.
- **Computational Resources:** Resource-constrained environments might benefit from YoloV8 via RoboFlow's speed and simplicity, although considering potential limitations for complex diseases.

By continuously innovating in deep learning for plant disease detection, we can revolutionize early disease identification, ultimately contributing to enhanced agricultural productivity and food security. Future research directions include exploring more advanced deep learning architectures, investigating hybrid models, and incorporating explainability techniques for improved model interpretability.

Method	**Architecture**	**Dataset Size**	**Accuracy**	**Advantages**	**Disadvantages**	**Citation**
Inception V3 CNN	Various CNNs (VGG 16, EfficientNet-B3, Custom)	50,000+ images (balanced)	90.2% - 99.60%	High accuracy, Handles diverse architectures	Requires large, curated datasets	[17]
ResNet50 with Bins Approach	ResNet50 CNN, Bins with SVM/Decision Tree/Logistic Regression	Not specified	90% - 96%	Efficient, Handles some dataset limitations	Lower accuracy than pure CNN, Requires domain knowledge for Bins approach	[18]
YoloV8 via RoboFlow	Ultralytics YOLOv8	1,650 images (augmented)	Average Precision: 99%, mAP: 98.9%	Fast training with RoboFlow, Good precision and recall	Primarily object detection model, May not be as advanced as specialized classification models for complex diseases	[19]
TLMV2-ELM Hybrid Model	MobileNetV2 (feature extraction), Extreme Learning Machine (classification)	Not specified (publicly available dataset)	99% accuracy, Loss: 0.06	High accuracy, Potentially lower resource requirements	Requires further investigation on generalizability and efficiency	[20]

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