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A Survey of Deep Learning Techniques for Maize Leaf Disease Detection: Trends from 2016 to 2021 and Future Perspectives

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Abstract

Background and Objectives: To a large extent, low production of maize can be attributed to diseases and pests. Accurate, fast, and early detection of maize plant disease is critical for efficient maize production. Early detection of a disease enables growers, breeders and researchers to effectively apply the appropriate controlled measures to mitigate the disease's effects. Unfortunately, the lack of expertise in this area and the cost involved often result in an incorrect diagnosis of maize plant diseases which can cause significant economic loss. Over the years, there have been many techniques that have been developed for the detection of plant diseases. In recent years, computer-aided methods, especially Machine learning (ML) techniques combined with crop images (image-based phenotyping), have become dominant for plant disease detection. Deep learning techniques (DL) have demonstrated high accuracies of performing complex cognitive tasks like humans among machine learning approaches. This paper aims at presenting a comprehensive review of state-of-the-art DL techniques used for detecting disease in the leaves of maize.
Methods: In achieving the aims of this paper, we divided the methodology into two main sections; Article Selection and Detailed review of selected articles. An algorithm was used in selecting the state-of-the-art DL techniques for maize disease detection spanning from 2016 to 2021. Each selected article is then reviewed in detail taking into considerations the DL technique, dataset used, strengths and limitations of each technique.
Results: DL techniques have demonstrated high accuracies in maize disease detection. It was revealed that transfer learning reduces training time and improves the accuracies of models. Models trained with images taking from a controlled environment (single leaves) perform poorly when deployed in the field where there are several leaves. Two-stage object detection models show superior performance when deployed in the field.
Conclusion: From the results, lack of experts to annotate accurately, Model architecture, hyperparameter tuning, and training resources are some of the challenges facing maize leaf disease detection. DL techniques based on two-stage object detection algorithms are best suited for several plant leaves and complex backgrounds images.

Introduction

The importance of maize production cannot be overemphasized. Maize is ranked among the most heavily grown and consumed cereals in the world [1],

[2]. However, the contributions of maize to people's economic well-being are hindered by disease-ridden crops that affect the yield, thus reducing income and affecting food security. It is estimated that about 14 million tonnes of maize were lost to Northern leaf Blight (NLB) in the United States between 2012 and 2015, which translates to about $1.9 billion [3]. The gravity of the situation warrants those efficient measures to control or mitigate any threat that may hamper the growth and production of maize are found. These control or mitigation strategies must be proposed to ensure food security globally.

In the hope to mitigate disease infestation on maize fields, preventive techniques need to be employed. Nevertheless, plant diseases can still strike even when all preventive protocols are in force. Therefore, it is imperative to know that an accurate diagnosis of a disease is an essential first step to timely control plant diseases. Plant diseases have long been studied. There are well-established control mechanisms for controlling plant disease, that is if they are detected early enough. The timely diagnosis and classification of plant diseases is a critical aspect in preventing yield loss and improving product quality [4], [5]. A relevant characteristic of a sound disease detection system will be its ability to identify early signs and symptoms of the disease. Notably, the system must include containment strategies that prevent or limit the disease spread once it is detected [6]. Plant disease phenotyping is one crucial process that allows early detection of a particular kind of plant diseases, enabling growers, breeders, and researchers to effectively apply the appropriate control measures to mitigate the disease's effects.

Plant phenotyping in the past involved human experts visually inspecting diseased plants to observe defects in various parts of the plant: leaves, stems, roots, in other to predict the presence of a particular kind of disease [4]. This detection technique by human experts is often time-consuming, subject to erroneous decisions, and impractical for largescale fields [7], [8]. Microscopic evaluation of morphology features like spores, mycelium to identify pathogens is another plant disease detection technique in literature [9]. Computer vision and machine learning can solve these issues by enabling high accuracy and scalable plant phenotyping. Recent techniques have focused on using automated systems to detect plant diseases in agriculture accurately. Computer-aided methods combined with crop images (image-based phenotyping) have become very dominant for plant disease detection [10]. Numerous image-based plant disease detection techniques have been developed, which shows better accuracy and precision than visual inspection [8]. Machine learning (ML) has been applied to many computer vision problems, including face recognition, speech processing, and disease tissue classification in medicine. The success of ML techniques is as a result of their ability to identify a hierarchy of features and generalized trends from available data [11].

In narrowing down on machine learning approaches, deep learning techniques have demonstrated high accuracies of performing complex cognitive tasks like humans [7]. Deep Learning (DL) is the state-of-the-art ML approach widely used to address problems in health care, agriculture, audio and speech processing [12]. Convolutional Neural Networks (CNNs) are state-of-the-art deep learning algorithms used to address computer vision problems recently, especially image classification tasks. Traditional ML approaches require a manual selection of features that are thought to be helpful in a classification task. However, CNNs can learn which features are most important and which are not. The usage of DL in agriculture and plant disease detection have proven to give very high accuracies enabling better agriculture and crop management quality [13].

This survey aims to present a comprehensive review of state-of-the-art deep learning techniques used for detecting disease in the leaves of maize. The survey documents all relevant proposals in the domain to enable readers to understand maize disease detection using deep learning methods proposed from 2016 to 2021. Most recent survey papers mainly focus on plant disease detection. Which encompasses many plants and not necessarily maize thus do not provide an in-depth discourse of the subject matter. This paper will act as a primary source for discussing maize leaf disease detection using deep learning methods to the best of our knowledge. The paper details concepts, approaches, available datasets, and the strengths or shortfalls of DL techniques for maize leaf disease detection.

The remainder of the paper is organized as follows. Next Section discusses the concept of deep learning, transfer learning and highlights some plant leaf disease datasets. In third Section, the methodology used in acquiring the candidate papers for review have been highlighted and detailed review of deep learning-based proposals for maize leaf disease detection is outlined. Open issues and future research directions are provided in fourth Section. Conclusions are made fifth Section.

Deep Learning and Plant Leaf Disease Datasets

This section discusses the concept of deep learning. It also elucidates some models that have been adopted for transfer learning. Finally, the section provides dataset used in the design of plant leaf disease detection to serve as a primer for new researchers in the field.

A. Deep Learning

Deep learning is recently gaining popularity and momentum because of its success in various applications. Deep learning is a sub-field of machine learning. It extends classical Machine learning by adding more depth (layers) to a model. Successive layered learning or a hierarchical way of representing data abstractly emphasizes deep learning. Deep learning does not mean any more profound understanding for using this approach. Instead, it refers to the successive layers of representation. The depth of the model is characterized by the number of layers in the model [14]. Modern deep learning approaches consist of tens or even hundreds of successive layers for data representation. All these layers learn automatically from data. These layers learn through neural networks models; the layers are stacked on top of each other. Figure 1 illustrates the basic layered structure of a deep learning model [15].

B. Convolutional Neural Networks

Convolutional neural networks have become very dominant in the field of deep learning and are the approach used for visual object recognition and other computer vision problems. CNN was first introduced over twenty years ago. However, they have become widely used today due to improvements in hardware and the development of very deep CNNs. CNNs are not only applied to images but show better results in speech recognition, and natural language processing problems [16]. Convolution is the essential operation of a convolutional neural network (CNN). This convolution operation is achieved by applying filters (also known as kernels) to input data, mostly an image. Convolutional filters are composed of two-dimensional matrices of real values: the dimensions of a filter are smaller than the dimensions of the input data used in training. The aim of convolution operations is to extract features from an input image and thereby preserving the spatial relationship between pixels [17].

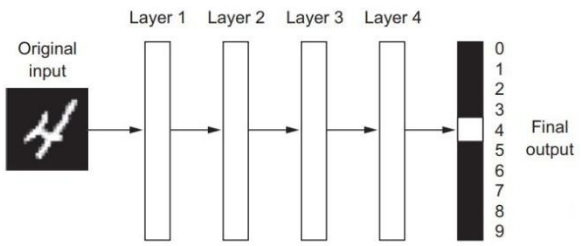

Fig. 1: Example of digit classification using deep learning [15].

A standard convolutional neural network structure comprises several essential building blocks that represent the layers of the network. The number of layers and combinations of building blocks varies depending on the architecture. Fig. 2 represent a standard convolutional neural network which consists of convolutional layers (Conv layers) classification layer (Softmax layer), fully-connected layers (FC layers), and compression layers (Pool layers) [18].

Feature maps (output) from previous layers are convolved with distinct filters and a scalar product is calculated over the entire length and the width of the given filter. The output of the filters is then pass through either a linear or most of the time a non-linear function [19]. It is very important to select good kernels to be able to capture salient and important information from the data. This allows for strong inferences about the content of the input data [20]. The result of the convolution operation is the output feature maps which the filters find.

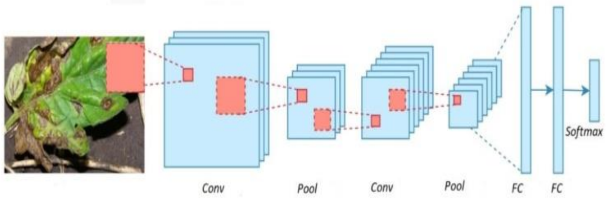

Fig. 2: CNN for plant disease detection [18].

The compression layer is a filter that non-linearly reduces the number of pixels, or compresses image dimension (down-sampling). This filter does not contain learned weights. The pooling layer's is responsible for secondary feature extraction by reducing the dimensions of the feature maps. It also increases the robustness of feature extraction.

For convolutional neural networks there is normally one or two fully-connected layers used as classifiers. All neurons in this layer are connected to all neurons in the previous layer. There is a last fully-connected layer before the output layer. In classification problems, the output of the convolutional neural network is reduced to activation function, the most commonly used function is Softmax. This is because it generates a well-performed distribution of the outputs. Support vector machines (SVM) can also be combined with CNNs for classification problems.

Activation functions play a very important role in the success of training deep neural networks. The role of activation function is to "mimic" the behaviour of a biological neuron by deciding if a neuron should turn off or on. Most commonly used and successful activation function is the Rectifier linear unit (ReLU). ReLu is very simple and effective and has become the default activation function used in deep learning. Other activations functions have been proposed to replace ReLu but the performance improvements tend to be inconsistence with different models and datasets. Other derivatives of ReLu are: Parametric ReLu (PReLu), Exponential linear unit (ELU) and Leaky ReLu (LReLu).

C. Modern Architectures and Transfer Learning

Deep learning algorithms, unlike typical machine learning algorithms, can automatically extract features either through semi-supervised or unsupervised learning and attempt to learn high-level features from huge amounts of data. One challenge about deep learning is the massive dependency on data because it needs large data to better understand patterns in data [21].

Transfer learning uses knowledge from a source domain to improve the learning ability of a target domain by transferring information between the two domains. One important requirement that will enable successful knowledge transfer is that both the source and target domains should be related closely [22]. Transfer learning is needed where there is limited amount of targeted training data: this may as result of expensive data collection and labelling, data being rear or data being inaccessible. Transfer learning has been applied successfully in many applications including image classification, software defect classification, text sentiment classification [21].

As early as 2012, deep neural networks were achieving significant results in tasks classification and detection of objects over large image datasets. For example, in the likes of the ImageNet (ImageNet Large Scale Visual Recognition Challenge) competitions. ImageNet image dataset has more than 20; 000 categories (classes) with over 80 million images. From 2012 to 2017, when the last competition was held, the winning architects were convolutional neural networks. It was the first time a deep learning technique, i.e., convolutional neural networks, showed a significant improvement over previous results obtained by standard machine learn ing techniques and manual processing of features. Over time, these architects have become more successful than man himself in tasks classifications and detection over the ImageNet image dataset. Thus, these architectures have become standard architectures that have proven successful not only over the ImageNet dataset but on significantly wider range of problems. This is ensured through the tech- niques of transfer learning or as a basis or idea for new architectures. Some of these modern architectures include: GoogleNet [23], AlexNet [24], ResNet [25], and VGGNet [26], DenseNet [27], EfficientNet [28] etc.

D. Datasets

Automated diagnosis and identification of plant diseases may allow for more rapid advances in plant breeding as well as easier monitoring of farmers' fields. However, given the multiple differences in lighting and direction, it is challenging for a simple algorithm to differentiate between the specific disease and other causes of dead plant tissue in a normal field. A vast amount of high-quality human-generated training data is required to train a machine learning system to accurately detect a certain disease from photographs obtained in the field. Therefore, datasets become an integral part of any machine leaning algorithm, because the amount and quality of the dataset goes a long way to affect the performance of an algorithm. This section of the review takes a look at some available datasets for plants disease detection.

The largest public database of leaf images is PlantVillage, [29]. collected and maintained by a non - profit project run by Penn State University in United States and EPFL in Switzerland. The database consists of 54309 pictures, of 14 types of plants, divided into 38 classes (healthy and diseased leaves). These, however, were captured with detached leaves on a simple background, and CNNs trained on them can't perform well on field photos. Fig. 3 shows examples of images from each class of the PlantVillage dataset.

Fig. 3: Sample images of from PlantVillage dataset [29].

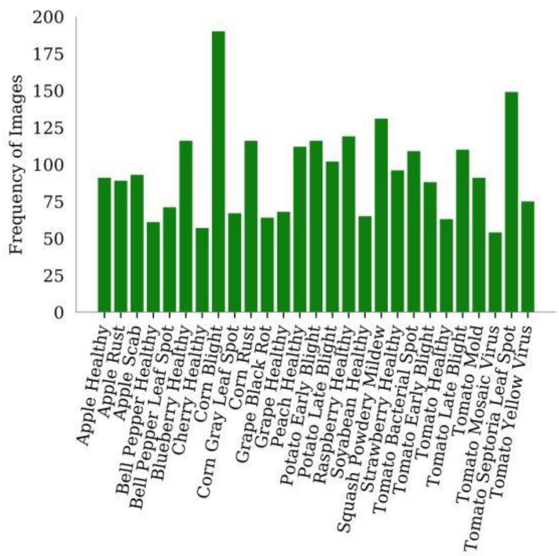

Fig. 4: Statistics from the PlantDoc dataset [30].

PlantDoc by Singh et al. [30] contains 2; 598 data points in total over 27 classes; 17 diseases and 10 healthy classes the dataset authors purport that

PlantDoc is a first of its kind that contains non-controlled image settings. This is envisaged to enhance performance of trained models used in practical real-life applications. Fig. 4 shows statistics of the PlantDoc dataset with a sizeable maize content

The dataset by Wiesner-Hanks et al. [31] is made up of full images of maize leaves shot in three different ways: using a handheld camera which produced 1787 images with 7669 annotations, camera mounted on a boom consisting of 8766 images with 55; 919 annotations and those pictures taken by a drone which is made up of 7669 images with 42; 117 annotations. There is no way to indicate the confidence of annotations. Some lesions are easily visible, which others are partially or entirely occluded from the focal plane. Other factors affecting the confidence of annotation are a heavy shade or being washed out by bright sunlight. It was reported that even experts found it difficult to distinguish between NLB and similar-looking diseases. The generalizability of the data is affected since image samples were taken in a single field in New York State. However, symptoms of the same disease can present or develop differently. Thus, the performance is hindered by the limitations mentioned earlier.

Since popular datasets cut across multiple plant leaves, the CMLD dataset [32] on the other hand, combines PlantVillage and PlantDoc maize or corn related data points to form a new dataset. Unrelated data samples were ignored in the creation of this new hybrid dataset. CMLD contains 4188 data points in total. The distributions are 1306 images for common rust, 574 images for grey leaf spot, 1146 images for blight, and 1162 healthy images.

Existing Deep Learning-based Proposals for Detecting Maize Leaf Disease

A. Methodology for Selecting State-of-the-Art Models

Following research works done by [33]-[35] a search was done in the following databases: IEEE Xplore, Scopus, ResearchGate, and Google Scholar. The keywords used in searching for articles were: “plant leaf disease detection”, “Maize leaf disease detection”, and “deep learning-based maize leaf detection”. The year range was limited to 2016 - 2021. The procedure for selecting the existing candidate works for this study is presented in Algorithm 1. The search results in IEEE Xplore using the keys words shows that in 2018, 77 research papers were published. Out of these three were for maize leaf diseases detection and none for Deep learning techniques for maize leaf detection There was an increase in the number of conducted research in the years 2019 and 2020. The publications for 2019 and 2020 were 148 and 208, respectively. This shows the growing interest in plant leaf disease detection and the desire to maximize gains in agriculture. However, the number of publications involving maize leaf disease detection remains at three. Deep learning techniques for maize leaf detection in 2019 and 2020 were one and two, respectively, in the IEEE Xplore. As of July 2021, there were 91 publications, with only one involving maize leaf detection using deep learning techniques.

Algorithm 1: Article Selection for the Survey

```
Result: researchArticles
databases = ["IEEE Xplore", "Scopus",
 "ResearchGate", "Google Scholar"];
keywords = ["plant leaf disease detection", "maize
 leaf disease detection", "deep learning-based maize
 leaf detection"];
for database in databases do
  for keyword in keywords do
    if publication_year >= 2016 && <= 2021 then
      return researchArticles;
    else
      return None;
    end
  end
end
```

B. Current State-of-the-Art Models

There have been many approaches and techniques to detect maize disease in plants accurately. This section of the review highlights DL approaches used, datasets used in the study, contributions and limitations of the existing DL techniques. This review seeks to review state-of-the-art works from 2016 to 2021.

Richey et al. [36], used supervised transfer learning: based the ResNet50 model for the identification of Northern Corn Leaf Blight disease in maize plants. Two publicly available datasets were used for training and validation. Tensorflow with Keras high-level API public deep learning libraries are used. The model performance included an F1 score of 0.99, Accuracy of 0.99 and precision of 0.98 and a Recall of 1.00. The model was then served to a mobile application for practical field purposes. Esgario et al.

Esgario et al. [37] also used transfer learning for classification and severity estimation of four biotic stresses in coffee leaves. Two different datasets were generated, leaf dataset and symptom datasets using standard and mixup image augmentation techniques. AlexNet, GoogleNet, VGG19, Resnet50, MobileNetV2 were trained using single-task and multi-task CNN architectures. The GoogleNet, ResNet50, and AlexNet performed better with multi-task learning. ResNet50 achieved the best results. Multi-task learning made learning much faster because only a single model was trained.

A limitation identified by the authors involved the low representativity of the dataset that covered only the principal biotic stresses that affect coffee trees.

Nevertheless, this could be improved by increasing the number of images, thus adding new kinds of stress to the dataset.

Sambuddha et al. [7] proposed an explainable machine learning framework for the identification of stress in soybean with remarkable accuracy. Their proposed xPlNet framework comprised two main phases: the deep convolutional neural network (DCNN) and explanation phasesThe classification accuracy achieved by their model was 94.13%.

Xihai et al. [38] used improved deep learning models, GoogleNet and CIFAR10 (transfer learning), to identify disease in leaves of maize plants. The GoogleNet model achieved the highest accuracy of 98.9% as compared to the CIFAR10 of 98.8% accuracy. However, the authors claimed that with their improved CIFAR10, the testing accuracy could be improved by 0:7% and the loss reduced by 10:2%.

Wu et al. [39] proposed a three-stage pipeline CNN to detect the presence of NLB in field images of maize plants using images acquired from an unmanned aerial vehicle (UAV). Their model achieved an accuracy of 95.1%. Liang et al. [10] proposed a Deep Convolutional Neural for the detection of rice blast disease. Three feature extraction methods were used for feature extraction: Convolutional neural network (CNN), Harr-wavelet (Haar-WT), and local binary pattern histograms (LBPH). Using t-Distributed Stochastic Neighbor Embedding (t-SNE) as a criterion for evaluating the performance of the three feature extractors, CNN showed a better performance than the other two handcrafted features. Support Vector Machines (SVM) when combined with all the feature extractors for classification, the CNN-based feature extractor shows far superior performance than LBPH and Haar-WT. The results showed that the quantitative analysis accuracy, receiver operating characteristic curve (ROC), and area under the ROC Curve (AUC) agreed with qualitative analysis using t-SNE. CNN and

CNN+SVM showed superior performance than LBPH+SVMand Haar-WT+SVM. It can, however, be alluded to that CNN and CNN+SVM are better for rice blast identification. CNN+SVM was a solid competitor for rice blast detection, but the latter is preferred. Their technique was limited to detection and failed to address the issue of the severity of the disease.

Panigrahi et al. [40] proposed a CNN-based model for the detection of three major corn diseases: northern leaf blight, common rust, and Cercospora leaf spot. The authors used images from the PlantVillage dataset for the study. A CNN model was proposed, which consisted of 3 convolutional layers and two fully connected dense layers. The dropout layer is used to prevent overfitting. The proposed model achieved an accuracy of 98.78% with less convergence time. Sibiya and Sumbwanyambe [41] designed a CNN model for detecting leaf disease of corn plants using a Java-based neural network framework, Neuroph. The training set included personal images captured from the field and the PlantVillage dataset. Their model had 50 hidden layers of CNN built for the classification of three maize diseases. The overall accuracy of the CNN was 92.85% but achieved individual accuracies ranging from 87% to 99.9%. The model could easily overfit because small amounts of data points were used in training.

Garg et al. [42] proposed a deep framework (cascaded CNN) to detect and automatically quantify the presence of a disease in plants. The model was trained using field images captured by using unmanned aerial vehicles (UAVs). Their framework extracted phenotypic traits to detect and estimate the severity of a leaf disease at the leaf level. The results of their experiment gave a severity correlation of 73%. A modified LeNet architecture proposed by Priyadharshini et al. [43] for the classification of three-leaf diseases of maize is discussed. The study was carried out by using images of maize leaves from the PlantVillage dataset. Principal component analysis (PCA) was used for preprocessing. To improve the classification accuracy of their proposed model, the authors adjusted the framework by varying the depth and kernel size. The model accuracy was 97.89%. The simulation results for maize leaf disease classification demonstrated the proposed method's potential in maize disease classification.

Richey and Shirvaikar [31] used an object detection algorithm, YoloV4, to detect the presence of NLB in the leaf of maize plants. Using a subset of the publicly available dataset by Wiesner-Hanks et al. [44] with augmentation techniques, 5699 images and a test set of 1251 images were used. Evaluating the model based on Intersection-over-Union (IoU) and Mean Average Precision (mAP), the model reported a 93.55%mAP with an average of 77.13% IoU.

Bhatt et al. [45], proposed a novel CNN technique for classifying corn leaves into Healthy, Common Rust, Late Blight, and Leaf Spot by using adaptive boosting and other classifiers to train on features from four CNN architectures (i.e., VGG-16, ResNet-50, Inception-v2, and MobileNetv1). Adaptive Boosting assisted the classifiers in developing a solid rule for class labels. An accuracy of 98% was achieved together with classification scores of 0:97, 0:98, 0:97 for precision, recall, and f1-score, respectively.

To improve the performance of CNNs in the detection of maize leaf disease classification, da Rocha et al. [46] used Bayesian optimization to help find optimal hyperparameter for training using the PlantVillage dataset. The significant contribution of their study was finding the best hyperparameters using Bayesian optimization. The authors employed K-fold cross-validation for training three CNN architectures: AlexNet, SqueezeNet and ResNet-50. Interestingly the three models obtained 97% accuracy, indicating that optimization produced improved generalization throughout all the models.

Waheed et al. [47], using an optimized DenseNet architecture proposed a novel technique for the recognition and classification of three maize leaf diseases. In determining optimal hyperparameter values, the authors used a grid search to find these optimal values. However, but may present a curse of dimensionality. DenseNet uses significantly fewer parameters as compared to other CNN architectures used in the experiment. Experimental results showed that DenseNet achieved an accuracy of 98:06% with fewer parameters and training time.

Lin et al. [48] proposed a novel multi-channel convolutional neural network (MCNN) to improve the identification of five maize leaf diseases. Their proposal employed techniques used in video saliency detection that imitates human visual behavior. Their model achieved an average accuracy of 92:31%,

Liu et al. [49] used transfer learning based on EfficientNet for the automatic recognition of maize leaf diseases. The model parameters trained on the ImageNet dataset were maintained during training, and the fully connected layers and Softmax were optimized. Images collected from the internet were used for training. The training speed was significantly improved with a recognition accuracy of 98:52%.

A transfer learning approach based on the Inceptionv3 and Inception-v4 approach was designed by Sun et al. [50] to classify maize diseases. The pre-trained model was fine-tuned, providing a new approach for maize disease identification. The dataset used was from AI challenger and consisted of eight categories. An experimental result indicated that transfer learning could help reduce the training time of the network.

Syarief and Setiawan [51] analyzed four classes of diseased maize leaf images using seven CNN architectures and three classification methods. The data was obtained from the PlantVillage dataset. The best classification method identified by the authors were AlexNet and SVM, with an accuracy of 93:5%.

Sumita et al. [52] proposed a real-time deep learning-based model that is deployed onto a raspberry pi for identifying and classifying major corn diseases. The bulk of the dataset used is from PlantVillage dataset, but few images were captured from corn plantations. Live images of an infected or healthy corn plant are captured by a Smartphone camera and sent to the raspberry pi for processing through a Wi-Fi network. The average accuracy of the model is 98:40%, but the accuracy reduces to 88:66% when deployed.

Tian et al. [53] also proposed a multi-layer deep neural network for the recognition of six different diseases of corn plants. Dataset used in the study is from experimental fields. VGG-16 is used for feature extraction. Smut and rust disease achieved 100% accuracy but with an overall accuracy of 96:8%. Several methods for classifying plant diseases that can learn from small amounts of data are proposed in [54].

PlantVillage dataset and coffee leaf datasets were used in the study. Transfer learning, triplet networks, and Deep Adversarial Metric Learning (DAML) [55] are the main building blocks of these methods. Very high accuracy of 99% was achieved, thus demonstrating the efficiency of transfer learning.

A summary of the discussed state-of-the-art models and proposals have been outlined in Table 1.

Open Issues and Future Research Directions

This section highlights some challenges in plant disease detection. It outlines some directions for future research in using deep learning techniques for plant disease identification and detection in intelligent agriculture, especially diseases in cereal crops.

From the discussions mentioned earlier, it can be found that one of the challenges facing plant disease detection is the lack of experts to annotate accurately. The problem arises when experts cannot rightly differentiate between dead tissues and diseases when compiling a dataset. This task requires experts and experienced professionals to identify plant diseases that are difficult and costly, especially for new or rare diseases. Furthermore, crop diseases vary in severity. The data collection is unquestionably important when using deep learning technologies to identify crop pests and illnesses.

Model architecture, hyperparameter tuning, and training resources also throw another challenge in plant disease detection. Shallow architectures are best suited for small datasets. Most recent models for object detection offer another angle to consider in selecting or building a model for disease detection and classification. The adaptive boosting (AdaBoost) technique is a choice to be considered to enhance the performance of detection models. Most DL techniques are focused mainly on the detection and classification of maize leaf disease. The paper recommends that future research on maize leaf disease detection, classification, and quantification of disease severity will help improve smart agriculture. Quantification is an area that is least explored by researchers in the field but has the possibility of providing more insightful data for rapid decision-making during farming.

Table 1: A summary of the discussed state-of-the-art models and proposals have been outlined.

	Authors	DL Algorithm	Dataset	Contribution	Performance	Limitation
1	Afifi et al. [54]	▪ ResNet18, ResNet34, ResNet50, ▪ Triplet networks ▪ Deep Adversarial Metric Learning	PlantVillage	Demonstrates the efficiency of transfer learning for corn diseases detection	An accuracy of 99% was reported by the authors	The proposed models have low accuracy under varied conditions
2	Richey and Shirvaikar [31]	▪ YoloV4	Subset of [44]	The authors used an object detection algorithm for the detection of NLB in the leaf of maize plants Evaluation	Their model reported a 93:55% mAP with an average of 77:13% IoU.	Their work did not consider multiple regions of interest.
3	Kanish et al. [42]	▪ A self-trained cascaded CNN model	They captured field images using UAVs	The authors proposed a framework for the detection and estimation of leaf disease severity	Experiments gave a severity correlation of 73%.	The dataset used by the authors were not extensive thus the reduced accuracy levels.
4	Liu et al. [49]	▪ EfficientNet	The authors sourced images from the internet	The authors fine-tuned EfficientNet for the automatic recognition of maize leaf diseases	They achieved a recognition accuracy of 98:52%	The authors used non-standardized images for their dataset
5	Sun et al. [50]	▪ Inception-v3 ▪ Inception-v4	AI challenger	The authors leveraged transfer learning capabilities to aid in classifying maize leaf diseases.	The transfer learning procedure reduced the training time of the network significantly	The proposed framework might not perform well on images that contain several leaves, due to the kind of images used for training
6	Syarief and Setiawan [51]	▪ AlexNet ▪ VGG16 ▪ VGG19 ▪ GoogleNet ▪ Inception-V3 ▪ ResNet50 ▪ ResNet101	PlantVillage	The authors classified maize leaf diseases using pre-trained models	AlexNet achieved the best average classification accuracy of 93:5%.	The best results of AlexNet with an SVM classifier recorded lower accuracies than the state-of-the-art
7	Sumita et al. [52]	▪ Self-trained CNN model	PlantVillage	A real-time corn disease identification and classification using a Raspberry Pi was designed and implemented by authors.	An average accuracy of 98:40% was recorded during model training, however, the accuracy reduced to 88:66% when deployed	Model overfitting on training data likely cause for reduction in the implementation accuracy.
8	Panigrah et al. [40]	▪ Self trained CNN model	PlantVillage	The authors proposed a CNN-based model for the detection of three major corn diseases	Their proposed model achieved an accuracy of 98:78% with little convergence time.	The model can under-fit due to small data samples used for training.
9	Blake et al. [36]	▪ ResNet50	PlantVillage	The authors proposed a real-time maize disease detection model using transfer learning.	They achieved an accuracy of 99%.	Their model however, performed poorly on field images.
10	Esgario et al. [37]	▪ AlexNet ▪ GoogleNet ▪ VGG19 ▪ Resnet50 ▪ MobileNet-v2	The authors used images captured using smartphones	A multi-task learning technique for classification and severity estimation of four biotic stresses in coffee leaves were proposed by the authors.	ResNet50 achieved the highest results among the candidate models.	In-field images were not used which could have positively impacted the model.

11	da Rocha et al. [46]	▪ AlexNet ▪ SqueezeNet ▪ ResNet-50	PlantVillage	The authors determined the optimum hyper-parameters using Bayesian optimization for disease classification.	All three CNNs obtained a 97% accuracy.	Model was not tested with field data.
12	Waheed et al. [47]	▪ DenseNet	The authors used images manually gathered from different sources	A novel technique for recognition and classification of three maize leaf diseases was proposed by authors.	The DenseNet model used achieved an accuracy of 98:06% with less parameters and training time.	Their framework may present a curse of dimensionality.
13	Wu et al. [39]	▪ Self-trained CNN model	Images acquired from [31]	The authors proposed a three-stage pipeline CNN to detect the presence of NLB in field images of maize plants.	Their model achieved an accuracy of 95:1%.	Their proposed model cannot detect severity of NLB in maize plants.
14	Liang el al. [10]	▪ Self-trained CNN model	Images were acquired from the Institute of Plant Protection, Jiangsu Academy of Agricultural Sciences.	A deep convolutional neural network for the detection of rice blast disease was proposed by authors	CNN and CNN+SVM showed superior performance.	Reliability and robustness of the model needs improvements.
15	Sibiya and Sumbwanyambe [41]	▪ Self-trained CNN model	Field images + PlantVillage database	The authors proposed a CNN for the classification of three maize disease.	An overall accuracy of 92:85%.	The model can easily overfit due to the small amount of data used in training the model.
16	Priyadharshini et al. [43]	▪ Modified LeNet architecture	PlantVillage	The authors proposed a LeNet method’s potential in maize leaf disease classification.	The reported model accuracy was 97:89%	It is expected that the model might perform poorly on field images; this is due to the controlled nature of the images used.
17	Bhatt et al. [45]	▪ VGG-16 ▪ ResNet-50 ▪ Inception-v2 ▪ MobileNet-v1	PlantVillage	The authors used a CNN for classifying corn diseases using adaptive boosting techniques.	An accuracy of 98% was achieved in their work	Some of models used in the ensemble had larger parameters and took longer periods to train. The accuracy of the ensemble was not verified with field image
18	Tian et al. [53]	▪ VGG16	Field images	A multi-layer deep neural network for the recognition of six different disease of corn was proposed by the authors.	They recorded an overall accuracy of 96:8%.	Their proposed method did not take into account the different characteristics of the plant at different stages of the diseased journey.

19	Lin et al. [48]	▪ Multichannel CNN	Images collected from maize planting bases	A novel multi-channel convolutional neural network (MCNN) for improving the identification of maize leaf disease was proposed by the authors.	An average model accuracy of 92:31% was recorded by the authors.	Their procedure involved complex image prepossessing steps.
20	Sambuddha et al. [7]	▪ Self-trainedCNN model	The authors used images from the field under controlled conditions.	An explainable ML framework for the identification of stress in soybean was proposed by the authors.	They achieved a classification accuracy of 94:13%	There was a high level of confusion among bacterial blight, bacterial pustule, and Septoria brown spots during the labeling process.
21	Xihai et al. [38]	▪ GoogleNet ▪ Cifar10 model	PlantVillage	The authors proposed an improved deep learning model based on transfer learning.	The GoogleNet model achieved the highest accuracy of 98:9%	The model required much training time and might not perform well on uncontrolled field conditions

Conclusion

The early detection of a plant disease enables stakeholders to apply the appropriate controlled measures to mitigate against the disease effectively. Recent techniques have focused on automated techniques using deep learning to detect diseases in maize plants accurately. This review details DL techniques that are used for automated maize leaf diseases detection and classification. The paper introduces plant disease detection and some of the shortfalls of traditional techniques used. Recent automated techniques, some essential datasets, and some DL architectures were also highlighted. The paper further gave a detailed account of recent DL techniques used to detect diseases in the leaves of maize plants and a discussion of their significant contributions and limitations. Challenges and future research directions in maize leaf disease detection are also presented in the paper.

Author Contributions

S. W. Kuseh and H. Nunoo-Mensah conceptualized, developed the algorithm for selecting the state-of-the-art DL techniques and wrote the initial draft of the paper. J. Yankey and F. A. Acheampong proofread and improved the structure of paper.

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Conflict of Interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

Abbreviations

ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
DCNN	Deep Convolutional Neural Network
NLB	Northern Leaf Blight
LBPH	Local Binary Pattern Histogram
t-SNE	t-Distributed Stochastic Neighbor Embedding
SVM	Support Vector Machine
ROC	Receiver Operating Characteristics
UAV	Unmanned Aerial Vehicle

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