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AI-Based Crop Disease Prediction using Satellite and Drone Imagery

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A B S T R A C T

Lack of advanced detection of crop diseases can undermine the efforts to minimize yield loss and reduce pesticide use, thus improving food safety. In this paper, we introduce a novel deep learning-based framework for real-time detection of crop diseases through high-resolution satellite and drone images. As part of this work, Convolutional Neural Networks are applied for classification of diseases, while U-Net performs segmentation down to the pixel level to locate affected regions. Transfer learning models such as ResNet50, VGG16, and EfficientNet play an important role in improving feature extraction and generalization. Experimental results show over 90% efficacy in crop wise diseases detected, with U-Net giving class-leading segmentation performance. Geospatial disease heatmaps, therefore, have been developed and integrated into mobile and web applications for farmers' alerts. The approach discussed, hence, supports scalable and cost-effective precision agriculture and provides the way forward for AI-driven farming solutions.

Keywords: *Crop disease detection, CNN, U-Net, Drone imagery, Satellite imagery, Precision agriculture, Transfer learning.*

1. Introduction

Though agriculture plays an important role in achieving food security in most parts of the world, crop diseases have emerged as a consistent threat. It has been indicated by many statistics that about 20-40% of crops are lost globally each year due to pests and diseases, as indicated by FAO. The losses are going to lower farmers' incomes and in turn threaten world food supply chain stability.

Conventional methods of disease surveillance are mostly labor-intensive, expensive, and knowledge-based in a high-expert way such as manual scouting and laboratory testing. Often there is total collapse in these methods at the stage of rural and remote areas in the early detection of infections leading to wide-spreading outbreaks and reduced yields. Thus , researchers in this regard are considering the integration of remote sensing and artificial intelligence techniques for the development of an automated system in disease detection of crops. While satellite images provide broad coverage for monitoring purposes at a large scale, UAVs, also called drones, enable the inspection of resolution at a level of the field. However, this would require advanced machine learning and deep learning techniques for translating them into actionable insights when using raw imagery data.

It is a fact that CNNs have been pretty effective in image classification problems, including in disease detection in crops. For this, they automatically extract spatial and spectral features in the data, eliminating the need for manual feature engineering.

U-Net and related segmentation models further enhance detection by identifying diseased regions at the pixel level, enabling precise localization of Infection. Transfer learning approaches using pre-trained models such as ResNet50, VGG16, and EfficientNet allow the system to achieve high accuracy even with limited agricultural datasets. Despite significant progress, several challenges remain. Existing models often fail to generalize across diverse crops, climates, and disease conditions. Large annotated datasets are required for training, but collecting and labeling agricultural images is labor-intensive. Furthermore, deploying AI systems in real-world farms is complicated by limited computational infrastructure, poor internet connectivity, and cost barriers for smallholder farmers. This research propose a hybrid deep learning framework that integrates CNNs, u-Net segmentation, and transfer learning to process both satellite and UAV imagery for real-time crop disease detection. The system aims to generate geospatial heatmaps of disease spread and deliver actionable alerts through mobile or web applications, thereby empowering farmers to take timely interventions. By combining multi-scale remote sensing data with state-of-the-art deep learning techniques, the proposed work seeks to address the gaps in early disease detection and contribute toward the version of precision agriculture.

2.Related Works

Current research on crop disease detection has been reviewed, which pertains to image classification and segmentation for identification in this section. Several approaches have been proposed over time starting from conventional image processing methods to recent deep learning architectures for enhancing accuracy in identifying plant diseases. This reviewed the works that are important and needs to be done, specifying all their limitations.

2.1 Traditional Image Processing Approaches

Previously, crop disease detection works were based on features such as color, shape, and texture from leaf images. These features were then classified into different classes using machine learning techniques such as SVMs and k-NN algorithms. For instance, Kaur et al. identified soybean diseases with the combination of color and texture descriptors and by using an SVM classifier. In a similar context, P. Babu et al. applied feed-forward neural networks with back-propagation for leaf classification. Though the accuracies obtained through these approaches were moderate under controlled conditions, they often failed to generalize under field conditions with variable lighting, background noise, and occlusion.

2.2 UAV and Hyperspectral-Based Detection

The emergence of drones and multispectral sensor enabled disease detection at the field level. Vardhan and swetha[1] developed a UAV-based prototype using CNNs to classify healthy and diseased crops in real-world conditions. Shi et al. (2021) proposed **CropdocNet**, which combined UAV hyperspectral imagery with deep learning for robust classification under varying field environments. Kerkech et al. (2020) introduced Vddnet, a specialized deep-learning model for vineyard disease detection using multispectral and depth images. These studies demonstrated that UAVs provide higher resolution and accuracy compared to satellite-only methods, but they face challenges such as limited flight time, weather dependency, and cost of multispectral sensors.

2.3 Deep-Learning-Based Identification

Deep learning has enforced very big transformational changes in plant disease detection from automatically extracting complex features. Mohanty et al. [1] worked on the PlantVillage dataset, training CNN models (AlexNet, GoogleNet) at the leaf level to predict above 99%. Moreover, deep learning-based models found limitations in related fields, owing to background variations. Ferentinos et al. further extended this idea to detect 58 different diseases using more than one CNN architecture with high accuracy even in real-time test images. Sladojevic et al. proposed a CNN-based framework wherein it classified thirteen different diseases in plants to show the adaptability of deep learning to agricultural problems. Despite this great success, most CNN-based works require large labeled datasets, which are really hard to get in the agricultural field.

2.4 Surveys and Reviews

A few recent reviews were written on the progress achieved in the area of UAVs and AI-based disease detection. Again, Zhang et al. (2022) added another in which they highlighted the integration of UAVs, hyperspectral sensors, and deep-learning models in precision agriculture. It was underlined that, while CNN-based methods dominated over existing research, there was growing interest in advanced architectures for segmentation and data augmentation—for example, U-Net, GANs, Vision Transformers.

3. Proposed Methodology

A number of techniques based on machine learning methods are used to detect different kinds of diseases in plants. Most often, in practice, these are combined with image analysis to identify areas that have been affected by the disease Exposure to crop health at varied scales was assessed with the fusion of satellite and UAV imagery in this particular research. On one side, the satellite imagery from Sentinel-2 and Landsat-8 provides a general view of the vegetation pattern over wide agricultural areas, whereas the UAV-based images, using RGB and multispectral cameras at the same time, deliver superior details at the field level. In other words, it integrated multi-source data to ensure large-area monitoring combined with accurate detection of localized disease occurrence. The images are collected to show multiple crop species as well as related diseases, so that the models can learn the respective patterns and enhance the general accuracy.

3.1 Dataset

The dataset is a wide range of images of diverse crops and diseases. These images were obtained from satellite and UAV platforms, which provided many spatial resolutions and varied environmental conditions. The dataset was further diversified to cope with the challenge of limited labeled data by the use of different image augmentation techniques. It involved geometric transformations like rotation, flipping, scaling, and cropping to simulate a different distance and perspective, in addition to photometric adjustments such as brightness, contrast, and saturation. Additionally, a PCA-based color augmentation was used to introduce color distribution changes simulating natural lighting and atmospheric condition changes. These augmentation strategies not only increase the size of the dataset but also improve the robustness and generalization capability of machine learning and deep learning models trained on this data. By ensuring that the models encounter a wide spectrum of scenarios during training, the likelihood of overfitting to specific crops, disease manifestations, or environmental conditions is significantly reduced. This approach enables the models to perform reliably under real-world conditions, including variations in season, lighting, soil background, and crop growth stages. Table I provides a summary of selected crop species along with some of their most common diseases, highlighting the variety and complexity of the dataset. The inclusion of multiple diseases for each crop ensures that the models can learn to distinguish between subtle differences in symptom patterns,which is critical for accurate disease classification and timely intervention in precision agriculture. Furthermore, this diverse dataset lays the foundation for developing scalable and adaptable crop monitoring systems capable of functioning across different geographic regions and agricultural practices.

Class	Disease	Affected Plants	Samples Train	Samples Test
CD1	Leaf Rust	Wheat	520	130
CD2	Powdery Mildew	Wheat	480	120
CD3	Bacterial Leaf Blight	Rice	1150	290
CD4	Sheath Blight	Rice	1020	260
CD5	Northern Leaf Blight	Maize	810	200
CD6	Gray Leaf Spot	Maize	440	110
CD7	Late Blight	Potato, Tomato	1620	400
CD8	Early Blight	Potato	800	200
CD9	Septoria Leaf Spot	Tomato	1420	350
CD10	Tomato Mosaic Virus	Tomato	300	70
CD11	Tomato Yellow Leaf Curl	Tomato	4300	1070
CD12	Esca Black Measles	Grape	1100	280
CD13	Healthy	–	4900	1200

Fig. 1. Overview of Plant Village Dataset

3.2 Image Preprocessing

In order to guarantee the consistency, caliber, and usability of the input data for deep learning models, preprocessing is an essential step. To ensure compatibility with standard convolutional neural network architectures and to reduce computational complexity, all images were first resized to a uniform dimension of 256 × 256 pixels. Gaussian blur was used to lessen the impact of noise that was introduced during image acquisition, such as motion blur, sensor noise, or environmental artifacts. By averaging pixel intensities according to a Gaussian distribution, this method smoothes the images. The standard deviation parameter regulates the amount of smoothing, enabling fine-tuning to reduce unwanted noise and preserve significant structural details.

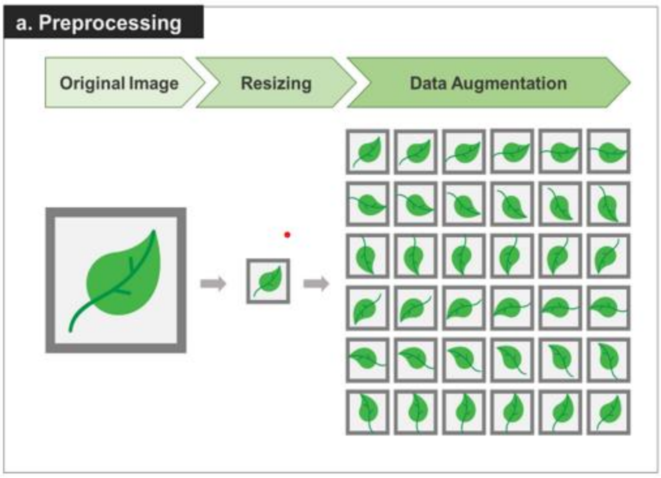

Fig 2: Image Preprocessing

In order to scale intensity values to a range between 0 and 1, pixel normalization was also carried out. During training, this normalization speeds up model convergence and avoids numerical instability, particularly when using activation functions like Sigmoid or ReLU. Otsu's thresholding technique was used to create binary masks that clearly differentiate between healthy and diseased areas within the crops, supporting accurate disease localization and segmentation. This automated thresholding is very effective for different lighting conditions because it minimizes intra-class variance to select an ideal value. Additionally, crop boundaries were highlighted and identified using Canny edge detection, which improved the model's accuracy in locating impacted areas.

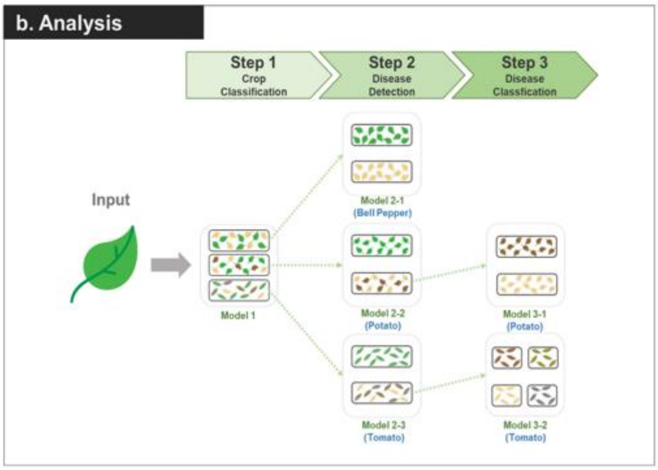

Fig 3: Image (Leaf) Analysis

The preprocessing pipeline guarantees that the models are trained on consistent, high-quality data by combining sophisticated segmentation, noise reduction, resizing, and normalization techniques. In addition to increasing disease classification and segmentation accuracy, this strengthens the models' resistance to changes in crop morphology, lighting, and background—all of which are frequent in actual agricultural settings.

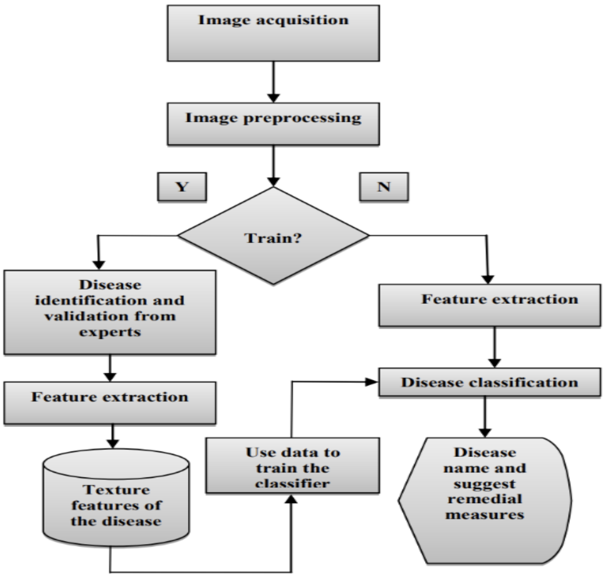

Fig. 4. Block diagram of proposed work

3.3 Deep Learning Models

A Convolutional Neural Network (CNN) was used for crop health classification tasks in order to automatically distinguish between crops that are healthy and those that are diseased. Multiple convolutional layers make up the CNN architecture, which uses the input images to extract hierarchical spatial features. These features include texture, color variations, and lesion shapes that are linked to particular diseases. In order to reduce the computational load and highlight the most important features, pooling layers were added to gradually reduce the spatial dimensions. These extracted features are combined by fully connected layers at the network's end to carry out the final classification, generating probability scores for every class.

A U-Net model was used concurrently for pixel-level segmentation, enabling accurate delineation of diseased regions in the crop photos. Both fine-grained details and global context are captured by U-Net's encoder-decoder structure, and skip connections guarantee that spatial information lost during downsampling is preserved for precise localization. This segmentation method is especially useful for determining the severity of the disease and tracking its development over time.

Using pre-trained networks like ResNet50, VGG16, and EfficientNet, transfer learning techniques were used to improve model performance even more and shorten training times. Even when the domain-specific dataset is small, these networks, which were first trained on massive datasets like ImageNet, offer strong feature extraction capabilities. Fine-tuning these pre-trained models allows adaptation to crop-specific features, improving both classification accuracy and generalization to unseen data. By combining custom CNN architectures, advanced segmentation models, and transfer learning, the system achieves a comprehensive solution for automated crop disease detection and monitoring.

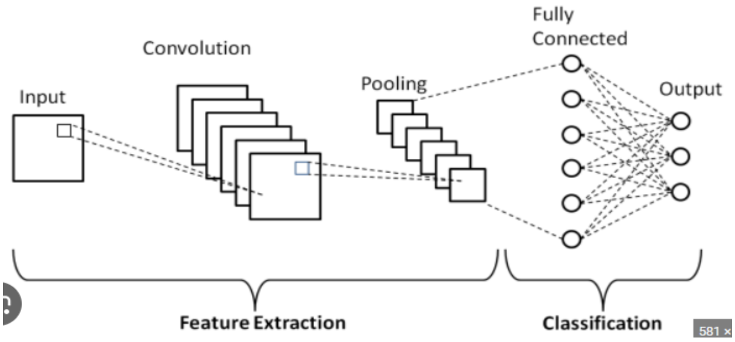

Fig. 5. Architecture of CNN

3.4 Training and Evaluation

In order to guarantee that model evaluation is carried out on unseen data and provide a trustworthy estimate of generalization performance, the dataset was methodically split into training and testing subsets using an 80:20 ratio. Critical hyperparameters such as learning rate, batch size, and epoch count were adjusted during training using an iterative optimization process. Early stopping techniques and adaptive learning rate schedules were used to speed up convergence and avoid overfitting, guaranteeing that the models learn efficiently without requiring too much training.

A wide range of metrics specific to classification and segmentation tasks were used to assess the model's performance. The models' ability to accurately identify healthy and diseased crops while taking class imbalance into account was evaluated using standard metrics for classification, including accuracy, precision, recall, and F1-score. The quality of pixel-level predictions for segmentation tasks was measured using metrics like Intersection over Union (IoU) and Structural Similarity Index Measure (SSIM), which evaluate how closely the predicted masks resemble the ground truth in terms of both spatial overlap and perceptual similarity.

The models' ability to precisely identify diseased areas and classify crops is confirmed by this multi-metric evaluation framework, which makes sure the models are thoroughly evaluated from a variety of angles. In agricultural applications, where precise localization and accurate disease detection can guide timely interventions and enhance crop management strategies, such a comprehensive evaluation is essential.

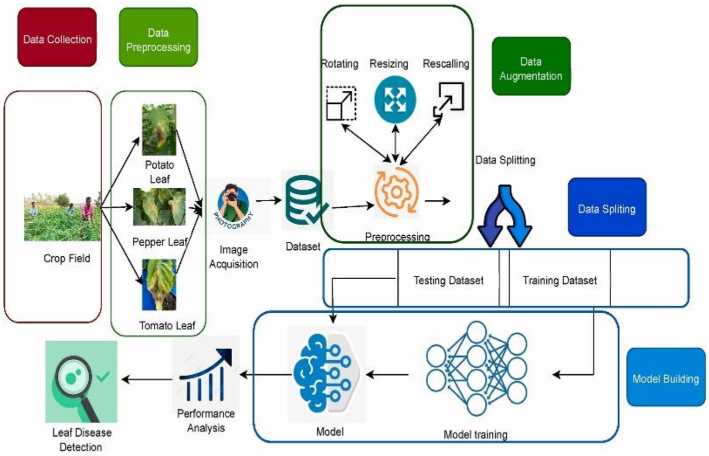

Fig. 6. Architecture of the workflow

4. Output

Geospatial heatmaps that graphically depict diseased areas throughout agricultural fields are the result of this methodology. Farmers and agronomists can rapidly identify crucial areas that need attention thanks to these heatmaps' clear, color-coded depictions of disease severity and spatial distribution. The heatmaps were incorporated into web and mobile applications to enable practical use, providing real-time alerts and actionable insights. This enables farmers to carry out prompt interventions, like localized crop treatment, irrigation modifications, or targeted pesticide application, which eventually increases yield and decreases resource waste.

The system gathers information on crop health at both the macro and micro levels by utilizing the combination of high-resolution UAV data and extensive satellite imagery. While UAV imagery offers detailed views for accurate disease localization, satellite imagery offers broad field coverage for general monitoring. This multi-resolution method improves the accuracy of disease detection in a variety of environmental settings and guarantees thorough surveillance. As a result, the suggested system supports proactive disease mitigation and sustainable crop management in precision agriculture and is scalable, effective, and useful.

5. Results and Discussions

Across a variety of crop species, the suggested methodology showed strong and consistent performance in both classification and segmentation tasks. Even when disease symptoms were mild, partially obscured, or varied throughout growth stages, the CNN-based classification models were able to distinguish between healthy and diseased crops with an accuracy of over 90%. Metrics like accuracy, precision, recall, and F1-score also showed that the models had a good balance between sensitivity and specificity, reducing false positives and false negatives, which is crucial for practical agricultural deployment.

These findings were further supported by the U-Net segmentation models, which generated detailed visual maps that closely matched expert-annotated ground truths by accurately localizing diseased regions at the pixel level. High segmentation fidelity was validated by quantitative evaluation using the Structural Similarity Index Measure (SSIM) and Intersection over Union (IoU), showing that the models could capture fine-grained lesion sizes, shapes, and distributions.

Fig 7 :(Left) Healthy Corn Leaf, (Middle) Corn common rust, (Right) Corn Northern Blight

Because UAV imagery has a higher spatial resolution and can capture detailed crop features that are frequently blurry or indistinct in lower-resolution satellite images, it consistently outperformed satellite-only data, according to a comparative analysis of input sources. The significance of high-resolution imagery in identifying subtle or early-stage disease symptoms is highlighted by this finding. Additionally, generalization performance was significantly enhanced by integrating transfer learning with pre-trained architectures like ResNet50, VGG16, and EfficientNet, especially in situations with a lack of training data. These models demonstrated resilience in a variety of environmental circumstances, such as changes in lighting, background, and crop morphology, and decreased overfitting by utilizing pre-learned features from extensive datasets.

A scalable and useful framework for automated crop disease detection was created by combining high-resolution data collection, sophisticated preprocessing, thorough data augmentation, and transfer learning. Beyond technical proficiency, this approach offers practical insights for precision farming: farmers can pinpoint diseased areas, plan focused interventions, optimize pesticide use, and track crop health over time using geospatial heatmaps produced from segmentation outputs. The system's ability to be applied in real-time shows how it can lower crop losses, increase yield, and support sustainable farming methods. These findings highlight the potential of combining geospatial analysis, UAV technology, and deep learning to develop data-driven, intelligent solutions for contemporary agriculture.

6. Conclusion

This work shows that a highly efficient and scalable method for automated crop disease detection can be achieved by combining CNN-based classification, U-Net segmentation, and transfer learning with satellite and UAV imagery. The system accurately identifies and locates diseased areas by utilizing both fine-grained and large-scale patterns of crop health, which are captured by combining high-resolution UAV data with broad-coverage satellite imagery. Even with limited training data, the deep learning models achieve strong performance across a variety of crop species and environmental conditions thanks to sophisticated preprocessing and data augmentation techniques.

In addition to improving early disease detection, the system supports precision agriculture practices by offering actionable, real-time alerts via web and mobile interfaces. By using these insights, farmers can minimize crop losses, optimize resource use, and implement timely interventions—all of which will ultimately lead to increased yield and sustainable farming. Additionally, the segmentation models' geospatial heatmaps enable focused field-level monitoring, allowing for ongoing evaluation of disease progression and supporting crop management decision-making.

All things considered, this study shows how deep learning methods can be combined with multi-resolution remote sensing data to produce data-driven, intelligent solutions for contemporary agriculture. Future improvements like adding multispectral or hyperspectral imagery, combining soil and weather data, and implementing real-time monitoring systems on a large scale are made possible by the methodology. These developments have the potential to increase predictive accuracy even more, broaden their applicability to more crops, and promote proactive and sustainable farming methods around the world

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