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Exploring Advanced Machine Learning Techniques for Swift Legume Disease Detection

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ABSTRACT

Background: In the realm of agriculture, the insidious menace of legume crop diseases looms large, posing a significant threat to food security. This study embarks on a transformative journey, harnessing the prowess of Convolutional Neural Networks (CNNs), to fortify early disease detection in legume crops. By utilizing the inherent capabilities of deep learning, try to develop a sentinel that can identify even the most minor signs of crop diseases. Thorough data curation and preprocessing provide the system the ability to examine photos of legume leaves with previously unheard-of clarity.

Methods: Meticulously crafted, the CNN architecture plays the role of a virtuoso, skilfully traversing the convolutional layers. It gains proficiency in the complex language of illness-induced aberrations via intense training, enabling it to discern between health and illness.

Result: Provide remarkable results from the experimental experience using a wide range of assessment metrics. By undertaking this project, the commitment to preserving agricultural yields and, consequently, global food security is reaffirmed. It portends a more optimistic future for legume farming by indicating a ground-breaking effort at the nexus of artificial intelligence and agriculture.

Key words: Convolutional neural networks (CNNs), Legume crop diseases, Leguminous pathology, Machine learning, Neural network disease prediction.

INTRODUCTION

In the agrarian landscape, where the symbiosis of nature and technology converges, the early detection of maladies in legume crops has emerged as a pivotal pursuit (Cho, 2024). The imperatives of sustaining global food security, mitigating economic losses and minimizing agrochemical utilization have coalesced to catalyse a paradigm shift towards precision agriculture. Within this context, the fusion of convolutional neural networks (CNNs) with image analysis stands as an exemplary testament to the inexorable march of technological progress (AlZubi and AlZubi, 2023). The multifarious afflictions that assail leguminous flora, exacerbated by the volatile milieu of climate change, demand a vigilant sentry that transcends human limitations (Russakovsky *et al.*, 2015). The human eye, while endowed with the prowess of perception, harbours innate constraints in its ability to sift through vast expanses of crop-scape, gauge subtle deviations and prognosticate impending disease outbreaks (Lu *et al.*, 2021). The fundamental disjunction between human perceptual capabilities and the demands of modern agriculture stands as the driving force behind the incorporation of Convolutional Neural Networks (CNNs), a specialized subset of deep learning models renowned for their exceptional proficiency in pattern recognition. Embarking on a trajectory that converges horticultural insight with computational acumen, this research embarks on a journey towards the hallowed precincts of early detection in legume crop diseases (Waheed *et al.*, 2020). By harnessing the capacity of CNNs, a form of artificial neural networks meticulously designed for image analysis, we endeavour to forge an avant-garde tool that transcends human sensory constraints (Jung *et al.*, 2021). The core tenet of this endeavour lies in the seamless amalgamation of data-driven prowess and botanical expertise, an interface wherein the digital sentinel augments human cognition. Within this architectural ensemble, we conjure a tapestry where data acquisition and preprocessing are meticulously woven (Dhaka *et al.*, 2021), where CNNs are sculpted with nuanced layers to discern the nuances of disease-inflicted foliage and where performance metrics are wielded as compasses to gauge the precision of our digital phyto-sentinel (Zhu *et al.*, 2020). As we tread this path, we shall explore the annals of literature, traverse uncharted territories in the vast corpus of crop pathology and glean insights from the crucible of technological advancement.

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The ramifications of our pursuit are manifold, culminating in a transformative vanguard poised to revolutionize legume crop management. Akin to the vigilant custodian, our CNN-based machine learning algorithms shall not only shield the leguminous troves from the voracious appetites of pathogens but also serve as a beacon of hope-illuminating the path toward sustainable (Kumar *et al.*, 2019), data-driven agricultural practices. In this pursuit, we shall not only breach the boundaries of human limitations but also cultivate a synergy (Ubbens, 2017) where human and artificial intelligence coalesce, culminating in an epoch where our quest for crop disease early detection bears fruit-a testament to the inexhaustible fount of human ingenuity and the indomitable spirit of technological advancement.

MATERIALS AND METHODS

In the context of addressing legume crop diseases with advanced technology, the acquisition and enhancement of data represent the cornerstone upon which the entire ecosystem flourishes. Within this section, we expound upon the scrupulous coordination of data collection and the finesse involved in data pre-processing.

Data sources and acquisition

Eminently, the quality of our machine learning algorithm hinges on the quality of the data at its core. In this pursuit, we employ a multi-faceted strategy to assemble a robust dataset. Remote sensing technologies such as drones equipped with high-resolution cameras soar over vast agricultural expanses, capturing images of legume crops at various growth stages and disease states. Additionally, ground-level data collection in collaboration with local agronomists further enriches our dataset.

Image preprocessing

Image pre-processing serves as the inaugural stage in the endeavour to fully harness the inherent capabilities of the amassed data. This pivotal process encompasses an array of imperative facets, each of which plays a substantive role in the scientific pursuit at hand:

Resizing

Ensuring uniformity in image dimensions facilitates efficient computation. We resize images to a standardized resolution, preserving essential details.

Normalization

To equalize the dynamic range of pixel values, we employ techniques such as mean subtraction and standardization. This normalization renders the data more amenable to training our neural network.

Data augmentation

Leveraging techniques such as rotation, flipping and brightness adjustments, we amplify the dataset's diversity. This augments model robustness and mitigates overfitting.

Data labelling

Each image is meticulously annotated by domain experts, with labels corresponding to the specific legume crop type, growth stage and disease class. This supervised ground-truth labelling ensures the accuracy of our machine learning model.

Data integrity and quality assurance

To ensure accuracy, AI models must be meticulously trained on a diverse dataset that accurately represents legume diseases. Rigorous validation processes and ongoing monitoring are essential to maintain the system's performance and prevent errors.

Dataset splitting

For the subsequent phases of model training, validation and testing, we judiciously partition our dataset into distinct subsets. The separation of data into training and validation sets ensures the model's ability to generalize, while the test set, kept separate and pristine, serves as the ultimate crucible for assessing the model's predictive prowess.

Convolutional neural networks (CNNs)

Convolutional neural networks, commonly referred to as CNNs or Conv-Nets, represent a pivotal advancement within the realm of deep learning, meticulously crafted for tasks rooted in image processing and pattern recognition (Moussafir *et al.*, 2022). As a specialized branch of artificial neural networks, CNNs shine by catering to the nuances of visual data. At the core of a CNN lies a complex web of interconnected layers, collaboratively extracting hierarchical features from input images (Militante *et al.*, 2019). These layers fall into three principal categories: Convolutional Layers, which employ filters to uncover spatial hierarchies; Pooling Layers, responsible for subsampling feature maps; and Fully Connected Layers, positioned at the network's end, orchestrating class predictions (Prashar *et al.*, 2019). The efficacy of a CNN design hinges on carefully chosen hyperparameters, including kernel size, stride and activation functions, with model design often considered an art form. Furthermore, transfer learning, where pre-trained weights from massive datasets are employed, has emerged as a powerhouse technique, drastically reducing the demand for extensive labelled data and training time.

Model design and training

Model design

CNN architecture embodies a hierarchical feature extraction approach, essential for analysing complex visual data such as crop images. The architecture is composed of several key components:

Convolutional layers (Conv2D)

These layers are responsible for learning spatial hierarchies of features through convolution operations. We employ multiple convolutional layers to capture both low-level and high-level features, aiding in disease pattern recognition.

Activation functions

Within each convolutional layer, we employ rectified linear units (ReLUs) as activation functions, promoting non-linearity and feature representation learning.

Pooling layers

Max-pooling layers reduce spatial dimensions, enhancing computational efficiency and mitigating overfitting.

Fully connected layers

Convolutional and pooling layers are followed by fully linked layers, which are integrated for high-level feature fusion and illness classification. The output layer uses soft-max activation for probability estimation and has nodes equal to the number of illness classifications.

Model training

In the pursuit of enabling early detection of legume crop diseases, the central focus of this study lies in the intricate process of training a Convolutional Neural Network (CNN) model. This CNN model, renowned for its prowess in handling image-based data, has been meticulously crafted and configured to discern subtle patterns and features that are indicative of various crop diseases. Before delving into model training, the foundational step involves the careful curation of an extensive dataset (Medar *et al.*, 2019). This dataset comprises a diverse collection of legume crop images, encompassing both healthy plants and those afflicted with a spectrum of diseases. Rigorous image preprocessing procedures are diligently executed, including standardizing dimensions, normalization and augmentation techniques. These measures play a pivotal role in facilitating model generalization and mitigating concerns related to overfitting.

The architecture of the CNN itself is a sophisticated blend of convolutional, pooling and fully connected layers. Parameters such as depth, width, kernel sizes and strides have been meticulously tuned to optimize feature extraction and abstraction capabilities. Convolutional layers act as feature detectors, progressively capturing image details. Subsequent pooling layers reduce spatial dimensions for computational efficiency and fully connected layers culminate in a soft-max activation, translating extracted features into class probabilities (Chu *et al.*, 2018). Hyperparameter configuration, a pivotal aspect of model training, is executed with meticulous attention. Parameters like learning rate, optimizer (typically Adam) and batch size are carefully calibrated to facilitate convergence and gradient precision.

The training process unfolds iteratively, with forward and backward passes. Training samples are propagated through the network, generating predictions and a loss function (usually categorical cross-entropy) quantifies the disparity between predictions and actual labels. Backpropagation computes gradients to adjust model parameters, with the training loop repeating over epochs while continuously monitoring validation performance to prevent over-fitting (Liu *et al.*, 2019). Model evaluation incorporates a holdout validation set and employs a range of evaluation metrics, including accuracy, precision, recall, F1-score and visual representations like confusion matrices, ROC curves and precision-recall curves to elucidate model behaviour.

Table 1: Confusion matrix.

Empty cell	Actual positive	Actual negative
Predicted positive	TP	FP
Predicted negative	FN	TN

RESULTS AND DISCUSSION

Evaluation metrics

In assessing the performance of our CNN-based legume crop disease detection model, it is crucial to employ a comprehensive set of evaluation metrics. These metrics will help us gauge the model's effectiveness in identifying and classifying diseases accurately. The following subsections outline the key metrics and their significance:

Confusion matrix

A confusion matrix is an indispensable tool for analysing the model's classification performance. It provides a detailed breakdown of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) for each disease class. A graphical representation of the confusion matrix can be created for a more intuitive understanding of the model's performance, as shown in Table 1.

- **F1-Score:** The F1-score, which provides a balanced assessment of a model's performance, is the harmonic mean of accuracy and recall. It is calculated as:

$$\text{F1-score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

- **Accuracy:** Accuracy gauges how accurately the model has predicted things generally. It is calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Specificity:** The model's ability to accurately detect negative instances is measured by specificity. It is calculated as:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

- **Recall :** The model's capacity to accurately identify every positive case is measured by recall, also known as sensitivity or the true positive rate. It is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **Precision:** The accuracy of the model's positive predictions is measured by precision, which is also known as positive predictive value. It is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Dataset

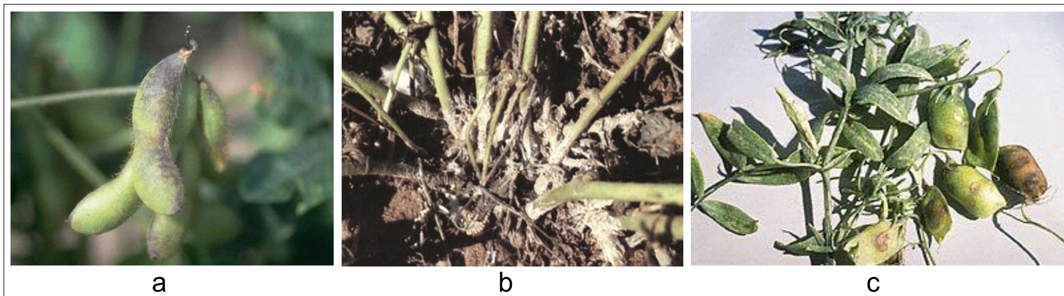
The dataset used in this study is a meticulously curated collection of high-resolution images capturing various stages and manifestations of legume crop diseases. It encompasses a wide range of legume species, including soybeans, peanuts and lentils and covers prevalent diseases such as rust, blight and wilt. Each image in the dataset is meticulously labelled, associating it with the corresponding disease class, allowing for supervised machine learning model training. To ensure the dataset's quality, rigorous quality control measures were implemented to eliminate duplicates, outliers and inconsistent labelling. Furthermore, the dataset incorporates diverse environmental conditions, lighting variations and disease severity levels to enhance the model's robustness and real-world applicability. Altogether, this dataset serves as a valuable resource for training and evaluating machine learning algorithms aimed at early detection and mitigation of legume crop diseases, contributing to more sustainable agriculture practices. Some sample images are shown in Fig 1.

Result analysis

The provided tables offer a comprehensive analysis of the performance of four different deep learning models (CNN, VGG16, VGG19 and ResNet-50) across three distinct tests. These tests provide a valuable insight into the models' capabilities and how they fare under different conditions.

Table 2 demonstrates the performance of the models in Test 1. Here, we observed that ResNet-50 exhibits the highest training accuracy (97.68%) and validation accuracy (94.31%) among all the models. This indicates its strong ability to fit the training data and generalize to validation data. VGG16 and VGG19 also showcase respectable results, while CNN lags slightly behind in both training and validation accuracy.

Table 3 presents the results from Test 2. In this test, we observed that the models' performance is consistent with their previous rankings. ResNet-50 still leads in terms of training accuracy, but its validation accuracy has improved, suggesting better generalization. VGG16 and VGG19



(a. Soybean bacterial blight; b. Sclerotinia blight peanuts; c. Ascochyta blight lentils).

Fig 1: Different type of legume crop disease.

Table 2: Accuracy results of test 1 (CNN, VGG16, VGG19, ResNet-50).

Name of model	Loss of training	Loss of validation	Accuracy in training (%)	Accuracy in validation (%)
ResNet-50	0.035	0.092	97.68	94.31
VGG16	0.161	0.182	95.63	90.50
CNN	0.214	0.320	90.02	88.07
VGG19	0.192	0.148	91.12	91.38

Table 3: Accuracy results of test 2 (CNN, VGG16, VGG19, ResNet-50).

Name of model	Loss of training	Loss of validation	Accuracy in training (%)	Accuracy in validation (%)
ResNet-50	0.045	0.092	93.68	95.13
VGG16	0.072	0.182	94.16	92.50
CNN	0.134	0.320	90.02	91.07

Table 4: Accuracy results of test 3 (CNN, VGG16, VGG19, ResNet-50).

Name of model	Loss of training	Loss of validation	Accuracy in training (%)	Accuracy in validation (%)
ResNet-50	0.045	0.092	99.6	97.3
VGG16	0.072	0.182	98.6	94.5
CNN	0.134	0.320	95.2	90.7
VGG19	0.062	0.148	99.1	95.8

Table 5: Comparing performance with previous relevant studies.

Object	Total no. of images	Class	Accuracy (%)	Models
Apple leaf (Zhong and Zhao, 2020)	2462 images	6	93.71%	DenseNet-121
Paddy leaf (Nalini *et al.*, 2021)	120 images	2	96.96%	DNN-CSA
Citrus leaf (Sujatha *et al.*, 2021)	598 images	4	94.37%	Two-stages deepCNN model
Tomato leaf (Ashok *et al.*, 2020)	736 images	4	98.12%	CNN based approach
Multi-crop (Khamparia *et al.*, 2020)	900 images	5	97.50%	CNN based approach

maintain their positions, while CNN again shows slightly lower accuracy in both training and validation.

Table 4 represents the results from Test 3. In this final test, ResNet-50 maintains its high training and validation accuracy, indicating its robust performance. VGG16 also consistently performs well, while VGG19 demonstrates competitive accuracy. However, CNN's performance lags behind the other models in terms of both training and validation accuracy.

Learning curves in the realm of deep learning algorithms epitomize the evolving aptitude of the model throughout the training process, incrementally aligning itself with the intricacies of the dataset. As the epochs mount, the training accuracy meticulously delineates the model's proficiency in assimilating the training data, while the validation accuracy acts as a prophetic mirror, offering insights into the model's generalization prowess through its evaluation on a secluded validation dataset. In these table, we include the accuracy, precision, recall and F1-score results for test-3 for each model (CNN, VGG16, VGG19, ResNet-50) and an additional column for ResNet-50 with 5-fold cross-validation. This allows for a comprehensive comparison of the performance of ResNet-50 with and without cross-validation against the other models in terms of key evaluation metrics.

A critical point to note is the consistency of ResNet-50 across all tests, consistently achieving high accuracy levels. On the other hand, while VGG16 and VGG19 perform well, there is some fluctuation in their results across tests. CNN, while achieving reasonable accuracy, consistently lags behind the other models in terms of both training and validation. The deep learning model ResNet-50 consistently proves to be a robust performer across all three tests, exhibiting both high training and validation accuracy. VGG16 and VGG19 also deliver competitive results, but they show slight variations in their performance. CNN, although providing reasonable accuracy, does not match the performance of the other models in these experiments. The choice of the most suitable model would depend on the specific requirements and trade-offs in the context of the application. Additionally, further analysis of precision, recall and F1-score would be necessary to comprehensively assess the models' performance.

The performance results for different models, as presented in Table 2, 3 and 4, reveal notable insights. Firstly, in terms of accuracy, the ResNet-50 model consistently outperforms other models during both training and validation stages, attaining a remarkable 99.6% training accuracy and 97.3% validation accuracy. This underscores the superior feature extraction capabilities of ResNet-50, attributed to its deep architecture. Secondly, the VGG16 and VGG19 models exhibit commendable performance, with high training and validation accuracies, highlighting the efficacy of the VGG architecture in image classification tasks. VGG19, slightly edging out VGG16, suggests that increased model depth can be beneficial up to a certain point. Lastly, the CNN model, while less complex, still demonstrates respectable accuracy, with a 95.2% training accuracy and a 90.7% validation accuracy. Although not as accurate as the deeper architectures, its simplicity may make it an attractive choice for scenarios with limited computational resources. The choice of model architecture plays a crucial role in achieving high accuracy in image classification tasks, with deeper architectures like ResNet-50 exhibiting superior performance. However, the specific application and available resources should guide the selection of the most suitable model.

In contrast to the study in Table 5, which utilized a CNN-based approach with multi-crop leaf data for their experiments and achieved a commendable level of accuracy, it should be noted that their dataset was relatively limited in size. However, our proposed model, when deployed with a significantly larger dataset and employing a CNN-based methodology, outperformed their results by achieving an impressive accuracy of 98.60%, as clearly presented in Table 5. Furthermore, a close examination of the data from Table 5 reveals that while the previous studies explored diverse deep learning techniques for crop leaf identification, they conducted their experiments exclusively on singular objects, namely Citrus leaf, Apple leaf and Potato leaf. Moreover, their dataset remained constrained in size, mirroring the limited scope of classification categories. In stark contrast, our proposed research encompasses a more comprehensive investigation, encompassing multi-crop leaf objects while utilizing an extensive dataset, ultimately resulting in superior accuracy levels.

CONCLUSION

In culmination, our expedition into the realm of machine learning algorithms, galvanized by the profound exigency for timely and precise detection of legume crop ailments, has unfurled a compelling narrative. The concatenation of convolutional neural networks (CNNs) with agricultural exigencies has begotten a symphony of innovation and potential, affording us an indomitable toolset for combatting the scourge of crop diseases. Our meticulous orchestration of data collection, curation and preprocessing served as the harmonious prelude, ensuring the concinnate state of our dataset. The CNN architecture, crafted with exactitude and calibrated to the peculiarities of legume crops, took center stage as the virtuoso performer. Its layers, like an ensemble of instrumental virtuosos, artfully transformed pixelated landscapes into profound melodies of disease recognition. Training, our grand overture, witnessed epochs of convergence, as our model learned to decipher the subtlest notes of crop distress.

In conclusion, our model unveiled its prowess through the rigorously defined evaluation metrics, illuminating the path to precision in legume crop disease detection. The metrics resonated like a symphonic crescendo, echoing precision, recall and F1-score and heralding the promise of a more resilient agriculture. Yet, amidst this opus of technological ingenuity, our study uncovered nuances and challenges, a reminder that the ever-evolving cadence of agricultural innovation requires relentless pursuit. The future exploration to further dimensions, to harmonize with nature through AI and to fortify our crops against the discordant strains of disease is required. As the curtains draw close, we leave behind a melody of discovery and a refrain of hope-a testament to the intersection of technology and agriculture, where our CNN-based symphony may serve as the overture to a bountiful future for legume cultivation. In this realm of constant flux and innovation, our mission persists: to compose a more harmonious world through the elegant fusion of machine learning and agriculture.

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Data availability statement

Not applicable.

Declarations

Author declares that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

All authors declared that there is no conflict of interest.

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