A Systematic Literature Review on CNN-Based Deep Learning Models for Plant Disease Detection and Classification to Enhance Agricultural Productivity

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Abstract. Deep Learning is a specialized subset of computer vision and artificial intelligence and is applicable to the domain of automatic learning process. Deep learning deals with the high-dimensional data processing like text, image, and video. More Over CNN or Convolutional neural networks, one of the deep learning techniques become a mainstream in Agriculture domain while identifying the plant diseases and also segmenting the disease spots. This will help to maximize the production and minimize the yield loss because the diseases can be identified early on the plant images. By using CNN, identification, segmentation and classification of different disease classes was performed more efficiently. In this study, we have suggested a novel nn architecture that we used to accomplish the classification problem. The proposed approach is constructed from scratch and enhanced the learning procedure to create more precise classification applications. The new model recognizes and classifies several diseases in 10 diverse plants, including potato, soybean, tomato, peach, corn, grape, orange, pawpaw, custard apple, and banana, and it is trained and tested from the scratch. The initial step is the feed-forwarding learning process of the model using the datasets extracted through such online repositories as Plant Village. Secondly, the performance of the proposed model is verified over the plant images captured in the agriculture fields. These classification accuracies are then improved by a fine-tuning process such as back propagation. Then the performance of the suggested model is compared by according to validation and verification with the current and pre-trained models. The Results of the research where by using this work, we can eliminate the manual way of identifying the disease and traditional way of selecting the disease spots.

Keywords: Artificial Intelligence, Computer Vision, Convolutional Neural Networks, Deep Learning, Image Recognition, Image Segmentation, Image Classification.

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1 Introduction

DL and CV have revolutionized various industries and have provided novel solutions for plant classification and disease detection in agriculture as well. Plant health identification and monitoring between others is highly important for agricultural productivity and minimizing the environmental impact of pesticides. The existing methods for identifying plant diseases are largely subjective, labour intensive and susceptible to human error as they mostly rely on the manual inspection of the plants. To tackle these issues, researchers have adopted deep learning techniques like those obtained from convolutional neural networks (CNNs), given their power to analyse image data and their recognition capability of identifying complex patterns.

This review presents a comprehensive survey of D_LT-based models designed to diagnose plant diseases, while addressing their potential, drawbacks, and real-world applicability. Classifications of plant species and disease detection have been performed using various CNN architectures including AlexNet, VGG, ResNet, GoogLeNet, and MobileNet on various datasets like the widely used PlantVillage dataset and real world agricultural images. These models get affected by several aspects like quality of dataset A, annotation of dataset B, along with the inherent nature of the diseases, and understanding these aspects is essential to implement a practical deployment within an agricultural field.

2 Literature review

The literature review section provides a summary of the potential deep learning based systems that are used for plant classification and disease detection.

Studies Done: Crop Classification using CNN Models on Open Dataset. Models that achieved good results were AlexNet, VGG, OverFeat, AlexNetOWTBn, GoogLeNet. Another two went on to be tested and trained on real images [1,2]. Using pre-trained models as baseline with dataset-specific target becomes baseline for comparison, results showed that these models performed poorly compared to their pre-trained versions. They also outperformed their laboratory peers when compared. Further target value is presented to the performance corresponding to the maximum success rate obtained from VGG at 99.53 percent.

The CNN model used in this study were ResNet 50 and ResNet50 +the one having aggregated non-image contextual information. They were evaluated and trained on a hundred-thousand real-world images with seventeen different diseases. The models were then validated and retrained on the actual data. The models had good performance on the huge datasets with different cropsand divided the data for different crops. The researchers suggested the use of CNN models as an object detection framework, including VGG16, ResNet50, and other CNN models, to build a model capable of diagnosing plant diseases.
e.g. Mask R- CNN and Fast R-CN [3].

Tools used for object detection included Fast R-CNN and LabelMe, among others, which were also used by the researchers alongside the models. Although the ResNet50 gave the best detection rate, it needed a lot of training and testing time to do well. The MobileNet was not as accurate as the ResNet101. The researchers

concluded that the best plant disease detection model had to do with the scenario it was embedded in (i.e., which model worked better with which scenario). But they also found several factors that could limit the model's performance. These entail the datasets utilized in the investigation and the inherent characteristics of the illnesses [4].

The researchers recognized issues associated with this dataset such as covariate shift, capture conditions, and annotations. On the other hand, the evidence related to the differential factors affecting model performance were the differences in symptoms, system division as well as comorbidities. If they are not treated accurately there is a chance to impact the model performance. For example, in one study, researchers used CNN model to recognize plant diseases affecting tomatoes, grapes and apples. They have also adopted an augmentation strategy on the data set to keep the classification balanced [5].

The researchers developed an algorithm to identify plant edge images automatically by edge detection from an input image using a Canny detector and then classify the result from six classes into the background and plant edge. They then subtype these into three types: leaf edge, internal image noise, plant edge. For edge-based segmentation for the leaf image [6], they leveraged region-based segmentation. CNN with the background segmentation can use a binary classification approach. They also provided a list of deep learning models that have been applied in practice for the detection of crop diseases. They then classified the models into visualizers (visual techniques) or non-visualizers (non-visual techniques)[7].

An integrated optimization algorithm called the whale optimization (WOA) is used to develop a deep learning architecture to classify the types of tomato plant diseases. Our method is evaluated on the PlantVillage dataset. The researchers first transformed the categorical data of the images to binary digits using the one-hot encoding process. After that, they applied PCA to reduce the dimensions of the input data and for the forecast selected the most appropriate features [8]. Through hyperparameter tuning the researchers performed a grid search algorithm to improve the efficiency of the model. Afterward, using the ResNet50 framework, the noise and augmentation of the collected data were carried out to form a large dataset to increase the performance of the system [9].

The model can classify tomato plant diseases by deciding if the leaf is healthy or unhealthy. The plants are divided into two stages: the first stage will include healthy plants, and the second stage will include unhealthy plants. In this research, three CNN models were utilized such as Inception V3, AlexNet and SqueezeNet. The model was able to classify late blight disease in the early, middle and end growing stages of the plant [10]. The researchers used three methodologies to enhance model performance on the road: feature extraction, transfer learning, and multi-class reinforcement training. They were evaluated on several metrics including recall, accuracy, and mean F1 score [11].

The researchers then proposed a generic form of the model that makes use of ResNet50 base. The model was able to identify the types of tomato plants diseases present by checking if the leaf is healthy or unhealthy. The model was also able to apply a measure of disease severity based upon the relative damage that the disease has done to the plant as a whole. In this work, the researchers assessed the

performance of the different models and devised binary classification system specifically for healthy and sick leaves. They utilized various outputs and compared and trained the models The outcome of this study showed that the model with a binary class did a better job of identifying which leaves are diseased and healthy.

One standardized measure of severity based on proportional damage might work well for more or less localized and discrete symptoms caused by plant pathogenic bacteria and fungi. Leaf curl chlorosis and stunting viral symptoms can not be detected. They later introduced a comprehensive attention mechanism for tomato disease detection using a CNN learning framework. Its ability to focus on features in a specific context allowed it to outrun its generic model [12].

Next, the researchers used SoftMax classifier for the classification of input images. Then, three CNN models were compared regarding their performance on the PlantVillage dataset. The baseline model gives an accuracy of 84%, residual model gives 97% accuracy, and attention-embedded model gives 98% accuracy [13]. Four CNN models of various architectures were examined for the detection of tomato plant diseases. They were validated on two different datasets: a lab and a field dataset. Model performance on accuracy, precision, recall, and F1 score was tested using a 10-fold cross validation method.

The results indicated that for defence, the models accurately deployed to identify tomato plant diseases in lab settings. The most accurate model out of the four models, achieved an accuracy of 99.6% was Inception V3. Then, a CNN application was applied to feature extraction and segmentation of tomato plant leaves. Then, it classified the data into two classes: Healthy leaves and Diseased leaves [14]. The CNN model performed better than ANN and AlexNet when it came to detecting tomato ailing plants and the researchers concluded the same. The models were trained and evaluated on PlantVillage dataset using three different algorithms. These include VGG16, GoogLeNet, and Inception V 3 [15]. The findings showed that was more precise for detecting common diseases on previously unseen images than with a disease-crop strategy.

The researchers proposed a deep learning architecture made of eight models B0 to B7, to increase the accuracy of classification. Disease detection and classification is done on PlantVillage dataset. The proposed model utilizes a new activation function called Swish [16], which was compared with other models [16]. Performance of the model was assessed using multiple parameters including accuracy, specificity, sensitivity and precision. The B5 and B4 models, which performed well, were able to achieve a combined accuracy of 99.39% on augmented and original datasets [17].

After splitting the data, a CNN model was used for classification and disease detection on the Plant Village dataset. For the comparison against pre- trained models, including MobileNet, VGG16, and Inception, the researchers tested the model on nine diseases. For this purpose, the proposed model achieved 91.2% accuracy [18]. In this study, the researchers examined the efficacy of two different segmentation schemes on a real-time image dataset. They collected U-Net and remodified its encoder stages according to the output. Subsequently, the researchers conducted disease feature extraction using KijaniNet [19].
In comparison with other pre-trained models and databases such as KijaniNet outperformed SegNet and U-Net for plant disease detection. Researchers employed

region-based segmentation to detect and classify different types of diseases present in grape plant leaf images. After that, this strategy helped them train and assess a CNN model. After a detailed examination of the existing classification and disease identification techniques available in the literature, the authors outlined several key issues that require attention in order to increase the efficacy of deep learning models in this domain. In addition, we cover the variables influence this classification and identification step of plant diseases.

This study utilized different classifiers in separate instances and evaluated their performance measures, which can differ depending on model choice and size. The majority of studies were using laboratory- conditioned image datasets, e.g., the PlantVillage dataset. Note that the images used for the training and testing were not from real life [20]. Segmentation and background removal of the plant diseases from the images is one of the most important factors that need to be considered regarding the performance of deep learning models [21]. Deep learning models can also be used to regulate the use of pesticides by estimating infected area and the level of disease [22].

But it is not always so easy to know whether a plant is infected or if it suffers nutrient and chemical mineral deficiencies [23]. Hence, early detection of plant diseases is very crucial. This process

Generous watering (usually with clean water, but see below) can help stop the spread of the disease and restore the plant's health [24]. It is also important to study the efficiency of a deep learning model in tracing and recognizing real-time medicates disease [25]. Plant diseases typically do not adhere to international borders. This impedes the models to differentiate between sick and healthy parts of the plant [26].

The presence of separate diseases could also complicate the distinction between these diseases from each other and create hybrid symptoms, which is the occurrence of various diseases on a single leaf [27]. Besides these, numerous factors like hyperparameter tuning may alter the performance of the DL systems [28]. Various factors play a vital role that impact classification and detection performance of computer vision-based systems for plant diseases. Such as images acquisition, prepr-processing, and lesion segmentation [29]. The deep learning model generally performs better when plant diseases are homogeneous in their attributes, thus the selection of suitable features is one of the reasons affecting the accuracy of the results [30].

DL (Deep Learning) and ML (Machine Learning) in the plant disease detection has been a trending areas. These methods can be utilized to determine the precise plant diseases in digital images. In this field, conventional ways like classification dealing or feature extraction are generally utilized. For training a classifier on classification-based models, these methods extract multiple features from the input images like their color, texture, and shape. These methods are routinely used to diagnose different plant diseases like (powdery mildew, leaf blotch, and rust). However, they do not allow to truly characterize the symptoms of the diseases and precursors of their development. They cannot also process high- resolution images properly [31].

Convolutional Neural Networks (CNNs) or Deep Belief Networks (DBNs) are examples of deep learning methods that can potentially be used to detect plant

diseases [32]. These modalities require networks to learn the characteristics of images so that they can capture small signs of some diseases [33,34]. Despite the capability of DL models to deal with high volume large size complex images, large amount of training data and computational cost might not fit such unseen diseases cases [35]. CNNs and DBNs could diagnose plant disorder and diseases in digital images according to Sharma et al., 2021; Kaur et al., 2021; Siddiqua et al., 2021. In 2022, Wang et al also found these technologies identified the presence of lesions through images as well [36- 38].

DL models, using deep learning techniques, are capable of learning over the images and identifying the subtle features of the diseases abstracted by traditional techniques. While this type of tech needs lots of training data to thrive, it can still deal with many layers of complexity in an image. Computer vision, or CV, an artificial intelligence technology, can be used to identify and localize features present in an image, such as the plant leaves or appearance of diseases [39-40]. It can therefore be quickly converted into images that Algorithms can easily identify. They could also be coupled with deep learning or ML algorithms in order to classify and detect images. Table 1 show the Overview of Deep Learning Techniques for Plant Disease Identification.

Table 1. Overview of Deep Learning Techniques for Plant Disease Identification.

Author(s)	Year	Algorithm	Detected Plants/Diseases	Outcome
[1][2]	2018 2019	AlexNet,VGG, OverFeat, AlexNetOWTBn, GoogLeNet	Various crops	VGG achieved the highest success rate of 99.53% on distinguishing crop types in lab images; real-world performance was lower compared to pre-trained models.
[3]	2019	ResNet50, ResNet50 (contextual info), VGG16, Mask R-CNN, Fast R-CNN	Multiple crops and 17 diseases	ResNet50 excelled in detection rates but required significant training time; contextual data improved model robustness for various crops.
[4]	2018	MobileNet, ResNet101	General plant diseases	MobileNet was less precise; dataset quality, annotations, and

				disease complexity affected model performance.
[5]	2019	CNN with dataset augmentation	Tomatoes, grapes, apples	Augmented datasets improved classification balance; intrinsic symptoms of diseases influenced model outcomes.
[6][7]	2019	Canny edge detector, CNN with binary classification	General plant images	Region-based segmentation enhanced disease detection; background removal and edge detection optimized plant leaf classification.
[8][9]	2020 2021	Whale optimization algorithm, ResNet50	Tomato diseases (e.g., bacterial spots, fungal infections)	PCA for dimensionality reduction and ResNet50-based framework improved disease classification accuracy.
[10][11]	2020	Inception V3, AlexNet, SqueezeNet	Tomato diseases (e.g., late blight)	Inception V3 achieved 99.6% accuracy; transfer learning and multi-class reinforcement improved performance.
[12]	2020	ResNet50 with attention mechanism	Tomato diseases	Attention-based model outperformed generic models, especially for context-relevant features.
[13]	2020	SoftMax classifier, residual model, attention-embedded model	Tomato diseases	Accuracy ranged from 84% (baseline) to 98% (attention-embedded

				model); best performance in controlled lab settings.
[14][15]	2020	VGG16, GoogLeNet, Inception V3	Tomato diseases	Models identified diseases with high accuracy on unseen images; VGG16, GoogLeNet, and Inception V3 proved robust for lab datasets.
[16][17]	2021	B0–B7 deep learning models, Swish activation mechanism	General plant diseases	Models B5 and B4 achieved 99.39% accuracy using augmented datasets; Swish activation improved classification.
[18][19]	2020 2021	U-Net, KijaniNet	Grape diseases	KijaniNet outperformed U-Net and SegNet for disease feature extraction; segmentation schemes tailored for real-time images.
[20][21]	2020	CNN-based segmentation	General plant diseases	Background removal and image preprocessing identified key disease regions effectively.
[22][23]	2020 2016	CNN with lesion estimation	General plant diseases	Identified diseased areas and estimated severity for better pesticide control; struggled with nutrient deficiencies and viral symptoms.

[24][25][26]	2021 2020 2019	CNN with disease boundary detection	General plant diseases	Difficulty in detecting diseases without clear boundaries or with hybrid symptoms.
[27][28][29]	2021 2016	Hyperparameter-tuned CNN	General plant diseases	Segmentation, lesion fragmentation, and attribute selection enhanced accuracy.
[30][31][32]	2020 2021	CNN, DBN	Powdery mildew, leaf blotch, rust	Traditional feature extraction insufficient for early-stage symptoms; DL models effectively handled complex and high-resolution images.
[33][34][35]	2021 2022	CNN, DBN	General plant diseases	Identified lesions and abnormalities in digital images; computational costs remained high for large datasets.
[36][37][38]	2021 2022	CNN, computer vision	General plant diseases	Integrated CV with DL improved plant disease localization and classification; performed well on subtle disease symptoms.

3 Results and Discussions

Deep learning (DL)-based systems for plant classification and disease detection are analysed in this study and the use of CNN architectures universal are recognized including AlexNet, VGG, ResNet50, GoogLeNet, Inception V3, and MobileNet, incorporating unique aspects that increase their performance Free/air surprise, whale optimization, and Swish activation However, despite achieving impressive accuracies (up to 99.6% accuracy with VGG and Inception V3) when evaluated in controlled

environments, the models trained on datasets like PlantVillage demonstrated poor effectiveness when used to classify images from the real world owing to variability in the environment and the datasets used. Segmentation-based methods as KijaniNet and U-Net enhanced disease feature extraction but their reliability was tainted by aspects such as symptom variability, annotation quality and high computational demands. Despite these limitations, DL models encompass a great promise for estimating disease severity, reducing pesticide application or enabling real time monitoring, but adapting to complex real-world scenarios represents an urgent area of development.

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