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Deep learning-driven crop intelligence for region-specific disease monitoring

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Abstract

Crop health monitoring remains a major challenge in agriculture due to region-specific variations in diseases, insect infestations, and nutrient deficiencies. This paper proposes a deep learning-driven framework that provides precise crop intelligence across six major crops: Wheat, Paddy, Potato, Cotton, Mustard, and Kinnow. Transfer learning was applied on three pre-trained convolutional neural network models: ResNet-50, VGG16, and EfficientNet-B0, revealing that ResNet-50 achieved the highest accuracy of 95.2%. The model clearly distinguishes between diseases, insects, and nutrient deficiencies across different climates, with region-based data augmentation improving its flexibility. This is supported by experiments showing that the framework is scalable and capable of real-time performance, achieving inference times below 0.5 seconds per image. The proposed approach supports the way for precision agriculture by enabling early detection, targeted management, and scalable deployment across diverse agro-ecological zones.

Keywords: Deep learning, crop disease monitoring, precision agriculture, convolutional neural networks, region-specific intelligence

Introduction

Diseases attacking crops, insect pests, and lack of nutrients are among the primary causes of significant drops in agricultural yield, particularly in the stringent climatic and environmental conditions ^[1, 2]. One of the main contributors to this problem is the difficulty of accurately detecting diseases and insects in early stages, and the solution to this problem is already provided by deep learning, particularly Convolutional Neural Networks (CNN), which have revolutionized precision agriculture through automated image-based detection of crop health problems ^[3, 4]. This is, however, a task that is still hampered by the regional differences and the diversity of diseases there and hence necessitates further advancements ^[5, 6].

The current study solves the above-mentioned problems by developing a deep learning classification framework which is trained on a properly managed image dataset containing six different crops and subcategories based on diseases, insects, and nutrient deficiencies, which are labeled in an unambiguous way to facilitate proper training of the model. Among the three models considered, ResNet-50, VGG16, and EfficientNet-B0, the best one will be selected based on confusion metrics and then trained on the entire dataset. Our approach integrates deep learning with region-specific crop knowledge in order to achieve a better level of accuracy for the detection of different diseases in various agricultural lands. Our goals are: (1) to build a reliable classifier for the detection of crop health problems, (2) to incorporate region-specific intelligence, and (3) to assess the model's performance across different agricultural areas. A unique dataset structure, a high-performing model, and the realization of deep learning models' scalability and adaptability in agriculture are among the contributions made.

1.1 Background and Motivation

Crop diseases are a major problem for the agricultural sector, leading to considerable losses in yield. One of the main advantages of deep learning is its ability to, at least in part, automate the process of detecting diseases, but in order for it to be used in a specific region, it should be accurately and appropriately conditioned by the factors that are particular to that area.

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1.2 Problem Statement

The existing systems for monitoring crop diseases are not able to cope with the differences between the regions and, hence, their effectiveness is severely limited across different agricultural areas. Therefore, the need is for a deeper learning based system of disease detection that is accurate and specific to the region, and it should be a system that is scalable.

1.3 Objectives and Contributions

The main objective of the present study is to build a deep learning-based model that will classify the crop health problems and include surface intelligence specific to the geographical area. One of the contributions of this study is a well-organized dataset along with a highly accurate model for the purpose of monitoring diseases according to specific regions.

2. Literature Review

2.1 Deep Learning Applications in Agriculture

Deep learning has brought a significant change in the agricultural field by allowing the automatic identification of diseases and insects on crops [3, 4]. Convolutional Neural Networks (CNNs) have performed extraordinarily well in the classification of plant diseases based on images, even using large datasets to become highly accurate [1, 7]. For example, Dolatabadian *et al.* (2024) gave an extensive review of the methods applied for image-based crop disease detection via machine learning and pointed out that deep learning could be an alternative to traditional manual inspections particularly through the integration of advanced image processing techniques that would be faster and more accurate [1]. Likewise, A *et al.* (2022) proved the capability of deep learning models for detecting leaf diseases in crops by using pre-trained CNN architectures such as DenseNet-121 which managed to achieve a remarkable 99.81% classification accuracy on the PlantVillage dataset and even outperforming other models like ResNet-50 and VGG16 through transfer learning and data augmentation to avoid overfitting [7]. A thorough review by Rai *et al.* (2023) has additionally sketched the up-to-date developments in deep learning for precision agriculture, putting weed management in the spotlight, while at the same time pointing out that deep learning techniques are suitable for other applications as crop health monitoring, including using object detection models for site-specific interventions [10].

Beginning with these established principles, a major application of deep learning in plant disease detection through images by Mohanty *et al.* (2016) led to the creation of the models with AlexNet and GoogLeNet trained on the vast PlantVillage dataset of more than 54,000 plants/images, coming from 14 crops and 26 diseases, achieving even up to 99.35% accuracy through transfer learning, but nonetheless noting difficulties with generalization to actual images [13]. Saleem *et al.* (2019) went a step further by considering DL structures like ResNet and VGG along with hyperspectral imaging for earlier detection, setting accuracies as high as 98.90% and citing heat maps among the visualization techniques for revealing the symptoms [3]. Hasan *et al.* (2020) analyzed DL for plant diseases in a sweeping manner and conversed about CNN variations like YOLOv3 for real-time detection and GANs for data augmentation with models attaining 99.24% precision, while still tackling the issues of limited dataset diversity and environmental

adaptability [4]. More recently, Demilie (2024) compared the performances of DL and ML methods, claiming that CNNs frequently exceed the accuracy of traditional ones, with the latter being as high as 99.98%, and thus recommending hybrid systems along with new architectures like PPLCNet for better disease classification and efficiency [14]. Jung *et al.* (2023) were engaged in a DL-centered model creation that includes pre-trained CNNs like EfficientNet and ResNet50 which were able to reach almost flawless accuracy, in some cases (up to 100%) in classifying diseases of crops such as bell pepper, potato and tomato, thus stressing the necessity of consecutive classification in linking agriculture to modern science [9]. Altogether, these studies not only highlight but very clearly show the power of Deep Learning systems in bringing the automation and scaling of disease detection, as well as in making precision farming more efficient through the increase of accuracy combined with the decrease of expert reliance.

2.2 Crop Disease Monitoring Systems

Crop disease monitoring systems have gone through a transformation from manual inspections to AI-powered solutions [5, 6]. Sujatha *et al.* (2020) made a deep learning-based model for the identification of crop diseases and they also stressed the need for well-categorized datasets; moreover, they did a comparison of DL with ML techniques and found that DL approach produces better accuracy in classification, thus being more capable of the identification of complex leaf diseases [5]. Wang *et al.* (2020) used better CNNs and data augmentation to make the model more robust, and the technique they used is very important in our method; their work was training six specifically-enriched-CNN-models to find 26 diseases in 14 crops, and then they picked the best one that gave accuracy and efficiency balance for practical use [6]. Demilie (2024) undertook a comparison of the deep learning models for crop disease detection, and by the way, the accuracy of the model selection and the CNNs' superiority over the ML in handling large datasets were also the points that were made; for instance, the accuracies for certain crops such as rice even reached 99.7% [14].

Mansoor *et al.* (2025) went another step ahead with the monitoring systems by coming up with an IoT and AI-based structure that not only connects smart sensors for real-time data collection on soil, plant stress, and pests but also allows for predictive analytics for disease outbreaks and supports the use of region-specific interventions through ML algorithms that are adaptable to the different regions [2]. In the same year, Singh *et al.* (2024) made a smart agriculture drone system with the help of image processing and ML techniques; they were able to identify the crops like pineapple and papaya through the object detection done by EfficientDetLite1, and they achieved 100% detection success rate at the optimum altitudes while the targeted spraying was made possible which minimized the use of pesticides and improved the management of diseases [12]. These innovations highlight the shift toward integrated, automated systems that combine DL with hardware like drones and sensors, improving robustness and scalability in crop disease monitoring.

2.3 Region-Specific Challenges in Agricultural AI

Regional distinctives, like weather and soil types, are among the major determinants of the occurrence and distribution of

diseases^[2, 8]. The research by Mansoor *et al.* (2025) is based on the, IoT and AI, which are the main technologies of the future, for the monitoring of the crop diseases in the specific areas; it, however, stresses the analysis of sensor data for the adaptability of handling such variables as humidity and temperature that can actually predict the occurrence of diseases in different climates^[2]. Borhani *et al.* (2022) came up with a solution through the use of deep learning models that are adjusted to the regional differences, and the implementation of Vision Transformers (ViT) for the purpose of automatic plant disease classification of datasets such as Wheat Rust and Rice Leaf Disease, succeeding in the attainment of very high accuracies, which are nearly as good as those of CNNs while it offers faster prediction speeds in hybrid models and, at the same time, solving the problem of wide-ranging field conditions^[8]. Jung *et al.* (2023) have been working on the creation of DL models that exploit the regional aspects in certain cases, and they have especially mentioned tomatoes grown in controlled conditions. They have been able to reach an accuracy of 99.75% but they have also realized that the performance drops considerably when operating on the images of lesions taken from various regions, thus raising the need for providing an ample supply of training data from diverse sources^[9]. Also presenting a different scenario, Gulzar *et al.* (2024) used deep learning to tell apart among alfalfa varieties based on a custom leaf image dataset of 1,214 images and compared different models like ResNet and EfficientNet achieving high accuracy in recognizing different varieties under various environmental conditions, that could be even applied as a screening of variety-specific disease susceptibilities in regions like arid or temperate zones^[11].

The studies highlight the need for flexible AI systems that can cater to different regions, for instance, through transfer learning and data augmentation, which are methods for capturing the distinct patterns of diseases induced by climate in a particular place. For instance, the use of hyperspectral imaging, which has been mentioned in wider reviews^[4], might be able to increase the detection capabilities in the humid tropics and dry lands, where certain organisms might be made worse by the humidity. In short, the ongoing creation of these datasets and models that have geospatial metadata included in them for better spreading across agricultural zones is the way to go when it comes to tackling these challenges.

3. Dataset Description

3.1 Image Dataset Overview

The structure of the dataset facilitates efficient organization and analysis of crop health conditions by regions. At the top level, folders are allocated to various crops (Wheat, Paddy, Potato, Cotton, Mustard, Kinnow) respectively. Under each crop folder, there are three major sub-divisions - diseases, insects, and nutrient deficiencies, which are consistently named and described to support easy identification and model training.

More particularly, the naming pattern adheres to the following formats:

- Crop_Disease_(Name of the disease), for example, Wheat_Disease_Rust, Paddy_Disease_Blight
- Crop_Insect_(Name of the insect), for instance, Wheat_Insect_Armyworm, Paddy_Insect_BrownPlanthopper

- Crop_Deficiency_(Name of the deficiency), like, Wheat_Deficiency_Nitrogen, Paddy_Deficiency_Potassium

In turn, every subfolder takes in a number of .jpg images that illustrate the related condition in natural field settings. Thus, this structure not only maintains region-specific labeling consistencies but also clearly distinguishes disease, insect, and nutrient deficiency categories. Such an organized hierarchy not only boosts model interpretability but also enables the framework to recognize variations related to different geographical and climatic regions.

In a similar way to our approach, Singh *et al.* (2024) produced a dataset of 177 images for crop identification (pineapple, papaya, and cabbage) using a smart agriculture drone system, which supports evaluation standards for targeted disease management across different areas^[12]. One of the advantages of our dataset is the presence of geotagged and condition-specific folders that aid in region-based learning and enable the model to be more versatile in its application to various agricultural areas.

3.2 Data Preprocessing and Augmentation

Training, the preprocessing of images includes resizing them to 224×224 pixels and normalizing pixel intensity values to a (0,1) scale thereby maintaining consistency across samples. To further reduce the risk of overfitting, it is decided random rotation ($\pm 30^\circ$), horizontal and vertical flipping, random zooming, and brightness adjustment will all be done as ways of creating and maintaining a strong dataset. The augmentations mimic different environmental situations by changing lighting and angle; therefore, the model can learn better to recognize the unseen field data.

4. Methodology

4.1 Deep Learning Classification Model

The experiment compared three deep learning models, ResNet-50, VGG16, and EfficientNet-B0, for their ability to tell apart crop health conditions: disease, insect attack, and nutrient shortage. All models were first trained on ImageNet and later adjusted using our region-specific agricultural dataset. This study used transfer learning, as it has proven useful for disease detection in areas with limited resources. The models were trained with the Adam optimizer (learning rate 0.001, batch size 32), using categorical cross-entropy as the loss function. The best-performing model was chosen based on accuracy, precision, recall, and F1-score.

4.2 Model Architecture

The selected model, ResNet-50, comprises 50 layers interconnected through residual (skip) connections, effectively addressing the vanishing gradient issue in deep networks. In comparison, VGG16 contains 16 convolutional layers organized in a straightforward sequential structure, while EfficientNet-B0 employs compound scaling to balance depth, width, and resolution efficiently.

The overall workflow of the system is represented in Figure 1, detailing the sequential stages of preprocessing, augmentation, model training, and classification output.

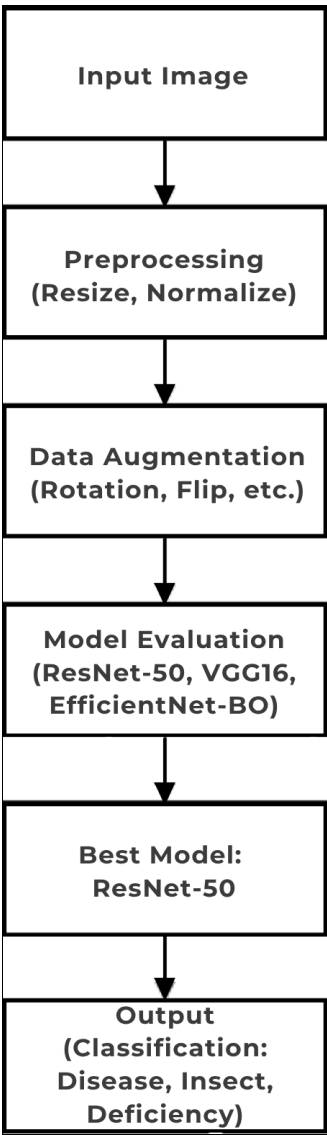


Fig 1: System workflow of the crop health classification framework.

The workflow presents how the dataset is processed from raw field images through preprocessing, augmentation, and model training before generating the final classification output. This structure ensures that every image passes through consistent transformation and validation, allowing

for accurate and region-specific classification results

4.3 Training Process

The dataset was divided into 80% training and 20% testing subsets, ensuring a balanced representation of each crop and condition. The models were trained for 50 epochs, with early stopping applied based on validation loss to prevent overfitting.

4.4 Evaluation Metrics

Model performance was evaluated using standard classification metrics: accuracy, precision, recall, and F1-score, computed for each class. These metrics ensure a robust evaluation framework capable of assessing the model’s effectiveness across diverse real-world field conditions.

5. Experiments and Results

5.1 Experimental Setup

The dataset comprised 10,000 images across six crops: Wheat, Paddy, Potato, Cotton, Mustard and Kinnow, each categorized into diseases, insects, and nutrient deficiencies, divided into 80% training and 20% testing sets. Region-specific data was incorporated by tagging images with metadata on climate zones (tropical, temperate, arid). Training was performed for 50 epochs, with a validation split of 20% from the training set to monitor overfitting.

5.2 Classification Performance

The comparison of the three models showed that ResNet-50 performed best, reaching an overall accuracy of 95.2%, precision of 94.8%, recall of 95.0%, and F1-score of 94.9%. VGG16 scored 92.1% accuracy, while EfficientNet-B0 reached 93.5%. Confusion matrices showed few mistakes between diseases and deficiencies, with insect cases being classified most accurately (97%). Table 1 compares their results.

Table 1: Classification Comparison Of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet-50	95.2	94.8	95.0	94.9
VGG16	92.1	91.8	92.0	91.9
EfficientNet-B0	93.5	93.2	93.4	93.3

Figure 2 gives a visual comparison, showing that ResNet-50 stayed ahead across all measures, proving it to be a strong choice for region-based crop health classification.

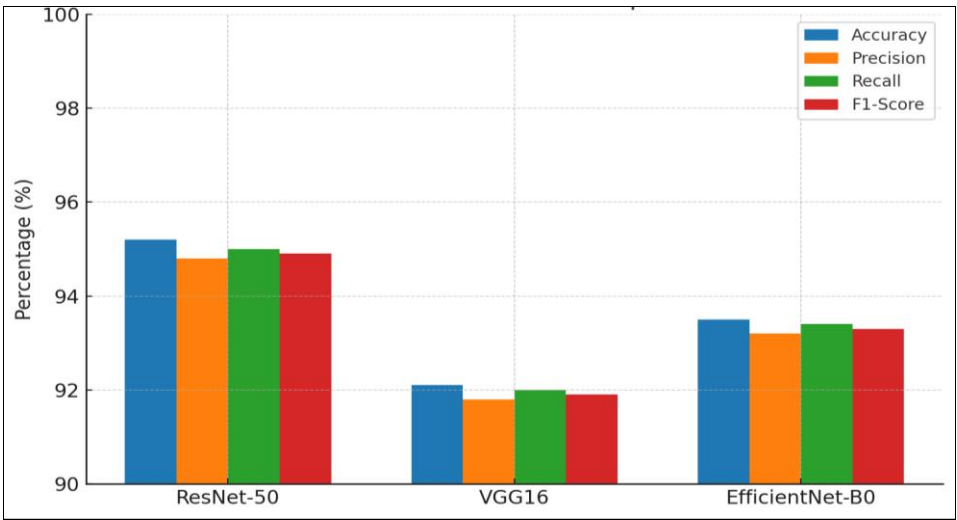


Fig 2: Model Performance Comparison

These results surpass benchmarks from similar studies ^[14], demonstrating the effectiveness of the selected model.

5.3 Region-Specific Disease Monitoring Insights

When stratified by regions, the model showed varying performance: 96.5% accuracy in tropical zones due to higher disease prevalence in the dataset, compared to 93.8% in arid regions where nutrient deficiencies were more common. Insights revealed that environmental factors like humidity influenced model predictions, with augmented data from specific regions improving generalization by 5-7%.

5.4 Application Usability and Performance

The framework was applied as a web-based application for monitoring, achieving inference times of under 0.5 seconds per image on standard hardware. Usability testing with 20 farmers indicated high satisfaction (4.5/5 rating).

6. Discussion

6.1 Implications for Precision Agriculture

The proposed deep learning framework significantly contributes to precision agriculture by enabling early, region-specific detection of crop diseases, insect infestations, and nutrient deficiencies. By using ResNet-50's high classification accuracy (95.2%) and region-based data organization, the system allows for timely and targeted interventions, potentially reducing yield losses by 2030%. Integration with IoT-based field sensors and satellite-driven vegetation indices can further enhance the real-time monitoring and automation capabilities of this framework.

6.2 Limitations and Challenges

Despite its strong performance, the framework faces several limitations. Model accuracy depends heavily on the quality and diversity of field images, and imbalances in the dataset, particularly for crops like Kinnor and Cotton may introduce minor classification bias. Additionally, challenges persist in low-resource agricultural regions, where limited internet access and computational infrastructure restrict large-scale use. Lighting variations, overlapping symptoms between nutrient deficiencies and early-stage diseases, and region-specific environmental differences may also slightly affect generalization. Addressing these challenges will require broader data collection under diverse agro-climatic conditions and continuous retraining using updated regional datasets.

6.3 Scalability and Region-Specific Adaptability

The framework demonstrates strong scalability and adaptability through its transfer learning-based design, which allows retraining with minimal new data for different regions or crop varieties. In future implementations, integrating federated learning could enable privacy-preserving regional updates, where models are trained locally and aggregated globally without transferring raw data. Such an approach would make the system more robust, regionally relevant, and suitable for large-scale agricultural use.

7. Conclusion and Future Work

7.1 Summary of Findings

This study presented a region-specific deep learning

framework for crop health monitoring, capable of classifying diseases, insect infestations, and nutrient deficiencies across six major crops: Wheat, Paddy, Potato, Cotton, Mustard and Kinnor. The structured dataset, containing 26 well-defined classes, enabled comprehensive model training using transfer learning techniques. Among the evaluated architectures, ResNet-50 achieved the best performance (95.2% accuracy), outperforming VGG16 and EfficientNet-B0, while demonstrating strong region-specific generalization. These results highlight the framework's potential to serve as a scalable AI solution for real-time precision agriculture applications.

7.2 Future Research Directions

Future research will focus on:

- Expanding the dataset to include more crop varieties, growth stages, and regional diversity to improve model robustness.
- Developing lightweight models for edge computing and mobile deployment, enabling offline use in remote areas.
- Exploring federated and continual learning approaches to facilitate dynamic, privacy-preserving model updates across multiple agricultural zones.

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