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SYSTEMATIC REVIEW OF DEEP LEARNING APPROACHES IN WHEAT LEAF DISEASE IDENTIFICATION

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ABSTRACT

Wheat is one of the most important staple foods in the world, supplying more than one seventh of the calories for global human consumption. However, wheat production is routinely affected by foliar diseases including leaf rust, stripe rust, powdery mildew, and so on. In addition to reducing crop quality, such diseases cause significant economic losses if they are not timely found and controlled. Conventional detection techniques such as manual field survey or laboratory diagnosis are usually labor-intensive, subjective and inapplicable for large scale agricultural surveillance. Thus, to mitigate these obstacles, deep learning (DL) techniques have been proposed as possible solutions for automated, accurate, and scalable progression using image-based analysis. In this review, we systematically summarize recent development of deep learning in wheat leaf disease detection. It covers common model architectures including Convolutional Neural Networks (CNNs), Efficient Net, and Vision Transformers (ViT) and involves comparison to feature extractor, evaluation metrics (accuracy, precision, recall, F1-score, IoU), and deployment issues are also discussed. Despite encouraging accuracies in artificial environments, there still exist several issues, including limited generalization of the models in real environments, lack of interpretability and absence of standardized benchmarks. In addition, this work can

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help researchers and practitioners to develop reliable interpretable and field-ready deep learning-based solutions that boost sustainable wheat farming.

Keywords: Wheat Leaf Disease, Deep Learning Techniques, Image-Based Disease Detection, Precision Agriculture

Introduction

Wheat is consumed as a staple food by humans in many areas of the world, especially in the form of bread, and is the fourth most cultivated crop after maize, rice, and barley. Wheat (Triticum aestivum) is a dominant cereal crop that provides over 35% of the world's population with food [1]. It is critical for food security, particularly in India, China, Russia and the United States. It has the ability to grow in a wide range of climates and can be found in a wide range of food products, making it an important component of global agriculture [2]. Based on FAO data, wheat represents more than 770 Mtons of production in 2022, with a major role in the human diet at global level in terms of caloric supply [3].

The quality of the food grain affects many aspects of human existence. With a worldwide food deficit, emerging countries, notably in Asia and Africa, are fighting food insecurity and malnutrition [4]. Crop diseases are the leading causes of product decrement and economic impairments in the field of global agriculture. Low crop production can have consequences for overall family welfare in rural areas [5]. Wheat is susceptible to a number of foliar diseases that include leaf rust, stripe rust, powdery mildew, septoria tritici blotch etc. Most of the diseases can be identified by the properties of those diseases [6]. Harmful wheat diseases There are more than two dozens of diseases of wheat. Under severe pandemic, 20–50% yield loss can occur and will affect significantly both crop quantity and quality. Moreover, stripe rust alone can cause up to 100% yield loss under conducive environments [7].

Disease surveillance of such crops is required, for the implementation of effective management for disease prevention is essential. The diagnosis of crop diseases is of great importance to reduce disease harming and guarantee the sustainable development of agricultural economy [8]. It is lined by goal two of sustainable development goal (SDG) zero hunger (to enhanced wheat crop yield and food security by timely disease detection) and goal 13 of SDG, climate action (to saves losses in climate sensitive crop diseases due to precision agriculture) [9].

Generally, the crop disease detection is carried out manually by naked eyes or microscopic approaches, it is time consuming and subjective, which prone to error [10]. Several spectroscopic and imaging methods have also been explored for detecting crop disease symptoms. While these methods can make relatively quick diagnosis of crop diseases, they are dependent on the support of sophisticated, expensive and bulky sensors and equipment [4].

With the progress of computer vision, there are more and more doubts on the wisdom of the image-based detection technologies for crop disease [11], which frees from the limit of time and cost. [6]. People only require simple cameras and consumer-grade electronic storage to complete crop disease identification, rather than going to the landlord. However, these methods are nearly task-specific, and require expert knowledge to design hand-engineered feature extractors, and do not generalize well

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except for the crop images under ideal experimental conditions. Developing an automatic crop disease diagnosis system that works for in-field images is crucial [12]. Deep learning frameworks form a critical part of detecting disease in wheat, and they have opened up the possibility of higher accuracy, early diagnosis, and applicability to large or production agricultural settings [13]. Unlike the conventional pictorial classification methods, deep learning technology, specifically, networks convolutional neural networks (CNNs) automatically recognizes advanced image features where different visually similar pathogens, leaf rusts, stripe rusts, and powdery mildew, are distinguished [8]. This type of models can be deployed on drones, smartphones and edge devices to allow real-time detection in situ even under changing lighting and environmental conditions. Through transfer learning and image augmentation, CNN systems need relatively small labeled data sets yet perform well, which makes them the most desirable technology in precision agriculture and long-term crop care techniques [14].

The objective of this review is to synthesize significant wheat leaf disease and its agronomic impact. Furthermore, present deep learning models used to detect the disease and compare current datasets, techniques, and performance evaluations. And finally, suggest forward looking towards future of deployment of sustainable AI in agriculture.

Taxonomy of Wheat Leaf Diseases

In recent years, identifying plant disease has remained a challenging task. Diseased plants typically have apparent spots or sores on their leaves, stems, flowers or fruit. As a rule, each disease or pest disorder develops a characteristic pattern of visible damage which is distinguishable to diagnose an abnormality uniquely [13]. Normally, the leaves represent the first choice to identify plant diseases and may be the symptoms of diseases appear on the leaves. Generally, the identification of fruit tree pathogens and insect pests present on-site or farm is done by agricultural and forestry experts through experience [14].

Table 1: Taxonomy of Wheat Leaf Diseases

Wheat Disease	Figure	Causal Agent	Symptoms	Visual Characteristics
Leaf Rust		Puccinia triticina	Lesions Small circular orange-brown pustules on leaf surface	circular pustules, mainly on the upper leaf surface

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Stripe Rust (Yellow Rust)		Puccinia striiformis f. sp. tritici	Rows of stripelike yellow pustules on leaves	Striated pustular pattern running along the veins on the leaves
Stem Rust		Puccinia graminis f. sp. tritici	Stems and leaves full of brown-red to dark-red pustules	Elongated pustules, often breaking epidermis
Powdery Mildew		Blumeria graminis f. sp. tritici	Powdery mildew on leaves both above and below represents fungal growth	White powder clumps on leaves and stems, curled leaves
Septoria Tritici Blotch		Zymoseptoria tritici	Necrotic, irregular lesions with chlorotic haloes on foliage	Specks grey brown, centers with yellow halo margins
Fusarium Head Blight		Fusarium graminearum	Whitened heads, pink/white fungal growth on heads	Discolored heads, shriveled kernels, presence of mycotoxins

Economic Impact of Wheat Leaf Diseases

The problem of plant diseases is a serious threat to the agricultural productivity. In situations where such pathogens are not detected during the decisive phases, food security is not fortified [15]. Examples include wheat leaf disorders such as stripe rust, leaf rust and Septoria tritici blotch, all having this destructive potential. Such conditions reduce the number and quality of the yields of grains and lead to severe economic losses among farming communities and nations that build their economy around wheat export [16]. Inexperienced farmers, especially, would wrongly diagnose infection signs and would carelessly use pesticide. This kind of improper management does not only endanger the quality and productivity of crops but also adds pollutants

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to the environment hence increasing the social and environmental expenses [17]. This dynamic is evidenced by the 2010 stripe rust epidemic in the United States: the outbreak resulted in losses exceeding 500 million USD due to intensive fungicide applications and reduced seed yields [18]. The similar dynamics can be observed in India and Pakistan where leaf rust and stripe rusts inflict their damage every year, because of high humidity and the susceptibility of cultivars. The effects go far beyond the direct decreases in production levels, including increased costs on fungicides, labour, and management which overwhelmingly affect smallholding households disproportionately [19].

Traditional Methods for Wheat Disease Detection

Clearly, there exists a sharp disparity at the amount of grain produced per hectare in several developing and developed countries [20]. The difference has been found to be largely attributed by a significant difference in the level of adoption to advanced tools and techniques in agricultural production systems. Historical and labor-intensive approaches toward disease detection, usually involving manual scouting augmented by the diagnostic capabilities of laboratories, are still common even though they possess significant weaknesses [21]. They are effective, but inherently time-consuming, require considerable domain knowledge, and can be easily as inaccurately diagnosed as symptoms are directly related to one another. As a result, research in the detection of disease in plants has become an imperative research avenue using image processing methods [22].

Table 2: Traditional Wheat Disease Detection Methods

Method	Description	Limitations	Reference
Visual Inspection	Expert agronomists visually assess disease symptoms on wheat leaves in the field.	Time-consuming, subjective, requires expert training.	[23]
Microscopy & Culture-Based Diagnosis	Pathogen samples are isolated from infected tissue and cultured or examined microscopically.	Labor-intensive, costly, slow (2–5 days), not feasible for large-scale surveys.	[24]
Molecular Techniques (PCR, qPCR)	DNA of specific pathogens is amplified to confirm identity using gene-specific primers.	Requires specialized lab setup, skilled technicians, and expensive reagents.	[25]
Spectral Imaging (Non-AI)	Uses visible or near-infrared reflectance patterns to identify physiological stress in leaves.	Limited in disease differentiation; affected by external conditions (e.g., light, moisture).	[23]
ELISA	Enzyme-linked	Lower sensitivity than	[26]

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(Immunoassay)	antibodies detect specific pathogen antigens in plant tissue samples.	molecular methods; risk of false positives/negatives.	

Need for Automated Disease Detection Systems

The integration of hi-tech innovations leads to a better performance of precision agriculture thus lowering waste of resources and increasing their profits [27]. The scale of wheat production at the global level and the labor intensive nature of manual control has created a pressing need of automated systems and remote-sensing enabled systems, which can give early detection of diseases and allow precision farming, reduce misuse of pesticides, and provide decision support tools to farmers. As shown in recent findings in the literature, smartphone app based deep learning methods can reach an accuracy of greater than 90 % of in-field disease classification of wheat leaves [28-68].

Deep learning is a subset of artificial intelligence. Its ability to automatically learn and extract features has received a healthy attention of both the academic and industrial circles in past years [29]. It has been used in other areas related to image and video processing, voice processing, and natural language processing and elsewhere in plant science in agriculture, but particularly relevant to plant disease recognition and pest range prediction [1].

The AI methods of detection, especially deep-learning systems, are a kind of detected method, which can be scalable, automatic, in real-time and based on the image-derived data used to recognize the disease. Fields trials that previously required human-based manual scoring have increasingly used image-based scoring through the use of convolutional neural networks (CNNs) to examine experimental plots of wheat [30]. Precise diagnosis and adequate treatment within the window period are the prevention of losing grains and the development of high wheat quality to plump the pockets of farmers. Furthermore, deep-learning platforms have a good result in the application of image classification in the wheat area [31-67].

Deep Learning in Agricultural Disease Detection

Omer et al. [32] used a deep convolutional neural network to classify four cucumber diseases namely downy mildew, anthracnose, powdery mildew, and target leaf spots, which demonstrated the 93.4 percent diagnostic accuracy.

Liang et al. [33] provide an article in which a dataset containing 2906 positives and 2902 negatives was created to detect rice blasts. The findings of the experimental research reveal that distinguishing features produced by convolutional neural networks (CNN) achieve better performance in comparison with those achieving by the traditional extraction approaches, local binary pattern histogram (LBPH), and wavelet transform (Haar-WT).

Leucker et al. [34] propose a hybrid technique combining template matching and support vector machine (SVM) to the early cercosporin leaf spot detection in sugar beet and offer a three-layer framework following which perfect outcomes are delivered. This structure makes it practically plausible that the process of quantization might operate continuously, and it can be easily adapted in in-field applications to

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identify and classify the local prevalence of plant disease.

Nagila et al. [35] conducted the study on supporting machine (SVM) and contrasting it with network (NN). These results are provided using 3 criteria, namely, accuracy, time needed to train and area detection on the basis of standard datasets that are extracted in the literature. The results of the study indicate that the SVM classifier has the latest, most correct and more productive working performance compared to the two methodologies, and thus its further implementation is justified.

A study conducted by [36] on the detection and classification of plant disease, by using a new type of a classifier that is known as a neural network. Some sort of comparative analysis was done in this paper on the performance of three different classifiers namely, neural network, histogram method and support vector machine (SVM). The results showed that SVM comes out with the best accurate results of the three [37].

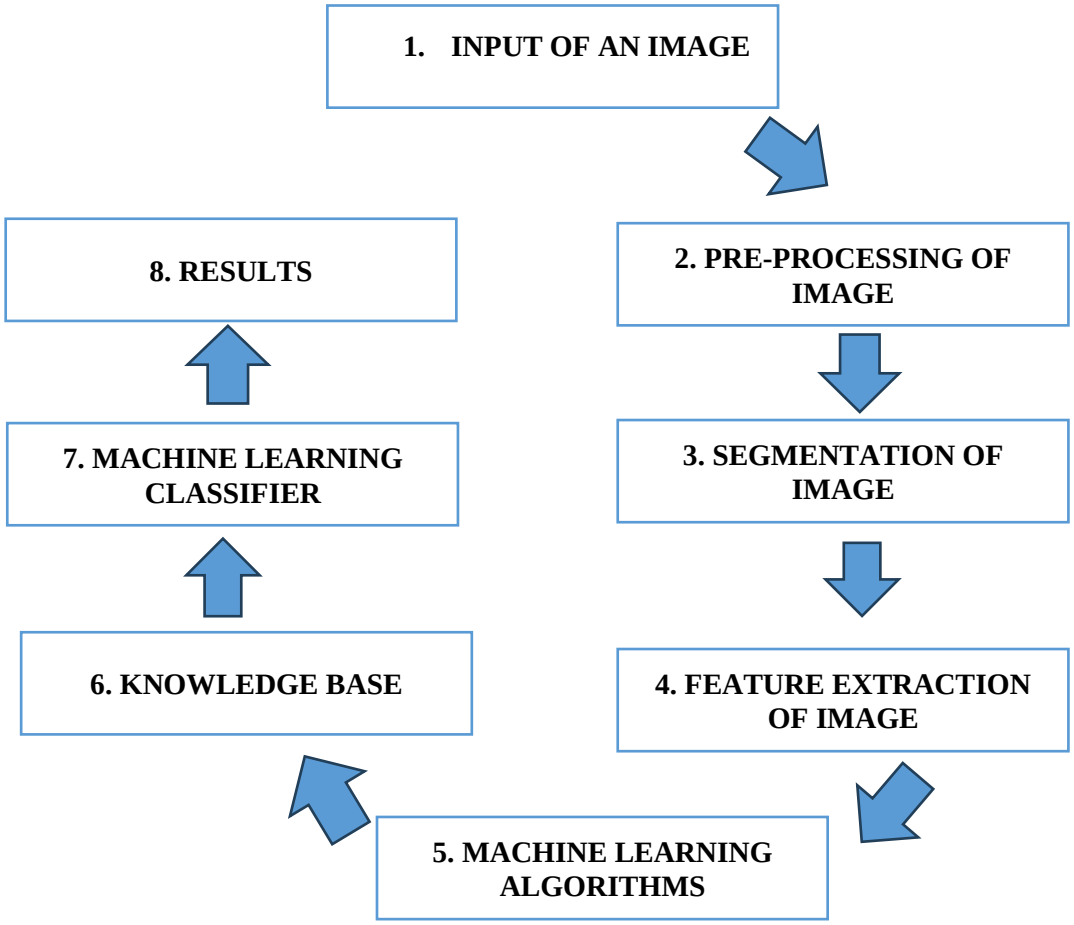


Figure 1 Block diagram of wheat disease detection process adapted from [38]

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Deep Learning Models for Wheat Disease Detection

Deep learning technology features in the identification of plant diseases—has garnered considerable attention. This is attributed to three factors: first, the existence of larger datasets; second, the flexible nature of multicore graphics processing units; and third, the evolution in training deep neural networks along with supporting software libraries like (CUDA) the computing unified device architecture [39].

Deep learning has already brought a revolution in the field of plant disease recognition through Convolutional Neural Networks (CNNs). These models can learn complex spatial features of disease symptoms from images of leaves; major performance improvement over traditional machine learning classifiers like SVM and KNN [40]. Another study showed that a CNN model that was trained on augmented images of wheat leaves achieved an accuracy of 96.4% in classification across five classes of diseases [41].

In the last few years, many deep learning models have been used for classifying and spotting wheat leaf sicknesses. The following discussion takes a look at the performance, technical aspects, strengths and limitations of deep learning models [66].

ResNet-50

This is a deep convolutional neural network with residual blocks. It was run on a combined dataset of PlantVillage and field images containing 5 classes of diseases along with preprocessing steps resizing the images, normalization, and dropout to avoid overfitting [42]. The model attained an accuracy of 96.4%. It also achieved high sensitivity (96.2%) and specificity (97.0%), meaning it performed well in detecting diseased samples and in not misclassifying healthy samples as diseased, respectively. Generalization, especially across different datasets, is what this model is known for. However, its performance in variable lighting conditions an usual scenario on field images was an issue because of mild overfitting [43].

VGG16 with Transfer Learning

The VGG16 model exploits pre-trained layers and tunes it on the Wheat Disease 2020 dataset, which is essentially composed of lab-based images with good quality. It went through data augmentation like flip and rotation to increase variability [44-65]. The model is quite simple, available, and achieved a worthy 94.2% accuracy; however, sensitivity and F1-score lagged a little bit due to real-world variation that was not much included. Its main limitation is the small size of the dataset and lack of field-level complexity—less robust in dynamic agricultural environments [45].

CNN + LSTM Hybrid

The CNN-LSTM hybrid model combined CNN's ability to extract spatial features with LSTM's ability to learn temporal features. This made it good for sequential field image inputs. It learned from the PlantDoc wheat image sequences, which showed how the disease got worse over time [46]. This method was 93.8% accurate, thanks to the use of temporal context, which made it easier to identify diseases at the sequence level. However, its high memory requirements and low scalability in real-time applications make it hard to use in places where resources are limited [47].

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EfficientNet-B0

EfficientNet-B0 is a lightweight CNN architecture that uses compound scaling to improve depth, width, and resolution. It learned from enhanced pictures of wheat fields in Punjab, India, using contrast enhancement and transfer learning [49-63]. This model had the highest accuracy (97.1%) and a very high F1-score (97.2%), which shows that it did well on all of the evaluation metrics. It works well, so it's great for mobile and edge deployment in farming fields. Still, the model had some problems because the training data didn't have a lot of different classes [48-64].

Vision Transformer (ViT)

The Vision Transformer (ViT), which is based on self-attention mechanisms and patch embeddings, on a mix of synthetic and real-world wheat disease images from four different types of diseases. Positional encoding and normalization were part of the preprocessing [50]. It got 95.6% accuracy, which shows that it is very sensitive and precise. This shows that the ViT can capture fine-grained spatial dependencies. But because it is so hard to compute and needs a lot of training resources, it is not as useful for real-time or mobile-based agricultural diagnostics [51].

Table 3: Recent Deep Learning Approaches for Wheat Disease Detection

Model Used	Feature Extractor	Dataset Details	Processing Techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)	Strengths	Limitations	Reference
ResNet-50	Residual Blocks (Deep CNN)	PlantVillage + Field Images (5 classes)	Image resizing, normalization, dropout	96.4	96.2	97.0	95.8	96.0	High accuracy, good generalization	Overfitting on field images under variable lighting	Leite et al. [43]
VGG16 + Transfer Learning	Pre-trained VGG Layers	Wheat Disease 2020 (custom lab	Fine-tuning, data augmentation (rotat	94.2	93.1	94.8	92.9	93.0	Simple to implement, widely available	Small dataset; lacks field variation	Saini et al. [45]

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CNN + LSTM Hybrid	CNN for spatial + LSTM for temporal features	Plant Doc wheat dataset (field image sequences)	Sequential preprocessing, temporal framing	93.8	92.4	94.2	93.6	93.0	Temporal context helps sequence detection	High memory demand, poor scalability	Khan et al. [30]
EfficientNet-B0	Compound scaling-based CNN	Augmented field images from Punjab, India	Contrast enhancement, transfer learning	97.1	97.5	96.8	97.0	97.2	Efficient, suitable for mobile deployment	Limited class diversity	Subramanian & Lakshmi [48]
Vision Transformer (ViT)	Self-attention encoder layers	Synthetic + natural image mix, 4 wheat diseases	Patch embedding, normalization, positional encoding	95.6	94.3	96.1	94.8	94.5	Effective in capturing spatial attention	Computationally expensive to train	Vasaiya &Vajpayee [51]

Challenges and Limitations of Wheat Leaf Disease Detection Using Deep Learning Techniques

The potential of deep learning in wheat leaf disease detection is high but its applicability is unattained due to some crucial limitations. All these challenges fit into three broader categories, which include data-related, model-related, and deployment-related [52].

Data-Related Issues

Lack of Large, Diverse Datasets

The main bottleneck is that the available large-scale datasets are scarce, annotated, and diverse, representing a range of wheat diseases in terms of environments, season,

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and growth stages. A majority of the available public datasets such as PlantVillage are gathered in controlled conditions and are not complex enough in terms of occlusions, diverse infections, or background clutter [53].

Class Imbalance Problems

The datasets, even those of wheat, tend to have imbalanced classes, with some diseases (e.g. leaf rust) being over-represented and others (e.g. Septoria or Fusarium) are under-sampled. It results in biased learning, with dominant classes being processed well by the model and rare yet vital diseases being underserved [54].

Model-Related Issues

Overfitting on Small Datasets

ResNet models have deep learning models that comprise millions of parameters. When presented with small or imbalanced data, such models will over-fit and will memorise noise rather than general patterns of the disease. Their performance on unseen field data is curtailed by over fitting [55].

Limited Generalization

Most models that are trained on clean, laboratory oriented datasets fail when used in the real world. Generalization is complicated by variations in lighting, camera angle, age of the leaf, soil background and level of disease [56]. Even very strong CNNs may underperform in this situation unless trained specifically on diverse, augmented data, or domain-adapted data [57].

Practical Deployment Challenges

Real-Time Detection in Field Conditions

Model deployment under real time field conditions is complex, as there is overhead on futile computation, availability of internet and also hardware capability. Heavy-duty input and segmentation jobs require a lot of memory and support of GPU resources that are not usually available in a farm [58].

Integration with Drones and Mobile Devices

Although the application of drones and smartphones in smart agriculture is on the rise, their application in yield monitoring of wheat disease detection is overwhelmed [59]. Those are power constraints, compression needs of the models, inferencing latencies, inability to match GPS/image data to target accurately. Most deep models are still unsuitable to mobile or UAVs at scale without major optimization (e.g., pruning, quantization) [60]

Future Work

Since there is still much advancement in deep learning in wheat leaf diseases detection, there are some important research gaps left to understand. These guidelines are necessary to fill the gap between experimental models and implementation in real life, enhance resilience, and increase the social impact of AI in farming.

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Real-Time Edge AI Implementation

Inference on edge devices (e.g. smartphone, drone) necessitates additional model-compression innovation (e.g. pruning, quantization), low-latency, thermally efficient design. This will make disease detection available to all and enable diagnoses in offline farm-punitive areas where the internet is not available [61].

Explainable and Interpretable AI (XAI)

The use of explainable AI, either in the form of Grad-CAM, SHAP, or by rule based reasoning layers will deliver increased confidence to non-technical users including farmers, agronomists, and policy regulators. The idea of interpretable AI does not only revolve around the scientific priority but also the ethical necessity of food security-important systems [62].

Conclusion

The application of deep learning in the detection of wheat leaf diseases has changed the prospects of early, correct and automatic diagnosis in the field of agriculture. Through using architectures (i.e., CNNs, EfficientNet, and Vision Transformers), researchers have reported high accuracy of their classifications and enhanced diagnostic performance among different types of diseases Nevertheless, although technological success has been achieved, there still appears to be practical deployment issues. The concerns of data sparseness, non-generalizability in practice environments, and a non-interpretable presentation have to be resolved to completely include AI models to sustainable farming. The majority of the existing research activities are lab-bound and do not satisfy the need of high-scale deployment, real-time inference, and cross-environment adaptation. For this purpose, there should continue the collaboration between AI researchers, plant pathologists, agronomists, hardware engineers, and policymakers who should work interdisciplinary. Future Systems should be explicated, low weight, morally trained and field-tested in varied agro-ecological conditions. It is only by such concerted efforts that deep learning becomes an agricultural aid, rather than research tools, to increase global food security, empower pertinence agriculture on a grand scale.

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