Proceedings of the

SECOND INTERNATIONAL CONFERENCE

ON

RECENT TRENDS IN MULTI-DISCIPLINARY RESEARCH AND INNOVATION

ICRTMRI' 25

19th September 2025

in Association with

BRITTS IMPERIAL UNIVERSITY COLLEGE
United Arab Emirates

Organized by

RESEARCH - INNOVATION - PROSPERITY

A.V.P. (Autonomous)
COLLEGE OF ARTS AND SCIENCE
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14.	ICRTMRI/25/ T2/14	EXPLOITING SQL INJECTION VULNERABILITY USING SQLMAP, HAVIJ AND JSQL	SABITHA BANU. A, RAMYA. M	289
15.	ICRTMRI/25/ T2/15	A COMPARATIVE STUDY ON PASSWORD CRACKING TOOLS AND ENCRYPTION TECHNIQUES	SABITHA BANU. A , VIJAYA NANDHINI. A	299
16.	ICRTMRI/25/ T2/16	PRESERVATION OF DIGITAL EVIDENCE - INVESTIGATING DELETED DATA THROUGH FTK IMAGER AND AUTOPSY	SABITHA BANU. A, SHANMATHA. H	308
17.	ICRTMRI/25/ T2/17	DEEP LEARNING APPROACH FOR CROSS-CROP PLANT DISEASE DETECTION	Dr. A. MURUGAN ANDHAM, Dr. R.NANDHA KUMAR	317
18.	ICRTMRI/25/ T2/18	DATA SECURITY IN CLOUD COMPUTING USING BDLUEFISH ALGORITHM	P. S. VIJAYA LAKSHMI, K. GOMATHY,KUMUDINI, BHANUPRIYA, LAKSHMI DEVI. S	322
19.	ICRTMRI/25/ T2/19	MACHINE LEARNING IN WIRELESS SENSOR NETWORKS AND INTERNET OF THINGS: ENHANCING INTELLIGENCE AND EFFICIENCY	Mrs. C. MAHESH SATHYA	330
20.	ICRTMRI/25/ T2/20	IN HIGHER EDUCATION, FEDERATED & EXPLAINABLE DEEP LEARNING FOR EARLY AT-RISK STUDENT PREDICTION	Mrs.C.SARANYA	334
21.	ICRTMRI/25/ T2/21	SECURE DATA AGGREGATION THROUGH WATER MARKING TECHNIQUES IN WIRELESS SENSOR NETWORKS	Dr. N. DIVYA, Mrs. P. SAKTHI KIRUBA	337
22.	ICRTMRI/25/ T2/22	REINFORCEMENT LEARNING FOR AUTOMATED INCIDENT RESPONSE IN CYBER SECURITY	Mrs. M. SENTHAMIL SELVI	343
23.	ICRTMRI/25/ T2/23	FEDERATED LEARNING FOR PRIVACY PRESERVING ARTIFICIAL INTELLIGENCE: A SECURE COLLABORATIVE APPROACH	Mrs. SANGEETHA PRIYA.A, Ms. ANEESHA BARVEEN.S	348
24.	ICRTMRI/25/ T2/24	ARTIFICIAL INTELLIGENCE: TRENDS, APPLICATIONS AND CHALLENGES	Dr. S. THILAGA VATHI, B. MANI SHANKAR	352
25.	ICRTMRI/25/ T2/25	PRIVACY-PRESERVING BIG DATA MINING WITH FEDERATED AND SCALABLE ALGORITHMS IN DISTRIBUTED ENVIRONMENTS	Ms.P.HEMALATHA, Dr.R.SUMANGALI	355
26.	ICRTMRI/25/ T2/26	BLOCKCHAIN TECHNOLOGY	Dr. M .PUSHPA, RETHANYA.T. T, NITHYA BAGAVATHI. P	364

DEEP LEARNING APPROACH FOR CROSS-CROP PLANT DISEASE DETECTION

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Abstract
One of the most serious threats to global food security is plant diseases compromising agricultural productivity and threatening the livelihoods of millions. These diseases can decimate crops, disrupt food supply chains, and escalate the risk of food shortages, underscoring the urgency of implementing robust strategies to safeguard the world's food sources. Deep learning methods have revolutionized the field of plant disease detection, offering advanced and accurate solutions for early identification and management. However, a recurring problem in deep learning models is their susceptibility to a lack of robustness and generalization when facing novel crop and disease types that were not included in the training dataset. In this paper, we address this issue by proposing a novel deep learning-based system capable of recognizing diseased and healthy leaves across different crops, even if the system was not trained on them. The key idea is to focus on recognizing the diseased small leaf regions rather than the overall appearance of the diseased leaf, along with determining the disease's prevalence rate on the entire leaf. For efficient classification and to leverage the excellence of the Inception model in disease recognition, we employ a small Inception model architecture, which is suitable for processing small regions without compromising performance. To confirm the effectiveness of our method, we trained and tested it using the widely acclaimed Plant Village dataset, recognized as the most utilized dataset for its comprehensive and diverse coverage. Our method achieved an accuracy rate of 94.04%. Furthermore, when tested on new datasets, it achieved an accuracy rate of 97.13%.

Keywords: Deep learning, Agriculture, Plant diseases, Image processing, Disease detection, Leaf splitting

1. INTRODUCTION

Agriculture is a vital source of food and economic systems, with diseases being the main causes of plant deterioration. Diseases cost the global economy approximately $220 billion annually, causing damage and sometimes total eradication of crops. Early detection of diseases helps neutralize them and save plants, avoiding losses and protecting crops. Traditional methods, such as human diagnosis, are insufficient due to lack of knowledge, experience, and time. Modern technologies, such as robots, drones, and sensors, have revolutionized field management for farmers. Machine learning and deep learning techniques are rapidly evolving in plant disease detection, with deep learning-based methods being particularly effective in image recognition. However, such a dataset is not available, making it challenging to build and affecting the performance of deep learning-based systems. The inability to access sufficient datasets obstructs the deep learning system's capacity to generalize patterns learned in plant disease recognition. This paper presents a novel deep learning system that overcomes the limitations of crop-specific training by generalizing plant disease recognition across all plant and disease types. Instead of relying on whole-leaf appearance, the approach identifies infection in small leaf patches by splitting each image into smaller regions, enhancing data augmentation and feature extraction. A lightweight Inception model is used for efficient, high-performance classification, along with calculating the disease's prevalence rate on the leaf for deeper analysis. The rest of the paper is organized as follows: Section 2 reviews related work,

Section 3 details the proposed methods and materials, Section 4 analyzes results, and Section 5 concludes the study.

2. RELATED WORK

Population growth and limited resources have increased the need for advanced techniques in crop supervision, especially for disease detection. Deep learning has shown promise in this area but faces major challenges: diverse plant species and disease variations, limited labeled datasets, environmental variability, data imbalance, and high computational demands. These factors hinder model robustness and generalization to unseen crops and diseases. Existing methods generally fall into three categories: detecting a specific disease in one crop, detecting multiple diseases in one crop, and detecting multiple diseases across various crops. Table 1 summarizes recent studies in this field. This section reviews works focused on identifying specific diseases in specific crops. In Fusarium head blight in wheat was detected using transfer learning with a pre-trained Mask RCNN and color image processing, showing effective detection of varied disease shapes. In a CNN-based method for rice blast recognition outperformed LBPH and Haar-WT, with CNN+ Softmax and CNN+SVM achieving superior results. For northern leaf blight in corn, proposed a multi-stage CNN approach that first classified image regions, then the full image. In ginkgo leaf disease was classified using VGG-16 and InceptionV3, with results differing between field and laboratory datasets. This section reviews studies addressing the recognition of multiple diseases within a single crop. For tomato, several works explored CNN-based methods, such as fine-tuned deep networks on multiple datasets, MobileNet and its enhanced versions, and specialized architectures like Multi-Scale AlexNet, ARNet, GPD CNN, DIMPCNET, and U-Net–based segmentation approaches. Apple leaf disease detection has been studied using MobileNet, ResNet50 with the Plant Pathology Challenge dataset, and INAR-SS for real-time recognition. Rice leaf diseases were classified using CNN with SVM , while AlexNet was adapted for Camellia oleifera. Corn disease detection was explored with VGG16, EfficientNet and DenseNet, and improved Faster R-CNN with pyramid networks. Ginkgo, grape, cucumber, bean, wheat, and balsam pear diseases were also studied with modified CNN or ResNet architectures.

Table 1. Recent studies on plant diseases recognition.

Crops	Diseases	Datasets	Deep Learning models
Wheat	Fusarium Head Blight	Self	CNN (Mask-RCNN)
Rice	Rice blast	Self	New CNN
Corn	Northern leaf blight	Self	CNN (AlexNet, GoogLeNet Inception)
Ginkgo biloba	Ginkgo leaf	Self	CNN (VGGNet-16, InceptionV3)
Tomato	6 Diseases	Self	CNN (VGG-16, VGG-19)
Apple	Alternaria leaf blotch	Self	CNN (MobileNet, RestNet152)
Rice	4 diseases	Self	New CNN, SVM
Corn	Leaf blight, rust	Self	CNN (VGG-16)
Apple	4 disease	Self	CNN (AlexNet, GoogLeNe Inception)
Tomato	10 diseases	Plant Village	CNN (Deconvolution Guided VGGNet)

Previous studies confirm that deep learning enhances plant disease recognition accuracy, often using data augmentation and transfer learning to address data scarcity. However, most approaches lack robustness and generalization, as they are tailored to specific crops or diseases within limited datasets, leaving the data deficit unresolved. Recently, advanced deep learning methods in structural damage detection such as CNN-based crack detection, region-based inspection, SDD Net, attention-based encoder–decoder models, and dual encoder–decoder architectures have shown strong performance in detecting subtle and diverse anomalies. Since structural damage detection shares complexity with plant disease identification, adapting pixel-wise segmentation techniques from this domain could help quantify disease severity and improve both robustness and generalization in plant disease detection models.

3. MATERIALS AND METHODS

The Plant Village dataset is an open-access benchmark widely used for plant leaf disease recognition due to its diversity, annotations, accessibility, and relevance to real-world challenges. It contains 54,305 images covering 14 crop types and 20 diseases, organized into 38 classes (12 healthy and 26 diseased). The images, sized 256 × 256 pixels, were captured in laboratory settings with uniform backgrounds. In this work, we use a new version of the dataset, where leaf images are segmented from their backgrounds (see Fig. 1).

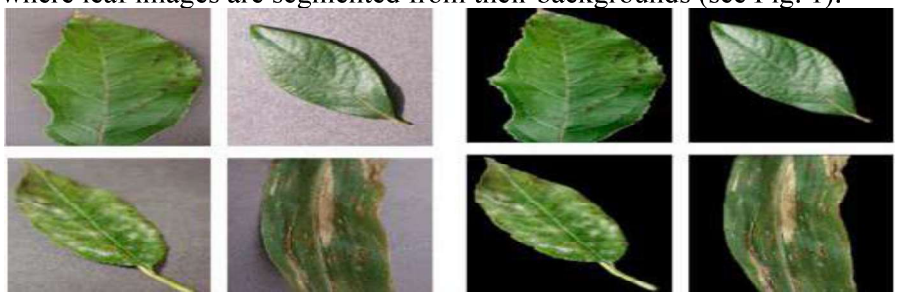
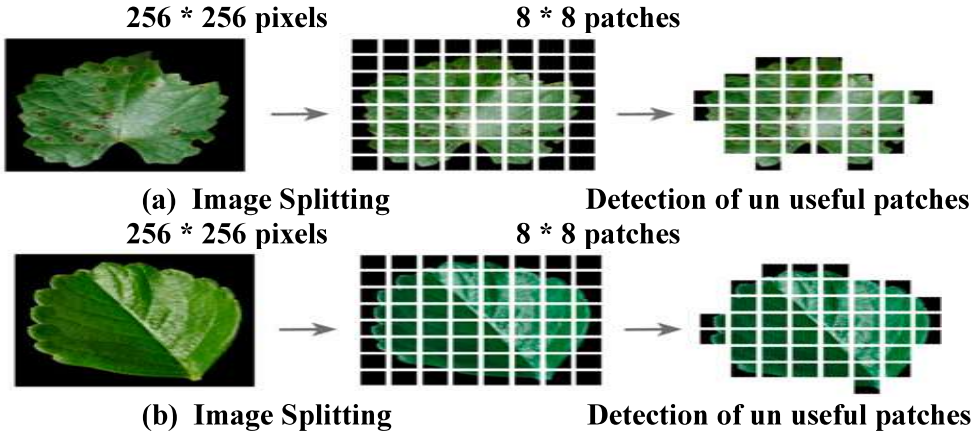
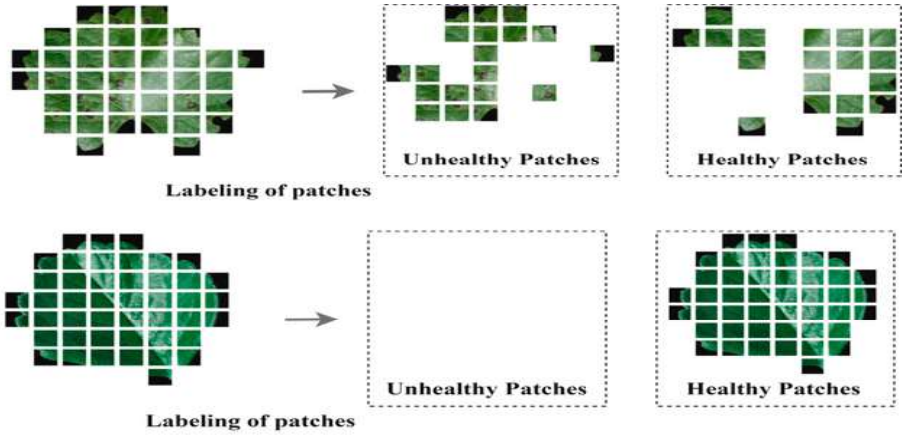


Fig. 1. Examples of Plant Village dataset images: (a) images with background, (b) images segmented from the background.

This section details the methodology for developing a generalized plant disease classification system. Once trained, the system can detect leaf infections without prior knowledge of crop or disease type and can also quantify the extent of infection within the leaf. The overall workflow is illustrated.



Detecting many disease types is difficult due to limited data. As an initial step, the system focuses on distinguishing between healthy and unhealthy leaves without identifying the exact disease. Healthy patches from all crops were used to extract healthy features, while infected patches from various diseases were grouped as a single “unhealthy” class. This strategy enables generalized detection, even for unseen diseases. The approach was applied to all split patches from the PlantVillage dataset, with labeling carried out over three months by experts.



To detect disease presence, the leaf image is divided into non-overlapping 32 × 32 patches, with irrelevant patches removed. Each remaining patch is classified as healthy or diseased. This process also enables estimation of disease extent: the prevalence rate (P) is computed by calculating the proportion of unhealthy patches relative to the total number of patches on the leaf.

4. RESULTS AND DISCUSSION

This section evaluates the proposed method for detecting infections across crops without specifying disease type and tests its ability to generalize to unseen crops and diseases. To position our work against state-of-the-art methods, results were compared with top approaches on the PlantVillage dataset. Evaluation employed standard metrics accuracy, loss, and confusion matrix—consistent with prior studies, enabling fair comparison. To address data imbalance and provide deeper insight, additional metrics such as precision, recall, and F1-score were also used.

Table 4. Performance on training and testing Sets .

Empty Cell	Accuracy	Loss
Train	0.9466	0.1336
Test	0.9404	0.1462

5. CONCLUSION

This paper presents a novel plant disease recognition system based on a small Inception model. By classifying patches instead of whole leaves, the system reduces dependence on leaf structure, augments data naturally, and enables disease detection across all crops and disease types, including those unseen during training. Experiments on the PlantVillage dataset and validation on the PDDB dataset demonstrate strong robustness and superior generalization compared to state-of-the-art methods, with a single model handling diverse crops and diseases. The study highlights the potential of deep learning for broad, automated plant disease detection, offering significant benefits for agricultural management. Nonetheless, real-world variability in environmental conditions may affect robustness. Future work should explore optimization strategies, sliding-window segmentation to improve detection capacity, and the adaptation of techniques from crack damage detection to further enhance generalization.

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