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Crop Pest and Disease Detection Using CNN – A Review

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ABSTRACT

Agriculture isvital to our society, providing sustenance and underpinning economic growth. Farmers across the globe cultivate diverse crops, enriching our lives and contributing significantly to national prosperity. However, their efforts are constantly challenged by the insidious threats of weeds, pests, and diseases. These silent adversaries can devastate crops, jeopardising yield and impacting farmers' livelihoods.Traditionally, farmers have relied on visual inspection and empirical knowledge to detect and manage these threats. However, this approach is often labour-intensive, time-consuming, and prone to human error. Fortunately, the advent of cutting-edge technologies like image processing, machine learning, and deep learning offers a glimmer of hope. Image processing techniques can analyse digital images of crops, meticulously dissecting colour variations, textures, and other subtle visual cues. This allows for identifying subtle signs of diseaseand pest damage, invisible to the naked eye. Moreover, these technologies have given accurate results based on image datasets to detect crop pests and diseases, which is helpful to farmers in implementingremedies.

Keywords: Crop Pests and diseases, Image Processing, Machine Learning, Deep Learning

INTRODUCTION

Crop pests and diseases pose major threats to agricultural production, leading to significant yield losses and impacting both farmers and agronomists. Traditionally, identifying these threats relied on visual inspection of leaves, stems, and other plant parts for visible signs of damage or disease. This approach, while effective in some cases, can be time-consuming, prone to human error, and often fails to detect early stages of infestation or infection. Estimates from the Food and Agricultural Organization (FAO) suggest that pests and diseases cause a staggering 40% loss in agricultural productivity, leading to an annual economic impact of around $200 billion. Currently, agronomists primarily rely on their experience and knowledge to identify pests and diseases, often leading to extensive pesticide use to mitigate the damage.

While this approach may improve crop yield and quality in the short term, it comes with a significant downside: environmental pollution and potential harm to human health.

Recognizing the limitations of traditional methods, researchers are turning to sophisticated technologies like image processing, machine learning, and deep learning to revolutionize pest and disease detection in agriculture.

By analysing digital images of crops, image processing techniques can identify subtle visual cues like colour variations and texture changes, often invisible to the naked eye, that indicate the presence of pests or diseases.

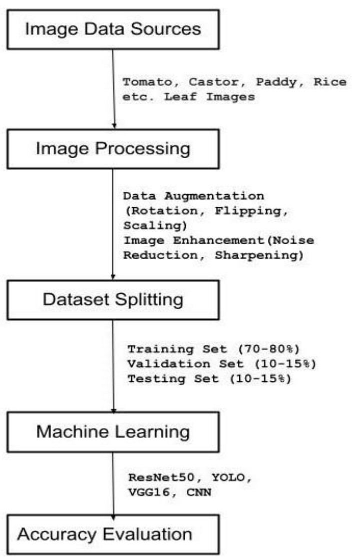
Trained on vast datasets of labelled images, machine learning algorithms develop the ability to recognize patterns and distinguish healthy crops from those affected. This allows for accurate and efficient identification of threats, enabling timely intervention.

Taking it a step further, deep learning algorithms mimic the structure and function of the human brain to extract even more nuanced information from images, revealing hidden patterns indicative of specific pests and diseases Analysing historical data and weather patterns, these technologies can predict future outbreaks, allowing farmers to prepare preventative measures and minimize potential losses. Looking towards the future, these technologies hold immense potential for agriculture. By enabling early and accurate detection, these tools can significantly reduce crop losses, leading to higher quality yields and increased food security. Improved efficiency and reduced pesticide use translate to lower costs and higher profits for farmers, contributing to the sustainability and profitability of agricultural operations. Precision agriculture, enabled by these technologies, minimizes the need for indiscriminate pesticide use, leading to a healthier environment and safeguarding human health. The integration of image processing, machine learning, and deep learning into agricultural practices promises a transformative future for our food systems. By empowering farmers and agronomists with timely and accurate information, these advancements can contribute to a more sustainable and productive agricultural sector, ensuring food security for future generations.

RELATED WORK

Nitin et al. (2023) The presented literature [1] introduces a data augmentation framework designed to enhance the recognition of castor insect pests through automated systems. Faced with a shortage of data for training machine vision models, the authors propose a framework for data augmentation through manipulation. Enhancing the learning strategy in computer vision design by increasing the variety in imagery data is the main goal. This method involves scaling, rotation, translation, and flipping to diversify the dataset. The authors emphasize its simplicity and effectiveness when combined with other manipulation-based techniques. Kernel filters, represented as n x n matrices, are employed for various effects. A patch shuffle regularization technique is highlighted for sharper image production.

The baseline scenario achieved validation accuracies of 71.23%, 72.55%, and 74.85% for VGG16, VGG19, and ResNet50, respectively. The proposed augmentation method resulted in significant improvements, with VGG16 achieving 82.18% accuracy, VGG19 at 76.71%, and ResNet50 at 74.12%.



Parasa, G. et al. (2023) The proposed framework [2] consists of three main stages: data collection, data preprocessing, and disease classification. Rice leaf images were sourced from Kaggle and Google to create a diverse dataset for disease detection. The dataset includes photos of fit rice leaves as well as leaves contaminated with several illness, including Leaf Smut, Bacterial Leaf Blight, and Brown Spot. In the data preprocessing stage, the collected images were resized to 256x256 pixels and augmented using data augmentation techniques including image rotation and flipping. This was done to make the dataset more robust and to improve the efficiency of the CNN model. In the disease classification stage, a CNN model was taught using the pre-processed data. The CNN consists of 15 layers, including five convolution layers, five pooling layers, and four dense layers. The model was taught using eighty percent of the data record, with the remaining twenty percent contained for independent evaluation of its performance. The proposed framework achieved an accuracy of 97.2% in classifying rice leaf diseases. This is significantly higher than the accuracy of previous methods. It is accurate, efficient, and scalable.

Z. Yuan, S. Li et al. (2022) The authors conducted a study [3] to investigate the issue of tiny pest illness with the small-scale datasets. The authors employed a one-stage detection model based on The authors employed a one-stage detection model based on YOLO, incorporating a CSPDarkNet backbone and a Path Aggregation Network (PAN) for enhanced performance. The authors also used multiple techniques for data augmentation, such as HSV colour perturbation, scaling, and flipping. These methods were shown to enhance the accuracy of the detection model. The study investigated the impact of neck modules and data manipulation methods on the tiny pest recognition accuracy, particularly considering the size of the training dataset. Results showed that increased training data significantly improves model accuracy by allowing it to learn more detailed features of small objects. However, the study also highlighted the importance of selecting data augmentation methods that match the specific task, as inappropriate methods can negatively impact model precision. Additionally, the researchers emphasized the need to tailor model architecture to the characteristics of the specific dataset, rather than simply adopting models that execute well on general datasets. For instance, multi-scale feature fusion's direction was found to play a crucial role in achieving accurate tiny object detection.

H. Kuzuhara et al. (2020) This study [4] aims to develop a system capable of accurately detecting small insect pests in images captured from real-world field environments. The authors propose a two-stage detection method that utilizes YOLOv3 and Xception models. The initial stage utilizes YOLOv3 with a low detection threshold to identify potential regions of interest (region proposals) within the input image.The second stage then re-identifies all region proposals using the Xception model. This two-stage approach effectively suppresses false positives and accurately detects small insect pests. The authors address the limitations of existing datasets for pest detection and identification, which are typically small and lack diversity. To overcome this challenge, they propose a two-stage data augmentation approach that involves pasting real segmented objects into natural images. This method effectively increases the size and diversity of the training data, leading to improved performance of the pest detection and identification model. The first stage uses YOLOv3 to detect region proposals, while the second stage uses Xception to classify the region proposals as either Phyllotretastriolata, Phyllotretaatra, or background. The proposed method is evaluated on a dataset of 30 high-resolution images for each species of insect pest. The findings indicate that the recommended strategy obtains an efficacy of 95% for both species.

D. Shah et al. (2022) The authors propose [5] a method to identify and categorize four types of pests found on soybean crops using deep convolutional neural networks (DCNN) and data augmentation techniques. The authors review several existing works that use different approaches for pest detection, such as transfer learning, feature extraction, and mobile applications, and compare their performance and accuracy. The authors describe the data set, the data augmentation process, the feature extraction in CNN, the pre-trained model ResNet-50, and the output classifier used in their proposed method. The authors present the results of their method on a data record of 1622 photos of diseased soybean leaves, and show that their method achieves a detection accuracy of 98.64%, which is significantly higher than other methods.

Suárez et al. (2021) This research [6] focuses on moth detection in real-world field conditions using a cloud-based system. The input image undergoes pre-processing (filtering, color balance, noise reduction) before object detection, which crops potential moth candidates. A DNN-based classifier then identifies the objects. If a moth is detected, a counter increases until a threshold is met, triggering a fumigation suggestion. The research highlights the challenges posed by real-world conditions like weather, lighting, and debris within the traps, which require careful image processing strategies for optimal accuracy.

K. R. B. Legaspi et al. (2021) This paper [7] presents a system for detecting whiteflies and fruit flies in images and videos using YOLO. The system was tested on a dataset of 1400 photos and achieved an 83.07% accuracy rate. Both whiteflies and fruit flies are detected with 100% precision by the system. This suggests that the system's optimistic predictions are correct. The method has 85.89% accuracy for whiteflies, 97.17% for fruit flies, and 83.07% for unknowns. The total precision stands at 83.07%. The precision of the system is far higher than the accuracy. Therefore, it has more difficulty obtaining all recognitions than executing accurate detections. This is especially noticeable when dealing with photos that has many bugs, particularly when they are stacked or very close to one another.

M. Lippi et al. (2021) The paper [8] proposes a method for detecting bugs in hazelnuts using the YOLOv4 object detection framework and data augmentation techniques. The YOLOv4 architecture consists of a backbone, a neck, and a head. The backbone network extracts meaningful features from image pixels, generating feature maps. The neck module then integrates feature maps from different scales, while the head component predicts the locations of objects (bounding boxes) and their corresponding class probabilities. The data augmentation techniques used in this study include color transformation, geometric transformation, mosaic augmentation, background blurring, and Gaussian noise. The proposed method demonstrates strong performance, achieving an average Intersection over Union (IoU) of 94.47%, a mean Average Precision (mAP) of 92.80%, and a processing speed of 6.3 frames per second (fps).

K. Prathima et al. (2021) The paper [9] proposes a plant disease detection system using convolutional neural networks (CNNs). The system is implemented on a Raspberry Pi and uses a VGG-16/VGG-19 pre-trained model to classify plant diseases. The authors gathered images dataset of diseased plants and used image augmentation to broaden the dataset's scope. They trained the model on this data and received 95% accuracy. The system also includes a pesticide sprayer that is activated when the model detects a disease. However, the paper does not include any experiments to test the performance of the system on real-world data. Overall, the paper proposes a promising plant disease detection system that has the ability to be used for practical purpose but, more study is needed to find how efficiently the system works on real-world data.

N. Mamdouh and A. Khattab (2021) The paper [10] provides a methodology for recognizing and quantifying olive fruit flies found in photos captured using intelligent pheromone traps. It is based on the YOLOv4 deep learning algorithm and is designed to be accurate and computationally efficient. The authors use a dataset of images of olive fruit flies and butterflies to train the model. They also use yellow mean color normalization to improve the model's performance. The results show that the framework is accurate and can detect olive fruit flies with a precision of 0.84 and a recall of 0.97. The writers also give a thorough description of the implementation of the framework. However, the paper does not include any experiments to test the framework's performance on real-world data.

C. Luo et al. (2023) The authors propose [11] a novel object-based image segmentation approach named OB-ViT designed to classify barley in remote sensing imagery. The proposed method first segments the remote-sensing images using the SLICO algorithm, generating superpixel items with comparable areas and forms. To match these objects with the ViT model's requirements, each superpixel must be transformed into a square image block, extracted with its centre of gravity as the centre. The recovered picture blocks and their respective superpixel feature coverage types are combined to generate the training data for a convolutional neural network, which includes both image data and labels, which then classifies the superpixels. Evaluated on a barley remote sensing dataset, this approach achieves an accuracy of 87.98%, surpassing the performance of existing semantic segmentation models.

M. Deserno and A. Briassouli (2021) This paper [12] presents two approaches for accurately identifying insects within the Yellow Sticky Traps dataset: Faster R-CNN Inception-ResNet-v2: This network achieves a weighted averaged accuracy of around 92.51% but is computationally expensive, requiring 4-5 days of training. EfficientNet: This network, particularly EfficientNet-B0, achieves comparable accuracy (98%+) at a significantly lower computational cost (3.2 hours of training). foreground objects are segmented using a threshold-based mask, followed by (2) classification of these segmented objects using EfficientNet. The original Yellow Sticky Traps dataset contained several issues, including incorrect annotations and missing labels. The authors have corrected these issues and made the corrected dataset publicly available. Faster R-CNN can achieve high accuracy for insect identification on the Yellow Sticky Traps dataset, but it is computationally expensive. EfficientNet offers a more efficient alternative, achieving comparable accuracy with significantly less training time. The threshold-based object segmentation method combined with EfficientNet classification can effectively identify insects, even with 100% confidence in some cases. The current approach generates false alarms by misclassifying other objects, like flies, as known insect classes. This can be addressed by adding a class for unknown objects in future work. Overall, this paper demonstrates the effectiveness of EfficientNet for accurate insect identification with reduced computational cost. This approach has potential applications in pest control, environmental monitoring, and agricultural research.

P. Ananthi et al. (2024) This study [13] explores the usage of deep learning techniques for identifying tomato leaf diseases. Three models, Densenet-169, Optimized Mobilenet-V2, and Resnet-50, were evaluated alongside an ensemble model combining all three. The ensemble model achieved the highest accuracy (99%) for disease classification, followed by Densenet-169 (98%), Resnet-50 (97%), and lastly Optimized Mobilenet-V2 (94%). The authors highlight that the effectiveness of these models can be influenced by several factors like dataset size and quality, chosen features, and computational parameters. In conclusion, this research suggests that an ensemble of deep learning models offers the most accurate approach for diagnosing tomato leaf diseases. However, it emphasizes the importance of considering factors that can impact model performance for real-world applications.

G. Boukhlifa and Y. Chibani (2024) This research [14] proposes a CNN-based Convolutional Autoencoder (CAE) model for identifying tomato diseases in controlled environments. The authors compare their model to existing methods, highlighting the trade-off between accuracy, model complexity, and resource requirements. While heavier models achieve higher accuracy (VGG16: 99.25%, Xception: 100%), they have significantly more parameters and require more memory. Lighter models (MobileNetV2: 90.30%) are faster and require less memory but have lower accuracy.The proposed CAE-based CNN model offers a balance between accuracy (99.13% average, 99.53% maximum) and efficiency (0.3 million parameters, 0.001 seconds inference time, 354.81MB memory usage). This makes it suitable for real-time applications on devices with limited resources.The study acknowledges challenges such as finding the optimal balance between accuracy and complexity and ensuring generalizability to other datasets and real-world conditions with higher variability in disease symptoms. Future research include evaluating model on various crops and datasets to develop a standardized solution for disease identification across different agricultural scenarios.

D. Soni et al. (2024) This research [15] paper tackles the issue of castor leaf disease detection in India, which significantly impacts farmers' income and livelihoods. The authors propose a real-time system using deep learning and YOLO object detection models to classify three main castor leaf diseases: Leaf spot, Wilt, and Alternaria blight. The paper's key contribution lies in the creation of a custom dataset of castor leaf images, including drone footage, which was manually labeled for training. They then compared the performance of YOLOv5, YOLOv7, and YOLOv8 on this dataset, finding that YOLOv8 outperformed the others in terms of mean average precision (mAP), precision, recall. The best performing model, YOLOv8, was deployed on the Xilinx Kria KV260 FPGA for real-time inference, demonstrating the feasibility of deploying such systems on edge AI devices. The results show that YOLOv8 achieved an impressive mAP of 92% on the custom dataset, indicating high accuracy in disease detection. The system was successfully tested on real-time images captured from a castor farm using a drone, confirming its practicality in field settings. The paper's significance lies in its potential to provide a useful tool for Indian farmers, enabling early identification of castor illness and potentially mitigating crop losses. Deploying the system on edge AI devices like the Kria KV260 makes it readily deployable in the field, without requiring constant internet connectivity. While the paper presents a promising solution, some limitations should be noted. For instance, the dataset was manually labeled, which can be arduous and lengthy process. Additionally, the paper provides limited details on the drone data collection process. Overall, this research offers a valuable contribution to the field of agricultural technology by utilizing advanced machine learning techniques and edge AI deployment for practical applications in real-world settings.

MOGILICHARLA S et al. (2024) This study [16] emphasizes the importance of accurate rice disease and pest identification for better agricultural management. The research explores using pre-trained models (like ResNet-50) alongside machine learning techniques (SVM, PCA) to achieve high classification accuracy (Model-2: 93.7%). This approach leverages the power of pre-trained models with refined feature sets through PCA, leading to potential benefits in both accuracy and model efficiency. These findings contribute to advancements in agricultural technology and address practical limitations like scalability and resource constraints. Future research directions include exploring pre-trained models further, integrating additional data sources (weather, soil), and investigating segmentation/object detection algorithms for even more robust disease and pest classification in rice cultivation.

SrinuBanothu et al. (2024) This study [17] investigates transfer learning for herb disease classification. The authors compared various pre-trained convolutional neural networks (VGG-16, Inception V4, ResNet-50, DenseNet-121) and found DenseNet-121 to outperform the others in terms of accuracy (92.81%), precision, sensitivity, specificity, and F1 score. They attribute this to DenseNet-121's simpler architecture and fewer trainable parameters, making it easier to train and potentially well-suited for incorporating new plant diseases into the model with less retraining complexity.

Table 1: Comparative analysis of deep learning models utilized for crop disease prediction.

Article No	Crop	Pests and Disease name	No of Images	Algorithm used	Accuracy
1	Castor	Castor semi looper, Bihar hairy caterpillar, leafhopper, thrips, whitefly,leaf miner. Leaf spot, Wilt, Alternaria blight	5916	VGG16 VGG19 ResNet50 YOLOv5 YOLOv7 YOLOv8	82.182% 76.713% 78.296% 85.7% 88.6% 92.1%
2	Paddy	Brown spot, Bacterial Leaf Blight, Leaf Smut,	8000	15-layer CNN	95 %
4	Cruciferae	Phyllotretastriolata,Phyllotretaatra	12000 4000	YOLOv3 Xception	77%
5	Soyabean	Eocanthecona bug A-1185, Larva Spodoptera D-634, Red hairy caterpillar C-998, Tobacco Caterpillar B-980	3202	ResNet 50	96.25%
6	Fruit crop	Moth, pheromonelure	16500	CNN	94.8%
7	Fruit crop	WhiteFlies, Fruit Flies	1400	YOLOv3	83.07
8	Hazelnut	Halyomorphahalys, Gonocerusacuteangulatus, Palomenaprasina	611	YOLOv4	94.5%
10	Olive ruit	Olive fruit flies	11872	YOLO	92.5%
11	Tomato	Leaf Mold, Early blight, Target Spot, Late Blight, Bacterial Spot, Septoria Leaf Spot, Mosaic Virus, Two Spotted Spider Mites, Yello Leaf Curl Virus	-	Optimized Mobilenet-V2, Resnet50, Densenet-169, Ensemble(all 3 combined) CNN-CAE	95% 96% 98% 99% 99.13%

CONCLUSION

Crop pests and disease detection is crucial for enhancing crop yields and supporting farmers. Advanced technologies, particularly robust algorithms, have emerged to effectively identify crop damage caused by pests and diseases. This review delves into segmentation algorithms, pre-processing techniques, and classification algorithms for pest and disease prediction. Various crops, including rice, castor, hazelnut, and olive fruit, were examined to determine the most effective algorithms. CNN emerged as the superior algorithm, achieving the highest accuracy and outperforming other algorithms in various performance metrics. Across all reviewed studies, RGB image datasets were utilized for pest and disease prediction in precision agriculture. Future research directions include the accumulation of hyperspectral and multispectral image datasets for pest and disease prediction, along with addressing other challenges in agriculture. We anticipate that this work will significantly benefit farming communities and foster further research advancements in cutting-edge technologies.

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