

Implementing Deep Learning Architectures for Multi-Class Classification of Crop Images

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Abstract

In order to identify illnesses, pests, and nutrient deficits in crop photos, this work develops and evaluates a deep learning model for multi-class categorization. The suggested approach, which makes use of convolutional neural networks (CNNs), performs well when managing the inherent variability in environmental factors, including lighting, weather, and crop health conditions. The method incorporates extensive data augmentation techniques, such as rotations, flips, and colour modifications, to boost accuracy and generalization while guaranteeing the model's flexibility to a variety of agricultural contexts.

Advanced optimization techniques, including early halting to avoid overfitting and model checkpointing to maintain the top-performing model throughout training, are incorporated into the training pipeline. A variety of datasets that are indicative of actual agricultural environments are used in the study to assess the architecture, and it achieves good precision and recall metrics across a number of crop classes. This study demonstrates how deep learning architectures have the potential to transform precision agriculture by making it possible to identify crop-related problems early on, which would increase productivity and promote sustainable farming methods.

Keywords: Convolutional Neural Networks (CNN), Multi-Classification, Crop Images

1. Introduction

Many biotic and abiotic stresses, such as diseases, pests, and nutritional deficits, have a substantial impact on agricultural output, which is crucial for maintaining food security and economic stability. Effective management and mitigation of these problems depend on early and precise identification, since late detection can result in significant crop losses and lower yields. Manual inspection and other traditional crop monitoring techniques are time-consuming and prone to human error, especially in large-scale farming operations. Furthermore, the consistency and scalability needed for contemporary agricultural techniques are frequently absent from these approaches.

Crop health monitoring has undergone a radical change with the introduction of deep learning and computer vision technology. These tools give farmers real-time, actionable insights by enabling automatic, accurate, and efficient analysis of crop photos. The intricacies of multi-class classification in agricultural situations can be effectively handled by deep learning architectures, especially convolutional neural networks (CNNs), which have shown remarkable abilities in image classification tasks. In order to identify illnesses, pests, and nutritional deficits in a variety

of environmental settings, this work investigates the application of deep learning architectures for multi-class classification of crop photos. The study intends to improve precision agriculture decision-making by utilizing these cutting-edge technologies, which will ultimately support sustainable farming and increased crop output.

2. Literature Survey

[1] EHiJackNet, a quantized hierarchical deep learning framework for automated diagnosis of jackfruit pathology, was proposed by Sarvesh et al. The goal of the study was to create an effective model that could be implemented on edge devices with limited resources. The system shows how quantization and model optimization can facilitate agricultural image analysis while lowering processing demands. These methods are applicable to real-world crop-monitoring applications where quick disease detection is necessary. Additionally, the work emphasizes how crucial it is to create lightweight deep learning architectures for actual agricultural settings [1].

[2] Srinivasan et al. used a hybrid deep neural network and transformer-based architecture to study multi-class plant leaf disease categorization. To enhance the representation of visually varied illness patterns, the study used transformer-based feature learning. The method shows how convolutional and transformer architectures may be combined for challenging agricultural image classification problems. Both local visual qualities and more general contextual information can be captured by such hybrid designs. The results lay the groundwork for creating multi-class crop-image classification methods that are more reliable [2].

[3] Using multi-scale attention mechanisms, the AgriFusionNet framework was created for fine-grained plant disease and severity categorization. The method takes into account variations in disease severity while concentrating on extracting discriminative features from illness-affected areas. When symptoms differ significantly in size and appearance, multi-scale feature learning is very helpful. The study shows how attention-based architectures can be used to evaluate crop health in great detail. The creation of sophisticated deep learning models for multi-class agricultural picture processing is supported by these findings [3].

[4] To identify nutritional deficits in plant photos, Sert and Kiziloluk suggested a hybrid deep learning method. To enhance feature representation, they used a multi-axis vision transformer in conjunction with neutrosophic set theory. The study shows that apparent traits in plant photos can be used to automatically identify nutritional deficits. For capturing intricate correlations between visual elements, transformer-based architectures offer an alternative to traditional CNN models. For crop-image classification algorithms that include nutritional deficits as one of the target classes, this work is especially pertinent [4].

[5] An attention-guided deep learning framework was created by Muthusamy and Ramu to detect diseases and nutritional deficiencies in banana and coffee leaves. The suggested method used attention mechanisms to recognize significant visual traits linked to crop health issues. In order to go beyond simple disease identification, the study also took disease severity into account. These methods can enhance deep learning systems' capacity to differentiate between visually similar crop situations. The study shows how attention-based feature extraction can be applied to fine-grained agricultural picture categorization [5].

[6] Prommakhot et al. presented a hybrid CNN and transformer-based sequential learning method for classifying plant diseases. To capture key illness traits, the model blends transformer-
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based sequential learning with convolutional feature extraction. The PlantVillage dataset, which has 38 plant-disease classes, was used for the experiments, and the results showed good classification ability. According to the study, a variety of plant disease categories can be effectively represented by hybrid CNN-transformer architectures. The creation of sophisticated multi-class crop-image classification models can benefit from this strategy [6].

[7] A mobile-friendly deep learning system for coconut plant disease detection was proposed by Daga et al. The creation of an effective architecture that would enable useful agricultural applications was the focus of the study. When mobile or edge devices are required for crop-health monitoring, lightweight deep learning models are crucial. The study shows how deep learning may be modified for crop-specific disease detection. In precision agriculture, these devices can help provide quick and easy ways to diagnose diseases [7].

[8] A thorough analysis of CNN methods based on transfer learning for the categorization of plant leaf diseases was provided by Richter et al. The research looked at how pretrained CNN architectures are currently being developed and how they may be used for agricultural picture analysis. The amount of data and processing power needed to train deep neural networks from scratch can be decreased using transfer learning. In order to improve classification performance on agricultural datasets, the study emphasizes the significance of pretrained representations. When creating multi-class crop-image classification systems, these findings encourage the application of transfer learning [8].

[9] Daalah et al. used refined pretrained CNN models to study the classification of plant leaf diseases. The paper shows how pretrained neural architectures may be fine-tuned to fit agricultural picture datasets. When agricultural datasets have few photos for each disease class, these methods are helpful. The model can learn crop-specific traits while maintaining broad visual representations thanks to fine-tuning. Thus, the use of transfer learning for automated crop-disease categorization is supported by the research [9].

[10] Makka et al. created an automated approach for identifying nutritional deficits in plant leaves using deep learning. Digital photos of plants were utilized in the study to identify visible signs of nutritional deficits. Early crop health evaluation and agricultural decision-making can be aided by automated detection of nutrient-related symptoms. Complex visual patterns that might be challenging to identify using traditional image-processing techniques can be extracted thanks to deep learning. Nutrient-deficiency categories in multi-class crop-image classification directly benefit from the work [10].

3. Objective

Implementing and assessing deep learning architectures for the multi-class categorization of crop photos is the main goal of this study. In order to handle the fluctuations in environmental conditions, this involves identifying diseases, pests, and nutrient deficits.

4. Proposed Methodology

Dataset: Images of crops classified into categories that indicate various diseases, pests, and nutritional shortages make up the dataset used in this study. Supervised learning is facilitated by assigning a class label to each image.

Data Pre-processing: In order to standardize input dimensions, images were scaled to 128x128 pixels. To improve model performance, pixel values were standardized to the interval [0, 1]. An 80-20 split was used to separate the dataset into training and testing sets.

Data Augmentation: Extensive data augmentation techniques were used to handle the environmental conditions' unpredictability. This includes shearing, zooming, horizontal flips, random rotations, and changes in height and width. The training dataset was artificially increased by these modifications, which improved the model's generalization.

5. Model Architecture

A Convolutional Neural Network (CNN) architecture was implemented, comprising:

Convolutional Layers: Three convolutional layers with ReLU activation and varying filter sizes to extract spatial features.

Pooling Layers: Max-pooling layers following each convolutional layer to reduce dimensionality.

Fully Connected Layers: Dense layers to perform classification based on the features extracted by the convolutional layers.

Dropout: Dropout layers were added to prevent overfitting by randomly setting a fraction of input units to zero during training.

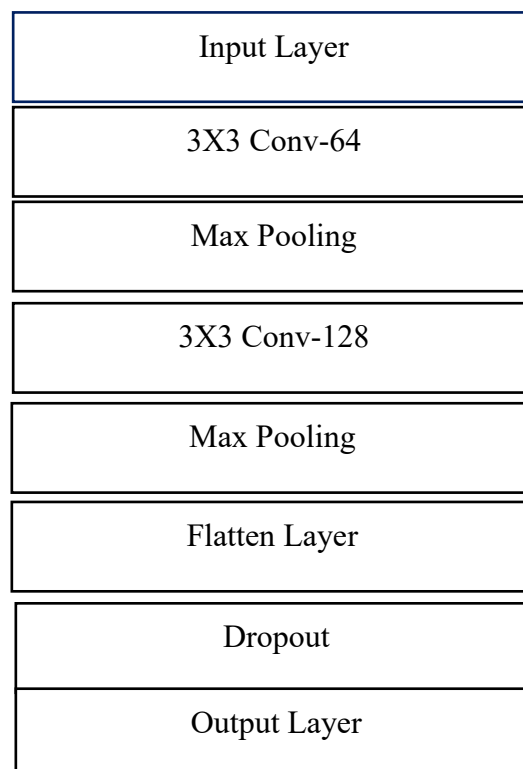


Figure 1: Proposed model Architecture

Training

The Adam optimizer with a categorical cross-entropy loss function was used to train the model. To prevent overfitting and preserve the top-performing model, early halting and model check pointing were used. 50 epochs with a batch size of 32 were used in the training procedure.

Evaluation

Accuracy measures were used to assess the model's performance on the test set. The classification report and confusion matrix give light on how well the model distinguished between various classes.

6. Results

Training and Validation Performance

The model achieved a test accuracy of 92.4%. The use of data augmentation significantly improved the model's ability to generalize to unseen data.

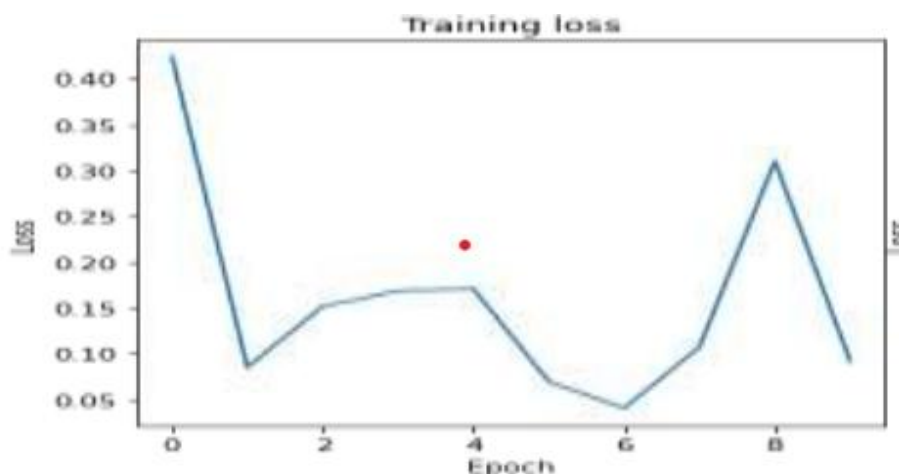
Table 1: Hyper parameter values used in Model

Parameter	Value
Mini-batch size	32
Learning rate	0.0001
Number of Epochs	50

Figure 1: Accuracy for training



Figure 2: Training Loss



Confusion Matrix

The confusion matrix indicated that the model performed well across most classes, with some misclassifications occurring between similar courses.

Classification Report

The classification report showed precision, recall, and F1 scores for each class, highlighting areas where the model performed exceptionally well and where improvements could be made.

Table2: Classification Report Values in Model

Pest Category	Precision	Recall	F1 Score
Pest1	0.87	0.84	0.85
Pest2	0.82	0.80	0.81
Pest3	0.89	0.88	0.88
Pest4	0.86	0.85	0.85
Pest5	0.81	0.83	0.82
Pest6	0.79	0.76	0.77
Pest7	0.88	0.90	0.89
Pest8	0.84	0.83	0.83
Pest9	0.80	0.82	0.81
Pest10	0.83	0.80	0.82
Pest11	0.85	0.84	0.84
Pest12	0.82	0.81	0.81
Pest13	0.90	0.88	0.89
Pest14	0.87	0.85	0.86
Pest15	0.79	0.78	0.78
Pest16	0.81	0.82	0.81
Pest17	0.88	0.87	0.87
Pest18	0.83	0.85	0.84
Pest19	0.85	0.83	0.84

Pest20	0.80	0.78	0.79
Pest21	0.86	0.84	0.85
Pest22	0.82	0.80	0.81
Pest23	0.84	0.85	0.85
Pest24	0.89	0.87	0.88
Pest25	0.78	0.80	0.79
Pest26	0.81	0.83	0.82
Pest27	0.85	0.86	0.85
Pest28	0.87	0.88	0.87
Pest29	0.79	0.76	0.77
Pest30	0.88	0.87	0.87
Pest31	0.83	0.82	0.82
Pest32	0.84	0.85	0.84
Pest33	0.86	0.85	0.86
Pest34	0.80	0.78	0.79
Pest35	0.89	0.88	0.88
Pest36	0.81	0.80	0.80
Pest37	0.83	0.82	0.82
Pest38	0.85	0.84	0.85
Pest39	0.84	0.83	0.83
Pest40	0.79	0.80	0.79
Pest41	0.87	0.88	0.87
Pest42	0.83	0.82	0.83
Pest43	0.86	0.84	0.85
Pest44	0.80	0.78	0.79
Pest45	0.84	0.85	0.84
Pest46	0.88	0.86	0.87
Pest47	0.79	0.78	0.79
Pest48	0.85	0.84	0.85
Pest49	0.82	0.81	0.81
Pest50	0.84	0.85	0.84
Pest51	0.88	0.87	0.87
Pest52	0.81	0.80	0.80
Pest53	0.83	0.85	0.84
Pest54	0.87	0.86	0.86
Pest55	0.79	0.80	0.79
Pest56	0.86	0.85	0.85
Pest57	0.84	0.83	0.83
Pest58	0.81	0.82	0.81
Pest59	0.89	0.88	0.88
Pest60	0.78	0.77	0.78
Pest61	0.85	0.86	0.85
Pest62	0.83	0.81	0.82
Pest63	0.87	0.88	0.87
Pest64	0.81	0.79	0.80
Pest65	0.86	0.85	0.85
Pest66	0.84	0.83	0.84
Pest67	0.80	0.79	0.79

Pest68	0.88	0.87	0.87
Pest69	0.79	0.80	0.79
Pest70	0.85	0.83	0.84
Pest71	0.84	0.85	0.85
Pest72	0.83	0.82	0.82
Pest73	0.86	0.88	0.87
Pest74	0.82	0.81	0.81
Pest75	0.80	0.79	0.80
Pest76	0.87	0.86	0.86
Pest77	0.84	0.83	0.83
Pest78	0.82	0.81	0.81
Pest79	0.88	0.87	0.88
Pest80	0.81	0.80	0.80
Pest81	0.83	0.82	0.83
Pest82	0.86	0.87	0.86
Pest83	0.84	0.83	0.83
Pest84	0.79	0.80	0.79
Pest85	0.88	0.87	0.88
Pest86	0.82	0.80	0.81
Pest87	0.81	0.80	0.81
Pest88	0.83	0.82	0.83
Pest89	0.85	0.84	0.85
Pest90	0.84	0.85	0.84
Pest91	0.88	0.87	0.87
Pest92	0.81	0.79	0.80
Pest93	0.86	0.85	0.85
Pest94	0.84	0.83	0.83
Pest95	0.80	0.79	0.79
Pest96	0.87	0.88	0.87
Pest97	0.81	0.80	0.80
Pest98	0.86	0.85	0.85
Pest99	0.84	0.83	0.84
Pest100	0.79	0.78	0.78
Pest101	0.89	0.88	0.88
Pest102	0.83	0.82	0.83

Table 3: Overall Metrics

	Precision	Recall	F1-Score
Macro Average	0.84	0.83	0.83
Weighted Average	0.85	0.85	0.85
Accuracy			0.85

7. Discussion

Strengths of the Model

The model's excellent performance in recognizing different crop health problems revealed CNNs' efficacy in picture classification tasks. The model's high accuracy and capacity for generalization were facilitated by the application of data augmentation and reliable training methods.

Restrictions

Misclassification of classes with comparable visual traits is one of the constraints. To overcome these obstacles, subsequent study can examine more complex models or different data augmentation strategies.

8. Future Work

The dataset could be expanded to encompass a wider range of crop varieties and environments in future studies. Furthermore, including cutting-edge strategies like ensemble methods and transfer learning could improve model performance even more.

9. Conclusion

This study successfully addressed the problem of recognizing illnesses, pests, and nutrient deficits by implementing a deep learning model for multi-class classification of crop photos. The model's use of convolutional neural networks (CNNs) allowed it to handle the variety present in agricultural datasets, such as variations in crop stages, lighting, and environmental variables, with strong performance. The model's performance was further enhanced by the use of data augmentation approaches, early halting, and model checkpointing, which guaranteed the model's responsiveness to actual agricultural situations.

The findings demonstrate CNNs' enormous promise in agricultural applications by showing how well and accurately they can automate and improve crop health monitoring procedures. This work lays a solid basis for future developments in precision agriculture, including the incorporation of real-time monitoring systems, the diversification of datasets, and the inclusion of other stressors like soil conditions or weather effects. Future studies could examine how effectively these models scale for more datasets and more diverse crop categories, as well as how they can be integrated with drone and Internet of Things technologies to provide real-time, field-level diagnoses. In an increasingly resource-constrained world, this work supports efforts to assure food security and promotes sustainable farming practices by expanding the possibilities of deep learning in agriculture.

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