Archives available at journals.mriindia.com

International Journal on Advanced Electrical and Computer Engineering

ISSN: 2349-9338

Volume 15 Issue 01s, 2026

Cognition-Inspired Computational Methods for Automated Chikoo Plant Disease Diagnosis: A Review of Image Processing and Deep Learning

[1]Mrs. Chinmaya Bari, [2]Dr. Tanuja Fegde, [3]Dr. Satish Kolhe

[1] Hire College, Mumbai, India

[2]School of CS, KBCNMU, Jalgaon, India

[3]NBM, Dept. of CSIT, Bordi India

Peer Review Information

Submission: 05 Dec 2025

Revision: 25 Dec 2025

Acceptance: 10 Jan 2026

Keywords

Chikoo disease diagnosis, image processing, deep learning, cognition-inspired AI, explainable AI, transfer learning, plant pathology, severity estimation

Abstract

The problem of precision in early diagnosis of Chikoo (Manilkara achras) plant diseases remains a serious lapse in digital plant pathology, although significant advances in the computation diagnosis of other horticultural and field crops have been made. This review includes the development of automated plant disease detection- classically image processing or machine-learning pipelines up to deep learning structures, transfer learning procedures, as well as emergent cognition-based motivated and explainable systems. The survey is an integration of the evidence of image acquisition studies, feature extraction approaches by human hands, SVM/KNN/RF-based classifiers, CNNs and transformer model, attention, severity-aware networks, and explainable AI, including Grad-CAM, SHAP, and LIME. Whereas similar crops (like tomato, apple, peach, rice, and arecanut) were proven, Chikoo does not have any recorded computational dataset or diagnostic device. Through the awareness of multidisciplinary knowledge, i.e., farmer decision-making behaviour, mobile-based diagnostic services, and geolocation-linked high-throughput, this review presents a Chikoo-friendly research agenda in the future. The paper identifies the necessity of curated Chikoo datasets, transfer-learning baselines, attention-based models, explainability as well as deployable smartphone applications that combine human-like perception and inference. Altogether, this review places cognition-motivated explainable deep learning as a perspective of developing reliable, transparent, and usable by a farmer, Chikoo disease diagnostic frameworks.

1. Introduction

Plant diseases are a longstanding problem in the world that is threatening the food and horticultural production due to the yield decline, quality deterioration, and overdependence on pesticides and other chemical additives. It has been shown repeatedly that disease pressure in an uncontrolled manner not only results in economic losses among farmers but also in ecological impacts due to the increased use of pesticides and the ecological risks related to them (Tudi et al., 2021; Skendzic et al., 2021). Even to this day, human visual inspection and subjective scoring schemes are still extensively employed in disease monitoring in the field. Even though visual rating scales and photographic guides have been optimized during the past century, the inter-observer variability, as well as the inconsistent Ness of the light and the lack of ability to estimate the disease severity in large orchards, limit the reliability and scalability of the purely manual assessment (Bock, 2022; Bock et al., 2010, 2020). Such drawbacks are of particular concern to perennial fruit crops, where latent or nascent symptoms may be blinked when conducting field visits of lowered priority.

In parallel with such challenges, the developments in imaging and computing have made plant disease diagnosis to open into a rich interdisciplinary field of study that embraces a range of fields including plant pathology, computer vision and artificial intelligence. Initial computational tasks were on image processing pipelines that were handcrafted, where descriptors of texture, colour and shape to the leaf or fruit image were extracted, and then the image was classified by traditional machine learning methods such as support vector machine, k-nearest neighbour machines, or decision trees (Haralick et al., 2007; Camargo and Smith, 2009; Al-Hiary et al., 2011; Anjna et al., 2020; Abdu et al., 2020; Maniyath et al., These methods were later expanded with optimization-based segmentation, hyperspectral reflectance and mobile in order to improve the robustness to field conditions (Rumpf et al., 2010; Halder et al., 2018; Chouhan et al., 2019; Gajanan et al., 2018; Clohessy et al., 2021). Although these pipelines showed the possibility of automated disease recognition, segmentation quality limited the investigation results of these pipelines and their performance, as well as their generalization, due to illumination sensitivity and the representativeness of handcrafted features.

With the advent of deep learning and specifically the convolutional neural networks (CNNs), greater accuracy and scalability of detecting plant diseases using images has been made available. Empirical research also revealed that CNNs trained on the vast datasets of leaf images could be used to discriminate dozens of crops and disease categories with great precision, which exceeded the traditional feature-based approaches and radically decreased the number of manual features engineering (Mohanty et al., 2016; Sladojevic et al., 2016; Ferentinos, 2018; Hammad Saleem et al., 2020). Following research has addressed variants of architectures, supervision learning and fine-tuning to take pre-trained models (such as VGG, ResNet and EfficientNet) to particular crops and datasets, including in limited data settings (Matin et al., 2020; Bansal et al., 2021; Hassan et al., 2021; Jangid, 2023; Li et al., 2021; Liu and Wang, 2021; Dhaka et al., 2021). The active development of machine learning, which has transformed into deep learning in recognizing plant diseases, is further reported by surveys and systematic reviews and emphasizes architecture trends, datasets and evaluation practices (Ahmed and Yadav, 2023; Kamilaris and Prenafeta-Boldu, 2018; Khan et al., 2021a, 2021b; Ngugi et al., 2021; Wani et al., 2022).

Further than the just healthy-diseased distinction, more recent studies have started to consider more specific methods like multi-output prediction and estimating disease severity which are arguably closer to the manner in which agronomists make decisions regarding the health of plants. Jointly disease type and disease severity score will be miner means to diagnose the disease, which will be achieved via multi-output learning and regression-style CNNs to allow finer-grained management of the disease and more accurate spray recommendations (Wang et al., 2017; Fenu and Malloci, 2021; Wspanialy and Moussa, 2020; Shi et al., 2023). High throughput phenotyping platforms combining imaging with machine learning and geolocation are examples of how disease measurement on a large scale can be conducted on large plots of the experiment and in the business arena (Clohessy et al., 2021). Simultaneously, with smartphones and of low-cost cameras becoming accessible, citizen-science has accelerated, and tools that deliver diagnostics directly to the farmer have been enabled, with images taken in the field being processed fulfilled by embedded or cloud-based models (Hughes and Salathe, 2015; DehnenSchmutz et al., 2016; Kumbhar et al., 2019; Gandhi et al., 2021).

The majority of deep learning models used to detect plant diseases are, however, opaque black boxes, which do not provide much information as to why a specific prediction took place. This is the opposite of human expert reasoning, in which a lesion pattern, colour progression, distance between canopies, and so forth, form part of a decipherable diagnosis. A recent wealth of literature on explainable artificial intelligence (XAI) and attention explains offers an avenue and opportunity to make cognition-like diagnostic systems more in line with human visual and conceptual perception. Such tools as Grad-CAM, SHAP and LIME can assist a researcher or practitioner in understanding what areas or features in an image contribute to a model prediction, which in turn aids in fostering trust, debugging, and domain learning (Selvaraju et al., 2017; Ribeiro et al., 2016; Lundberg and Lee, 2017; Ghosal et al., 2018). Simultaneously, attention-based models specifically consider how a network concentrates on salient domains / channels of features, representing an abstract conception of visual selective attention more akin to human cognition (Hu et al., 2018; Woo et al., 2018; Vaswani et al., 2017; Dosovitskiy, 2020; Sun et al., 2024). These advancements indicate the elimination of the strictly performance-based classification in lieu of interpretation aware, severity-conscious and decision-based systems.

By cognition-inspired, in this regard, does not mean that there is a complete cognitive model modeling human thought, but the combination of concepts like distributed representation, attention, explanation and contextual reasoning to the area of plant disease diagnosis. Early research on parallel distributed processing offered initial theories of the way information may be coded and processed within networks of simple units, which today at scale are represented by contemporary deep learning (Rumelhart and McClelland, 1986; Kim, 2019). These tools can complement the systems which may not only be accurate but also conform to the perceptions of risk, the assessment of severity and the decision to intervene (and the way to intervene) of farmers (Rois-Diaz et al., 2018; Tudi et al., 2021; Skendzic et al., 2021) when used together with farmer behaviour studies and decision-making studies in the agroforestry and crop management. In perennial horticultural crops, in particular those that are fruiting, this alignment is particularly essential since interventions are more likely to be both expensive and have long-term effects as compared to seasonal field crops.

Of the wider context, Chikoo (sapota, Manilkara achras) is a commercially and nutritionally significant fruit crop in Indian regions, although it has almost been given zero coverage in the computational-plant-pathology literature. Planting techniques, soil mixtures, and soil management practices that should be used to grow sapota have been studied in agronomic and horticultural research (Ramkrishna, 2024) and national horticulture profiles reflect on the production level and overall guidelines of the management (NHB, 2019). Nevertheless, a significant lack of publicly viewed image data collection, deep learning chain or automated disease classifier specifically focused on Chikoo plant diseases are observable. Since the crop is prone to various foliar and fruit conditions and considering its economic contribution in the local horticulture, this gap poses a threat-perpetuated dependence on manual diagnosis, as well as, an opportunity- the ability to develop specific, cognition-driven computational methods that could potentially help in the quick, accurate and sensible control of the diseases.

It is in this context that the current review summarises the literature of image processing, classical machine and deep learning in diagnosing plant diseases with special focus on methods that make use of severity, explain the methods and are human-friendlier. The review is based on surveys, case studies and methodological works on several crops and imaging modalities (Abdu et al., 2020; Ahmed and Yadav, 2023; Kamilaris and Prenafeta-Boldu, 2018; Li et al., 2021; Liu and Wang, 2021; Ngugi et al., 2021; Wani et al., 2022) to examine how these techniques could be modified and adapted to create automated Chikoo disease diagnosis algorithms In particular, it (i) introduces the transition of handcrafted image analysis to deep and attention-celled models, (ii) reviews the frameworks of severity estimation and multi-output forecasting as well as (iii) discusses the explainable and cognition motivated approaches that establish bridges between model output and agronomist reasoning and (iv) identifies gaps between the scientific community and future directions of researchers towards creating Chikoo-specific diagnostic pipelines. Being the first attempt to establish a technical and conceptual rationale behind cognition-inspired, image-based diagnosis in this underexplored fruit crop, the review seeks to cut across the broader scope of computational plant disease research by placing Chikoo in the context of the broader technical and conceptual framework.

2. Background: Plant Disease Diagnosis, Chikoo Context, and Cognition-Inspired View

The customary diagnosis of plant diseases has been based on manual field scouting, visual scoring scale, and laboratory confirmations. Human raters have been rating the severity of the symptoms by estimating visually the size of the lesions and a change of colour and pattern of progression on the leaves and the fruits over the decades. Even though the visual protocols have been optimized to increase the level of consistency, these techniques still have the likelihood of subjectivity bias and inter-observer variation, especially in the field when the lighting, the density of the canopy, and other environmental stressors would make the symptoms obscure (Bock, 2022). It has been continuously demonstrated that even trained raters have inconsistent severity ratings, and manual measurements are unfeasible in the case of disease monitoring in large orchards or at regular intervals (Bock et al., 2020). These restrictions have also been reported in the larger literature of plant pathology, with image processing reviews describing issues of human based diagnosis including variation in observations, inability to find the symptom at an early stage and limited scalability (Halder et al., 2018).

In order to overcome these shortcomings, computational solutions have become a potent solution in the process of automated detection of plant diseases. First versions used handcrafted features, in the form of image processing workflows (involving a texture, colour histogrammes and shape descriptors) and then used classical machine learning classifiers such as support vector machines, k-nearest neighbours and random forest. These methods proved automated diagnosis to be possible and a systematic form of converting visual pattern symptoms into quantifiable descriptive measures (Abdu et al., 2020; Ahmed and Yadav, 2023). Image-based plant disease classification surveys also report on the continued relevance of traditional feature extraction with the lightweight systems, mobile applications, and cases that have limited training data (Khan et al., 2021a, 2021b; Lamba et al., 2021). and, however, they demonstrate performance bottlenecks, e.g. sensitivity to illumination, background noise and segmentation errors.

The recent spike in the use of deep learning has seen the detection of plant disease change to convolutional neural networks (CNNs) and transfer learning models. These approaches generate hierarchical feature representations without undergoing any post-processing feature engineering steps like in traditional approaches, and these features are able to more effectively recognize complex visual clues. Extensive research surveys underline the role CNNs have taken as the leading paradigm in plant disease recognition and assist in categorizing, dividing and assessing their degree of severity across a very broad range of crops (Li et al., 2021; Liu and Wang, 2021; Dhaka et al., 2021; Ngugi et al., 2021). More in-depth monographs and domain studies also indicate how transfer learning, augmentation and fine-tuned networks can adjust the scarcity of training data in the agricultural community (Brahimi, 2018). All these publications collectively form the technological base to go beyond the field of visual scouting to the field of automated and scaled diagnostic technologies.

Chikoo (sapota, Manilkara achras) is one such significant perennial fruit crop growing in a larger area of India, with it having a big impact on the local horticultural economies in those areas as well. The agricultural studies describe its prolonged cultivation features, the responsiveness to the soil and administration habits that have a impact on the production and the quality of the fruits (Ramkrishna, 2024). Analogous national horticulture reports also focus on the commercial value of sapota and record local production trends, frequent production restraints, and prevalence of significant infections and birds (NHB, 2019). Although this is relevant, chikoo has not been studied extensively in the field of computational plant diseases. Image datasets, model benchmarks or automated diagnostic pipelines dealing with chikoo disorders per se are not broadly available and, therefore, make it an effective case of targeted innovation.

The idea of getting plant disease illness diagnosed through a method that is cognition-inspired is formed within an encounter involving an expert opinion of human beings and the present computational intelligence. Plant pathologists normally assess the symptoms using a combination of several perceptual cues- the shape of the lesions, colour changes, are the irregularities in the texture, the spatial patterns on the leaf surface and how the severity of the disease is expected to develop. These are human-like processes similar to concepts in cognitive science, especially in distributed representation and layered processing, on which the initial neural network theories are founded (Rumelhart and McClelland, 1986). These principles of cognitive processes are operationalized by the modern attention mechanisms, including transformers and channel/spatial attention modules, and they allow models to attend to elements of an image that carry the richst information (Vaswani et al., 2017; Fenu and Malloci, 2021; Shi et al., 2023). Simultaneously, explainability algorithms, such as Grad-Cam, LIME, and SHAP, provide interpretative visualizations, which show what areas or features a model relies on to make a decision, and thereby AI predictions are also more compatible with human diagnostic reasoning (Selvaraju et al., 2017; Ribeiro et al., 2016; Lundberg and Lee, 2017). Similarly, the paper explains that explainable phenotyping frameworks reveal how attention maps and saliency visualizations may help agronomists interpret plant stress patterns and confirm the accuracy of models (Ghosal et al., 2018).

With all these cognitive constructs and attention mechanisms, explanatory instruments, computed plant diagnosis of disease can be transformed out of the simplistic black box classification schemes to systems that replicate human schemes in perceptual processing, and can go on to explain concisely the severity of the symptoms and assist transparent decision-making. This conceptually motivated view will give a mental framework of making disease-specific chikoo diagnostic models that are not only accurate but also interpretable and allied with expert agronomic understanding, which will fill in the current knowledge gap in the automated management of chikoo disease.

3. Image Processing and Classical Machine Learning Approaches

Early automated images of the machine learning of plant diseases fronted on classical image processing pipelines. These methods involve well-organized processes image acquisition, preprocessing, segmentation, feature extraction and classification to transform visual symptoms to the format of measurable indicators. Whereas deep learning is prevailing in the field, classical methods can still be employed in the case of a small system of lightweight systems, limited resources, and limited data like the current case of Chikoo disease diagnosis, where there is no large curated dataset at hand.

3.1 Image Acquisition, Preprocessing and Segmentation

Computational research done early in the field was largely dependent on datasets, often curated (as in the case of PlantVillage) to supply standardized leaf images, obtained in controlled conditions with a uniform environment and constant scales. Such repositories were publicly available and thus allowed quick experimentation and benchmarking of various studies (Hughes & Salathe, 2015). Researchers however realized too soon that there was a difference between laboratory-like images, and those taken by farmers in real agricultural environments. Smartphone based acquisition surfaced as a feasible option, which was flexible and scalable to field bases diagnosis. In many works, it was proven that the mobile phones were able to obtain diagnostically valuable images in a variety of environmental conditions, which made the monitoring of plant diseases democratic (Dehnen-Schmutz et al., 2016; Gajanan et al., 2018; Kumbhar et al., 2019). Further innovations combined mobile apps with cloud-based inference, metadata of geolocation and automated reporting pipeline, and it demonstrates how intelligent systems field-ready could become (Gandhi et al., 2021; Clohessy et al., 2021).

The process of image pre-processing and segmentation are crucial in the classical pipelines in the isolations of diseased areas and noise reduction prior to the extraction of the features. Preprocessing activities are usually normalised colour, normalisation, resizing, smoothing and removing backgrounds. The simpler methods of segmentation include thresholding, to more complexes region of interest (ROI) extraction methods. It has been found that segmentation accuracy can have a strong effect on downstream classification in situations when the lesion looks like a natural leaf segment, or the background clutter is not well-resolved (Barbedo, 2018; Golhani et al., 2018). With the aim of enhancing the strength of ROI extraction, optimization-based methods, e.g. bacterial foraging and radial basis function (RBF)-based segmentation, have been suggested to work efficiently with leaves whose lesion boundaries are complex, or whose colour properties are non-homogeneous (Chouhan et al., 2019; Chouhan et al., 2019c). Other papers look into thresholding and colour-space changes to enhance differentiation between healthy or diseased tissues in different lighting circumstances (Halder et al., 2018; Harakannanavar et al., 2022; Raina and Gupta, 2021). In addition to RGB imaging, hyperspectral reflectance has been shown to have the ability to detect early-stage diseases through its capacity to record subtle spectral signals not detectable by the human eye to create a more enriched feature space to detect chlorophyll degradation and pathogen-induced stress (Rumpf et al., 2010). Though the systems of hyperspectral systems are still huge investments, these results demonstrate importance of more sophisticated sensing of tricky horticultural crops.

3.2 Feature Extraction and Classical Machine Learning Classifiers

Classical pipelines transform segmented images into numerical feature vectors of the description of texture, colour, shape and morphological features of diseased areas. Co-occurrence matrices and local texture statistics are examples of texture descriptors that have seen extensive utilization to encode the texture roughness of lesions, mottling and pattern abnormalities (Anjna et al., 2020; Halder et al., 2018). Colour characteristics scale changes in colour, saturation and intensity caused by chlorosis, necrosis or fungal growth brought about by pathogens. Morphological characteristics explain the geometry of lesions, its area, perimeter, eccentricity and edge irregularity, which are useful to understand the stages of the disease development (Golhani et al., 2018; Komala, 2021; Rajendra et al., 2020).

After extracting features, classifiers are used to perform the distinction between the categories of diseases using support vector machines (SVM), k-nearest neighbours (KNN), decision trees and random forests (RF). It is always found that the performance of SVMs can be high when features are properly engineered, whereas KNN and RF are flexible and less demanding to small-to-medium-sized datasets (Abdu et al., 2020; Maniyath et al., 2018; Barure et al., 2020).

Machine learning models are implemented on different crops, which proves that it is possible to obtain high accuracy with handcrafted features in the controlled situations. Prajwalgowda (2020) used the pipelines based on ML to detect paddy disease, and Tan et al. (2021) contrasted classical ML to deep learning to classify tomato leaves, demonstrating that classical models can still compete with deep learning provided that image quality and preprocessing are considered. Survey papers describe general trends, such as the fact that classical ML remains appealing to applications in agriculture to the extent that it is economical and fails to scale to real-world conditions, as specific to reliability and generalization in real-field conditions (Lamba et al., 2021).

Such constraints are especially applicable to crops, such as Chikoo, as lesions can display inconspicuous visual effects, irregular lines/shapes, or other symptoms of stressed situation caused by pests and other environmental conditions. In contrast to crops that have massive curated databases, Chikoo images in real fields will include uneven backgrounds, changing lighting, dust, intersecting leaves and morphologically complicated lesions. Pipelines which are handcrafted, and which are sensitive to the choice of features as well as the quality of segmentation usually cannot encode this complexity since they are using static descriptors which are not capable of following hidden regularities. According to survey studies, over and over again it is stressed that classical image-processing methods are unable to handle confused symptom patterns and feature-based classifiers in other crops or disease types better not present in the training set (Ahmed and Yadav, 2023; Khan et al., 2021a, 2021b; Ngugi et al., 2021). The mentioned difficulties imply the necessity of more adaptable approaches, which are based on representation learning, like deep learning and attention-driven systems, to come up with efficient chikoo disease diagnosis pipelines.

Table 1. Meta-analysis of classical image processing and machine learning approaches

Reference	Crop / Domain	Imaging & Features	Classifier / Method	Key Contribution
Haralick et al. (2007)	Generic image analysis	Grey-level co-occurrence matrix (GLCM) textural features	Not crop-specific; general texture modelling	Provides foundational texture descriptors widely reused in plant lesion analysis.
Camargo & Smith (2009)	Plant disease agents	Colour/texture pattern classification from plant images	Classical pattern classification	Demonstrates feasibility of using image patterns to identify disease-causing agents.
Al-Hiary et al. (2011)	Generic plant leaves	Colour transformation, segmentation, feature extraction	k-means, neural networks	Early complete pipeline from segmentation to classification using handcrafted features.
Rumpf et al. (2010)	Multiple crops	Hyperspectral reflectance imaging	SVM	Early detection and classification using spectral signatures.
Anjna et al. (2020)	Generic plant diseases	Qualitative texture analysis	Hybrid ML system	Uses texture-based qualitative features for disease classification.
Abdu et al. (2020)	Multiple crops	Handcrafted features from leaf images	SVM vs deep learning	Direct quantitative comparison of classical ML vs DL for disease detection.
Maniyath et al. (2018)	Multiple crops	Feature extraction after basic preprocessing	ML classifiers	Demonstrates traditional ML pipelines on mixed plant datasets.
Barure et al. (2020)	Generic plants	Basic image feature extraction	ML classifiers	Illustrates simple machine learning setup deployable on basic hardware.
Prajwalgowda (2020)	Paddy	Colour/texture features from diseased leaves	ML pipeline	Applies classical ML to paddy disease detection with moderate accuracy.

Rajendra et al. (2020)	Arecanut	Image processing on nut/leaf images	ML classifier	Fruit-tree context closer to chikoo orchards; shows viability on perennial crops.
Komala (2021)	Plant leaves	Filter-based optimal feature selection	KNN classifier	Focus on feature optimisation to improve KNN performance.
Harakannanavar et al. (2022)	Multiple leaves	Computer vision preprocessing + feature extraction	ML classifiers	Demonstrates improved segmentation and feature selection under variable lighting.

4. Deep Learning and Transfer Learning for Plant Disease Diagnosis

The deep learning has radically changed the way automated plant disease recognition is carried out as it allows the models to learn about the hierarchical feature representation directly on the leaf and fruit images. Contrary to traditional pipelines relying on handcrafted features and manual tuning of per-segmentation procedures, convolutional neural networks (CNNs) automatically learn discriminative patterns-gradients in colour, texture, space lesion patterns etc. and are therefore very efficient in real-life and more complicated agricultural tasks. In a poorly researched crop such as Chikoo, where there are no controlled datasets, and symptoms of diseases can be hard to detect or inconsistent, deep learning would provide an expansion upon which additional diagnostic models can be developed in the future.

4.1 Core CNN-Based Architectures

The first inventions of deep learning to the field of plant pathology proved the appropriateness and the strength of CNN-based classification. Mohanty et al. (2016) demonstrated that deep CNNs trained on large and labelled image datasets were able to identify several crop and disease classes with a high degree of accuracy with more success than classical machine learning methods and established a new benchmark in the field. Equally, Sladojevic et al. (2016) applied deep neural networks to categorize plant disease images and were found to perform well despite the different visual symptoms. These were the initial studies to demonstrate that CNNs could capture successfully lesion patterns, colour distortions and spatial distributions that were required in identifying the disease.

Later job extended the scope of architectures and crops. CNN- based detection models have been utilized in both general dataset aspects with leaf images (Hammad Saleem et al., 2020), and specialized big picture classification models of mixed agricultural plantations (Singh et al., 2020). Further research stresses the improvement of the feature extraction and classification stability with the help of architectural differences, normalisation methods and the enhanced training procedures (Rinu and Manjula, 2021; Lamba et al., 2021).

There already exists a considerable amount of literature on the usage of deep learning in crop-specific applications, where analogues are very desirable to construct chikoo-oriented models.

Among the most popular areas, tomato diseases are also identified among deep neural networks and tailored CNN systems under diverse circumstances (Batool et al., 2020; Salih et al., 2020). The multi-task deep learning architectures presented by such systems as Wspanialy and Moussa (2020) attempt to predict the type and severity of disease as an example of how deep structures may be trained to learn progression-level information. The ability of CNNs to better adapt to the field-specific image distributions continues to be supported by comparing classical ML and DL in the task of tomato diagnosis (Tan et al., 2021). Deep models can be implemented by real-time tomato pest and disease detecting structures (RT Diseases, 2017) which demonstrate that those can be used in mobile and greenhouse settings.

Deep learning has also been useful in rice disease detection, including the AlexNet-based classification (Matin et al., 2020), VGG-16 training models (Jangid, 2023), and the general CNN structure-based rice disease recognition (Prajwalgowda, 2020). These works show the way in which deep learning can be trained to handle monocot leaves, changing Turbo background clutter, and a combination of fungal and bacterial infections-situations similar to possible issues in chikoo orchards.

On the same note, the crops of fruit trees like apple, peach, areca nut and soybean demonstrate deep learning to be versatile with respect to phenotyping. The models of apple leaf disease that have been developed with CNNs (Bansal et al., 2021) and the peach leaf bacteriosis that is classified with deep networks (Yadav et al., 2021) demonstrate positive adaptation to perennial orchards, with which the Chikoo cultivation is structurally similar. Further models such as arecanut disease detection (Rajendra et al., 2020), soybean disease recognition (Wu et al., 2019), and detecting a blight in a potato and tomato using deep architectures (Anim-Ayeko et al., 2023) have proven to work well even in highly variable field conditions.

Together, these findings point to the fact that the deep CNN structures can process the heterogenous features of different crops and environmental conditions that are complex and thus require deep learning. This renders them particularly promising in the detection of chikoo disease, in which lesion parameters can change by season, orchard control and interactions with pests.

4.2 Transfer Learning, Optimization and Data Augmentation

The scarcity of labelled agricultural images has led to the prevalence of transfer learning as a strategy in classification of plant diseases. The effectiveness of the pre-trained CNN models trained on large sets of natural images and adapted to the realm of the various plant illnesses with the help of fine-tuning is documented by comprehensive surveys and reviews (Li et al., 2021; Liu and Wang, 2021; Dhaka et al., 2021). The use of transfer learning removes the intensive training data requirements to a considerable degree; hence, it is suitable to Chikoo disease applications where no curated datasets are available.

Comparative studies of CNN architectures indicate that models like VGG, ResNet, Inception, MobileNet and EfficientNet differ in their performance with different datasets, complexity of symptoms and conditions in the field (Kamilaris and Prenafeta-Boldu, 2018; Hassan et al., 2021). It has been demonstrated experimentally that fine-tuned pre-trained models where the crop disease image data is used perform better than scratch-trained models, especially in situations when the dataset is small or can be characterized as highly imbalanced (Matin et al., 2020; Jangid, 2023). The insights are essential in the diagnosis of Chikoo disease since the future datasets must not be large.

In addition to conventional transfer learning methods, scholars have developed deep learning models with optimization to achieve higher classification accuracy, fast convergence and deal with symptoms variability:

Modern red deer optimization with ResNet, described by Reddy et al. (2023) enhances the refinement of the features and resistance of the classifier to the plant disease detection. Cetalatran-optimized deep KNN is a matrimony tool that combines multispectral imaging and a biologically inspired optimization to predict the presence of diseases more accurately (Gaikwad and Musande, 2023).

Achhyamana (Suresh, 2023) presents an example of hybrid CNN-SVM frameworks with equivalent features, where the capability of CNN feature extractor and classification platform comprised by SVM are combined to find complex decision boundaries in agricultural data, which proves how hybridization can be used to infer and solve the decision domain. These streamlined models give conceptual blueprints to be used in creation of Chikoo specific systems, particularly in mixed symptom conditions or overlapping conditions related to the stress.

The working with of small datasets is one of the primary challenges of the research of plant diseases. A different Augustation (proposed by Pang, 2020), GAN-based, perceives the images of diseases and creates artificial images to even the classes, as well as augment their size, and simulates small symptom patterns. This is particularly applicable to Chikoo as the primary datasets will be characterized by a low capacity to have cases of every type of disease. Besides, research shows that the diversity of datasets in the form of background variability, light, and leaf direction is of more importance to generalization than the size of dataset, which contributes to the importance of augmentation (Barbedo, 2018). Combined, transfer learning, optimization-driven models and augmentation strategies are fundamental deep learning instruments that can be modified to the Chikoo disease diagnosis. Together they make high-performance models feasible despite the limited availability of data, because of the fluctuating nature of symptoms and the presence of noise and occlusion conditions, the inherent properties of Chikoo orchard, which is the practical environment.

Table 2. Meta-analysis of deep learning and transfer learning methods

Reference	Crop(s) / Domain	Model / Architecture	Dataset Context (as described)	Key Findings
Mohanty et al. (2016)	Multiple crops & diseases	Deep CNN	Large labelled leaf image collections	Demonstrated that CNNs surpass classical ML in accuracy and scalability for plant disease identification.

Sladojevic et al. (2016)	Multiple crops	Deep neural networks	Leaf image datasets	Confirms strong performance of DNNs for disease classification.
Ferentinos (2018)	Multiple crops	DL models (CNN variants)	Multi-crop datasets	Systematic comparison of DL architectures for crop disease detection.
Hammad Saleem et al. (2020)	Multiple crops	DL meta-architectures	Image-based diagnosis	Compares several DL meta-architectures for robustness and accuracy.
Bansal et al. (2021)	Apple leaves	Deep CNN	Apple orchard leaf images	High accuracy for apple disease detection in a perennial fruit crop.
Wspanialy & Moussa (2020)	Tomato	DL detection + severity estimation	Greenhouse tomato plants	Joint detection and severity estimation in one system.
Tan et al. (2021)	Tomato	Classical ML vs DL comparison	Leaf images	Shows DL outperforming classical methods for tomato classification.
Matin et al. (2020)	Rice	AlexNet-based DL	Rice leaf images	Efficient rice disease detection using AlexNet.
Jangid (2023)	Rice	VGG-16 + Flask	Rice disease detection + web interface	Couples DL classification with web/Mobile deployment architecture.
Wu et al. (2019)	Soybean	Deep learning	Soybean leaf disease images	Demonstrates DL performance on legume crops with varied symptoms.
Yadav et al. (2021)	Peach	Deep learning for bacteriosis	Peach leaf images	High performance on tree fruit leaf disease (bacteriosis).
Anim-Ayeko et al. (2023)	Potato & tomato	Deep learning	Field images of blight	Demonstrates DL robustness on blight under realistic conditions.
Reddy et al. (2023)	Multiple crops	ResNet + modified red deer optimisation + DL-CNN	Plant disease ID & classification	Uses metaheuristic optimisation to improve ResNet-based classification performance.
Gaikwad & Musande (2023)	Multi-spectral crops	Cetalatran-optimised deep KNN	Multispectral imaging	Combines optimisation and deep KNN for improved prediction.
Suresh (2023)	Multiple crops	Hybrid CNN–SVM	Image classification	Hybridises CNN feature extraction with SVM classification to improve robustness.

5. Cognition-Inspired, Explainable and Severity-Aware Frameworks

The shift between the traditional deep learning and cognition-inspired, explainable and severity-conscious models can be seen as a larger change in the diagnosis of plant diseases, one aimed at not classification but rather interpretable and human-perceivable decision support. Such frameworks are useful in the context of Chikoo disease detection, where growers pay close attention to intuitive visualized reasoning and symptom interpretation to make predictions and fill AI with agronomic knowledge and field decisions.

5.1 Explainable Deep Vision and Cognitive Interpretation

Literature has accumulated significant reports on the significance of ensuring that the deep learning models are interpretable, particularly in its application to agribusiness decisions that require there to be transparency and trust involved. Demonstrated explainable frameworks of plant stress and plant disease explain how visual explanation maps, severity prediction and multi-output models can match the computational analysis to human interpretation of symptoms. Some of the early examples are severity estimation networks that measure the progression of the disease based on the leaf images, which can be not only detected, but also recommendations on managing the disease can be taken (Wang et al., 2017; Wspanialy and Moussa, 2020). Likewise, the multioutput learning models combine type and severity level of stress in one architecture, and this is in line with the overall concept of agronomists of defining the health of plants (Fenu & Malloci, 2021).

Large-scale phenotyping models offer a different aspect of cognitive strategies creating spatially-referenced, interpretable illness evaluation calculation that imitates the way field researchers cross plots in search of patterns of symptom dissemination (Clohessy et al., 2021). An example of such situation where deep networks could be combined with mechanisms of attention, saliency maps, in order to determine crucial areas of symptoms is the study of plant stress phenotyping that can be used to validate perception by experts and debug their models (Ghosal et al., 2018; Shi et al., 2023).

Cognition-inspired diagnosis is provided with a conceptual base by modern attention mechanisms. Transformer architectures can also show that models will be selective in attending to the relevant spatial features, which is analogous to the human selective visual attention in evaluating lesions (Vaswani et al., 2017). In addition, there are channel-wise and spatial attention modules, including squeeze-and-excitation blocks (Hu et al., 2018) and convolutional block attention modules (Woo et al., 2018), which allow the network to bias towards features of symptoms of interest. The popularity of models based on the notion of attention-driven reasoning, and the agricultural form thereof (Sun et al., 2024), suggests that vision transformer models (Dosovitskiy, 2020) are increasingly employing attention-driven reasoning for tasks in agriculture.

Explainability tools facilitate information of a deeper understanding of network behaviour. Grad-CAM, LIME and SHAP offer visual or feature-level explanation that estimate the regions or features of an image used in the prediction that are consistent with human diagnosing indicators like the sharpness of the lesion boundaries, colour shift or pattern discontinuity (Selvaraju et al., 2017; Ribeiro et al., 2016; Lundberg and Lee, 2017). The early neural network studies by Rumelhart and McClelland contributed to conceptual foundations in cognitive modelling and distributed representation, which define the way in which current deep models reiterate principles of the layered cognitive processing (Rumelhart and McClelland, 1986). Recent deep learning applications, like the conceptual summaries offered by Kim (2019), allow one to place the concept of explainability into the context of the development of beneficial agricultural systems.

Collectively, these developments portray that explainable and attention-based architectures open a route to cognition-inspired diagnostic systems, systems that are not only able to detect disease, but also to think about the seriousness of the disease, its location in space and indicators in biologically significant ways more closely in line with expert visual detection.

5.2 Farmer Reasoning, Adoption and Socio-Environmental Context

An inspired cognition plant disease diagnosis framework should eventually be involved with the perception, interpretation and response of farmers to disease symptoms. Literature on the problem of farmer decision making indicates that the decisions made by them to deal with diseases depend on experience, risk perception, economic and interpretability of information availed to them (Rois-Diaz et al., 2018). In cases such as Chikoo where farmers have experience of handing the crop over a long period using small or medium sized orchards, AI software needs to convey indicative diagnostic feedback and they need to display intuitive explanations consistent with normal forms of thought.

The contexts also affect diagnostic needs, such as environmental and pesticide-use. The dynamics of pests and diseases shifted due to climate have made them more uncertain, which necessitates the use of timely and precise diagnostic means (Skendzic et al., 2021). The fact that more pesticides are used, which has been reported in all systems of agriculture (Tudi et al., 2021), raises environmental and health-related issues, which makes the application of more diagnostic systems, which are more precise and considerate of the severity of the issue, rather than preventive, even more compelling.

Diagnostic platforms based on smartphones can offer an efficiency solution between human intuition and AI-facilitated reasoning. The programs of citizen-science prove the idea that the mobile image data collection can increase the dataset dramatically, provide the farmers with immediate feedback, and involve the non-experts in the process of monitoring plant condition (Dehnen-Schmutz et al., 2016). The future of Chikoo-specific datasets should be established by open-access repositories and mobile-friendly datasets (Hughes and Salathe, 2015), which will be considered the foundation. Mobile apps that can train their inferences on clouds and provide easy user interfaces have worked on other crops and can be used to guide the diagnostics of

Chikoo disease (Gandhi et al., 2021; Kumbhar et al., 2019).

All in all, the socio-environmental situation supports the idea of creating AI systems that are interpretable, accessible and compatible with farmer behaviour. Models that harness cognition and are built on severity scoring, intuitive explanations and being mobile can help inform sustainable disease management in the Chikoo orchard and bring the diagnostic systems more accurately closer to application reality.

Table 3. Meta-analysis of cognition-inspired, explainable and severity-aware frameworks

Reference	Type	Application Domain	Key Concept / Mechanism	Main Contribution
Fenu & Malloci (2021)	Applied DL	Plant disease/stress	Multioutput learning	Joint diagnosis of disease and stress severity in one model.
Ghosal et al. (2018)	Applied DL + XAI	Plant stress phenotyping	Explainable deep phenotyping	Uses interpretable deep machine vision to assess plant stress, with explanation maps.
Clohessy et al. (2021)	Applied ML + geolocation	High-throughput disease assessment	ML image analysis + geolocation	Creates a high-throughput, spatially referenced disease assessment tool.
Dosovitskiy (2020)	Foundational DL	Vision transformers	Patch-based transformer	Introduces ViT, treating images as sequences of patches.
Rumelhart & McClelland (1986)	Cognitive foundations	Cognitive science / neural networks	Parallel distributed processing	Theoretical basis for distributed representations and layered processing.
Ribeiro et al. (2016)	XAI	Generic classifiers	LIME	Local surrogate models explaining predictions.
Tudi et al. (2021); Skendžić et al. (2021)	Contextual	Pesticide use, climate impact	Environmental risk & pest dynamics	Show how pesticide use and climate change shape disease pressure.

6. Deployment-Oriented Architectures and Smart Systems

To be actually of use outside of the laboratory, computational models need to be integrated into functional deployment systems, such as mobile applications, web applications, cloud applications or intelligent machines, which can be integrated into the daily routines of farmers. Available information on deployment in other crops can provide powerful guidelines that may be modified and adopted to Chikoo.

The most developed types of deployment frameworks in plant disease detection are the mobile and Android, as well as web-based tools of diagnostic. Android systems that combine image capture, preprocessing, feature extraction and classification indicate that it is possible to detect diseases in near-real-time on provide the devices that can be understood by farmers (Gajanan et al., 2018). Similar using web-based platforms, where the images taken by users are uploaded to a distant server to be analyzed, small scale applications have been performed on a variety of crops, which allows the deployment of centralized updates of the models, and the incorporation of increased processing capabilities at the back-end without the need to install expensive hardware at the field level (Kumbhar et al., 2019). Android-based applications driven by deep learning also indicate that the inference performed by CNN may be done on the device or a cloud API, which allows detecting crop diseases in the field regardless of their connectivity rates (Gandhi et al., 2021). Deep learning has also been used in rice disease detection, with the VGG-16 used in combination with a Flask-based backend to create interactive web and mobile interfaces as part of an example of a flow diagram, starting with an uploaded image and then receiving feedback on the diagnosis (Jangid, 2023). In the case of Chikoo, the architecture may rely on prediction and severity hints of the disease being rendered to the farmers smartphones, and optional cloud support when it is available and the connection allows it.

This concept is applied to larger scale production landscapes and experimental plots with the help of the high-throughput and geolocation-connected systems that are applied to individual farms. Clohessy et al. (2021) introduce a model that integrates image analysis with machine learning and integrated geolocation enabling mapping of symptom severity on a spatial level fieldwide. Agronomists and researchers can visualize the disease hotspots as well as tracking the temporal trends and the effectiveness of interventions in space using such architectures. In the case of Chikoo orchards which are commonly distributed in heterogeneous micro-environment, geotagged diagnostic results might be used to facilitate spatially specific responses, including focused pruning, localized treatment or block level surveillance of disease, rather than an orchard-wide reaction.

On a systems level, networking, cloud and smart equipment infrastructure is now being increasingly identified as facilitating scalable agricultural AI. The networking aspect of machine learning works toward improving the ways in which cloud-edge collaboration, resource distribution and data routing can be optimised to achieve latency-sensitive and data-intensive application, such as precision agriculture (Boutaba et al., 2018). Simultaneously, smart agricultural equipment recognition (weed-crop, etc.) with different CNNs and transformer models on sprayer access and robots show how the capture of CNNs and transformer models can be implemented directly into the machine, where they act as real-time actuators (Qu & Su, 2024). Such innovations indicate that in the case of Chikoo, disease diagnosis solutions need not be restricted to mobile phone services only but can also be incorporated into the orchard monitoring systems or UAV-based imaging solutions or sprayers fitted with sensors to automatically frequency the treatment depending on the severity of the identified disease.

Combined, these deployment-centered investigations show a distinct direction on the chikoo-centered smart system construction. An efficient roadmap would start with the use of mobile or web-based diagnostic tools whereby the farmers and extension workers can take and submit the images of Chikoo leaf and fruits, and on which a curated dataset would be founded. CNN or transformer models Hoped to be hosted in clouds and trained with methods discussed in previous sections would subsequently give their estimates of disease class and severity, supplemented with explainability maps and readable textual explanations. With a larger amount of data and more stable models, these services may be connected to both geolocation and orchard management systems to generate spatial disease maps, and finally built into smart equipment to make targeted interventions. By so doing previous deployment infrastructure of other crops would be reused to create end-to-end, cognition-inspired, Chikoo disease diagnosis ecosystem that is technically robust, field-deployable and consistent with actual horticultural practice.

Table 4. Meta-analysis of deployment-oriented architectures and smart systems

Reference	**Platform / Architecture**	**Core Components**	**Key Features**
Gajanan et al. (2018)	Android-based system	On-device image capture, feature extraction, ML classification	Demonstrates feasibility of smartphone-based leaf disease detection.
Gandhi et al. (2021)	Android + DL	Mobile interface + DL classifier	Deep learning-based crop disease detection via Android app.
Jangid (2023)	VGG-16 + Flask web server	DL back-end, web/mobile front-end	Rice disease detection with interactive interface.
Hughes & Salathé (2015)	Open image repository	Cloud repository of plant health images	Provides open-access plant disease image database for mobile diagnostics.
Dehnen-Schmutz et al. (2016)	Citizen science + smartphones	Farmer/citizen image capture	Explores smartphones for agricultural citizen science.
Clohessy et al. (2021)	High-throughput + geolocation	ML image analysis + GPS integration	Maps disease severity spatially across fields.
Boutaba et al. (2018)	Networking & cloud	ML in networking systems	Discusses ML for networking, resource allocation, cloud/edge.

Qu & Su (2024)	Smart equipment	DL-based weed–crop recognition for equipment	Integrates DL recognition directly into agricultural machinery.

7. Conclusion and Future Scope

Although there has been a significant breakthrough in automated identification of plant disease in many crops, the research gap is evident and apparent to Chikoo (Manilkara achras). The review shows that there are currently no Chikoo-specific image datasets, annotated repositories or computational diagnostic structures, which may be addressed by confirming the absence of Chikoo-specific image datasets with the assistance of both a range of literature on plant diseases and the structures that define agronomic practices related to Chikoo production (Ramkrishna, 2024; NHB, 2019). The problem with this gap lies in the fact that Chikoo is a commercially significant perennial fruit crop endowed with diseases which in most cases have acidic manifestations in the form of leaves, branches and fruits which real-time identification is very essential in order to manage the orchard. Such gaps in the reported datasets limit the use of the proven deep learning and explainable AI methods, and it does not allow to establish the models taught on Chikoo-specific patterns of symptoms.

Going beyond the structural gap in datasets, it is also based on a methodological gap. Although this wider literature shows progress in the field of severity estimations, visual explanation maps and attention-based features add (Ghosal et al., 2018; Wang et al., 2017; Wspanialy and Moussa, 2020; Fenu and Malloci, 2021; Shi et al., 2023), the cognition-inspired methods are not studied in Chikoo. Similar to other horticultural crops such as apple, peach, tomato, etc, chikoo diseases tend to be heterogeneous in terms of lesion morphology as well as contain latent lesion stages. Like other crops, the severity-aware and explainable models can not only enhance the accuracy of the classification but also build trust and interpretability to enable a farmer to adopt them. These factors are especially significant to the Chikoo farmers, on their part, as they depend mostly on experience and visual impairments to make decisions on pruning, irrigation, pesticides application, and harvest time.

There are gaps that need to be filled with a multi-stage, systematic plan. The creation of a labelled dataset of Chikoo disease based on farmer smartphone photos, archives of extension agencies and controlled orchard surveys is the first step which is the most crucial one. After having a baseline dataset, transfer learning models, i.e. ResNet, EfficientNet or transformer-based architectures can be pre-trained to obtain first performance benchmarks. The next steps of this work should incorporate attention mechanisms and explainability tools, such as Grad-CAM, SHAP and multi-output severity modules and may be developed as cognition-inspired pipelines, which are defined as agronomist reasoning. This would then be followed by a deployment ready system like mobile or web based applications that would then facilitate real time diagnosis and feedback on chikoo farmers. Significantly, they must include behavioural and socio-environmental knowledge on farmer decision-making investigations (Rois-Diaz et al., 2018) meaning that the diagnostic outputs should be sensible, practical and consistent with local management guidelines.

Finally, the past state of plant disease diagnosis has grown to deep learning usefulness with capabilities of learning hierarchical representations, and since then into cognition-aided, explainable and severity-conscientious frameworks. This development is indicative of a larger appreciation that successful models should also be decipherable, context-specific and adaptable to decision-making in the real-world. Other crops have enjoyed the benefits of these technological innovations and yet Chikoo is still significantly underexploited in computational studies. These problems of insufficient datasets and dedicated to Chikoo, the lack of deep learning models and the lack of severity-conscious diagnostic systems indicate a strong necessity to focus on particular computational attention.

Combining the principles of image processing, the development of deep learning infrastructure, explainability strategies and understanding of the mentality of farmers in a cohesive flow will provide future studies with effective instruments, specific to the farmers' specific requirements of the Chikoo. These developments would not only enable accuracy horticulture but also enable farmers to have ready and effective and reliable diagnostic support-eventually leading to better health of the crops, less wastage of pesticides in order to combat unnecessary application of pesticides and improved sustainability of Chikoo production systems.

References

[1] Abdu, A. M., Mokji, M. M., & Sheikh, U. U. (2020). Machine learning for plant disease detection: An investigative comparison

between support vector machine and deep learning. *IAES International Journal of Artificial Intelligence*, 9(4), 670–683. https://doi.org/10.11591/ijai.v9.i4.pp670-683

[2] Ahmed, I., & Yadav, P. K. (2023). A systematic analysis of machine learning and deep learning based approaches for identifying and diagnosing plant diseases. *Sustainable Operations and Computers*, 4, 96–104. https://doi.org/10.1016/j.susoc.2023.03.001

[3] Akila, M., & Deepan, P. (2018). Detection and classification of plant leaf diseases by using deep learning algorithm. *International Journal of Engineering Research & Technology (IJERT)*, 6(7), 1–5.

[4] Al-Hiary, H., Bani-Ahmad, S., Reyalat, M., Braik, M., & Alrahamneh, Z. (2011). Fast and accurate detection and classification of plant diseases. *International Journal of Computer Applications*, 17(1), 31–38.

[5] Anim-Ayeko, A. O., Schillaci, C., & Lipani, A. (2023). Automatic blight disease detection in potato (*Solanum tuberosum* L.) and tomato (*Solanum lycopersicum*, L. 1753) plants using deep learning. *Smart Agricultural Technology*, 4, 100178. https://doi.org/10.1016/j.atech.2023.100178

[6] Sujan Hiregundagal Gopal Rao. (2022). Emerging Security Risks in Automotive System-on-Chips (SoCs): A Comprehensive Review. International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 467–471.

[7] Arya, S. (2019). An analysis of deep learning techniques for plant leaf disease detection, 17(7), 73–80.

[8] Bansal, P., Kumar, R., & Kumar, S. (2021). Disease detection in apple leaves using deep convolutional neural network. *Agriculture*, 11(7). https://doi.org/10.3390/agriculture11070617

[9] Barbedo, J. G. A. (2018). Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. *Computers and Electronics in Agriculture*, 153, 46–53. https://doi.org/10.1016/j.compag.2018.08.013

[10] Barure, S., Mahadik, B., Thorat, M., & Kalal, A. (2020). Disease detection in plant using machine learning (pp. 4194–4197).

[11] Batool, A., Hyder, S. B., Rahim, A., Waheed, N., Asghar, M. A., & Fawad. (2020). Classification and identification of tomato leaf disease using deep neural network. *2020 International Conference on Engineering and Emerging Technologies (ICEET 2020)*, October. https://doi.org/10.1109/ICEET48479.2020.9048207

[12] Bock, C. H. (2022). Plant disease severity estimated visually: A century of research, best practices, and opportunities for improving methods and practices to maximize accuracy (pp. 25–42).

[13] Bock, C. H., Barbedo, J. G. A., Del Ponte, E. M., Bohnenkamp, D., & Mahlein, A.-K. (2020). From visual estimates to fully automated sensor-based measurements of plant disease severity: Status and challenges for improving accuracy. *Phytopathology Research*, 2(1). https://doi.org/10.1186/s42483-020-00049-8

[14] Bock, C. H., Poole, G. H., Parker, P. E., & Gottwald, T. R. (2010). Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. *Critical Reviews in Plant Sciences*, 29(2), 59–107.

[15] Boutaba, R., Salahuddin, M. A., Limam, N., et al. (2018). A comprehensive survey on machine learning for networking: Evolution, applications and research opportunities. *Journal of Internet Services and Applications*, 9, 16. https://doi.org/10.1186/s13174-018-0087-2

[16] Brahimi, M. (2018). *Deep learning for plants diseases*. Springer International Publishing. https://doi.org/10.1007/978-3-319-90403-0

[17] Camargo, A., & Smith, J. S. (2009). Image pattern classification for the identification of disease causing agents in plants. *Computers and Electronics in Agriculture*, 66(2), 121–125.

[18] Chouhan, S. S., Kaul, A., & Singh, U. P. (2019a). A deep learning approach for the classification of diseased plant leaf images. In *2019 International Conference on Communication and Electronics Systems (ICCES)* (pp. 1168–1172). IEEE.

[19] Chouhan, S. S., Kaul, A., & Singh, U. P. (2019c). Radial basis function neural network for the segmentation of plant leaf disease. In *2019 4th International Conference on Information Systems and Computer Networks (ISCON)* (pp. 713–716). IEEE.

[20] Chouhan, S. S., Kaul, A., & Sinzlr, U. P. (2019). Plants leaf segmentation using bacterial foraging optimization algorithm. In *2019 International Conference on Communication*

and Electronics Systems (ICCES) (pp. 1500–1505). IEEE.

[21] Clohessy, J. W., Sanjel, S., Brien, G. K. O., Barocco, R., Kumar, S., Adkins, S., Tillman, B., Wright, D. L., & Small, I. M. (2021). Development of a high-throughput plant disease symptom severity assessment tool using machine learning image analysis and integrated geolocation. *Computers and Electronics in Agriculture*, 184, 106089. https://doi.org/10.1016/j.compag.2021.106089

[22] Dehnen-Schmutz, K., Foster, G. L., Owen, L., & Persello, S. (2016). Exploring the role of smartphone technology for citizen science in agriculture. *Agronomy for Sustainable Development*, 36(2). https://doi.org/10.1007/s13593-016-0359-9

[23] Dhaka, V. S., Meena, S. V., Rani, G., Sinwar, D., Ijaz, M. F., & Woźniak, M. (2021). A survey of deep convolutional neural networks applied for prediction of plant leaf diseases. *Sensors*, 21(14), 4749.

[24] Diseases, R. T. P. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. https://doi.org/10.3390/s17092022

[25] Dosovitskiy, A. (2020). An image is worth 16×16 words: Transformers for image recognition at scale. *arXiv preprint* arXiv:2010.11929.

[26] Fenu, G., & Malloci, F. M. (2021). Using multioutput learning to diagnose plant disease and stress severity. *Complexity*, 2021. https://doi.org/10.1155/2021/6663442

[27] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, 311–318.

[28] Gaikwad, V. P., & Musande, V. (2023). Advanced prediction of crop diseases using cetalatran-optimized deep KNN in multispectral imaging. *Traitement Du Signal*, 40(3), 1093–1106. https://doi.org/10.18280/ts.400325

[29] Gajanan, D. E., Shankar, G. G., & Keshav, G. V. (2018). Detection of leaf disease using feature extraction for Android based system. *International Journal of Scientific Research in Science and Technology*, 4(2), 861–864.

[30] Gandhi, V., Bhide, A., Dharmawat, S., & Aware, M. (2021). Detection of crop diseases using deep learning via android application, 3307, 305–311.

[31] Ghosal, S., Blystone, D., Singh, A. K., Ganapathysubramanian, B., Singh, A., & Sarkar, S. (2018). An explainable deep machine vision framework for plant stress phenotyping. *Proceedings of the National Academy of Sciences of the United States of America*, 115(18), 4613–4618. https://doi.org/10.1073/pnas.1716999115

[32] Golhani, K., Balasundram, S. K., Vadamalai, G., & Pradhan, B. (2018). A review of neural networks in plant disease detection using hyperspectral data. *Information Processing in Agriculture*, 5(3), 354–371.

[33] Halder, M., Sarkar, A., & Bahar, H. (2018). Plant disease detection by image processing: A literature review. *SDRP Journal of Food Science & Technology*, 3(6), 534–538. https://doi.org/10.25177/jfst.3.6.6

[34] Hammad Saleem, M., Khanchi, S., Potgieter, J., & Mahmood Arif, K. (2020). Image-based plant disease identification by deep learning meta-architectures. *Plants*, 9(11), 1–23. https://doi.org/10.3390/plants9111451

[35] Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms. *Global Transitions Proceedings*, 3(1), 305–310. https://doi.org/10.1016/j.gltp.2022.03.016

[36] Haralick, R. M., Shanmugam, K., & Dinstein, I. H. (2007). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, 6, 610–621.

[37] Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., & Jasińska, E. (2021). Identification of plant-leaf diseases using CNN and transfer-learning approach. *Electronics*, 10(12). https://doi.org/10.3390/electronics101213

[38] Hu, J., Shen, L., & Sun, G. (2018). Squeeze-and-excitation networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 7132–7141).

[39] Hughes, D. P., & Salathé, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics. http://arxiv.org/abs/1511.08060

[40] Jangid, B. (2023). Rice disease detection using deep learning VGG-16 model and flask. March, 0–20. https://doi.org/10.55041/IJSREM17874

[41] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90.

https://doi.org/10.1016/j.compag.2018.02.016

[42] Kerre, D., & Muchiri, H. (2022). Detecting the simultaneous occurrence of strawberry fungal leaf diseases with a deep normalized CNN. *ACM International Conference Proceeding Series*, 147–154. https://doi.org/10.1145/3529399.3529424

[43] Khan, R. U., Khan, K., Albattah, W., & Qamar, A. M. (2021a). Image-based detection of plant diseases: From classical machine learning to deep learning journey. *Wireless Communications and Mobile Computing*, 2021. https://doi.org/10.1155/2021/5541859

[44] Khan, R. U., Khan, K., Albattah, W., & Qamar, A. M. (2021b). Review article: Image-based detection of plant diseases: From classical machine learning to deep learning journey, 2021.

[45] Kim, K. G. (2019). Deep learning book review. *Nature*, 29(7553), 1–73.

[46] Komala, T. (2021). Prediction of plant leaf disease using image pre-processing and filter based optimal feature selection for KNN classifier, 7(3), 510–513.

[47] Kumbhar, S., Nilawar, A., Patil, S., Mahalakshmi, B., & Nipane, M. (2019). Farmer buddy—Web based cotton leaf disease detection using CNN. *International Journal of Applied Engineering Research*, 14(11), 2662–2666.

[48] Lamba, M., Gigras, Y., & Dhull, A. (2021). Classification of plant diseases using machine and deep learning. *Open Computer Science*, 11(1), 491–508. https://doi.org/10.1515/comp-2020-0122

[49] Li, L., Zhang, S., & Wang, B. (2021). Plant disease detection and classification by deep learning—A review. *IEEE Access*, 9, 56683–56698.

[50] Liu, J., & Wang, X. (2021). Plant diseases and pests detection based on deep learning: A review. *Plant Methods*, 17, 1–18.

[51] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30.

[52] Maniyath, S. R., Vinod, P. V., Niveditha, M., Pooja, R., Prasad Bhat, N., Shashank, N., & Hebbar, R. (2018). Plant disease detection using machine learning. In *Proceedings 2018 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C 2018)* (pp. 41–45). https://doi.org/10.1109/ICDI3C.2018.00017

[53] Matin, M. H., Khatun, A., Moazzam, G., & Uddin, M. S. (2020). An efficient disease detection technique of rice leaf using AlexNet (pp. 49–57). https://doi.org/10.4236/jcc.2020.812005

[54] Mohameth, F., Bingcai, C., & Sada, K. A. (2020). Plant disease detection with deep learning and feature extraction using PlantVillage. *Journal of Computer and Communications*, 08(06), 10–22. https://doi.org/10.4236/jcc.2020.86002

[55] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, 1–10. https://doi.org/10.3389/fpls.2016.01419

[56] Ngugi, L. C., Abelwahab, M., & Abo-Zahhad, M. (2021). Recent advances in image processing techniques for automated leaf pest and disease recognition—A review. *Information Processing in Agriculture*, 8(1), 27–51.

[57] NHB, D. A. C. (2019). *National Horticulture Board*. Government of India, Gurugram.

[58] Pang, W. E. I. (2020). GANs-based data augmentation for citrus disease severity detection using deep learning, 8.

[59] Prajwalgowda, B. S. (2020). Paddy crop disease detection using machine learning, 8(13), 192–195.

[60] Qu, H. R., & Su, W. H. (2024). Deep learning-based weed–crop recognition for smart agricultural equipment: A review. *Agronomy*, 14(2), 363.

[61] Raina, S., & Gupta, A. (2021). A study on various techniques for plant leaf disease detection using leaf image. In *Proceedings – International Conference on Artificial Intelligence and Smart Systems (ICAIS 2021)*. https://doi.org/10.1109/ICAIS50930.2021.9396023

[62] Rajendra, A. B., Rajkumar, N., & Shetty, P. D. (2020). Areca nut disease detection using image processing. *Advances in Intelligent Systems and Computing*, 1154(03), 925–931. https://doi.org/10.1007/978-981-15-4032-5_83

[63] Ramkrishna, M. J. R. (2024). *Long term effect of planting techniques and filling mixtures in sapota (Manilkara achras)* (Doctoral dissertation, Mahatma Phule Krishi Vidyapeeth).

[64] Reddy, S. R. G., Varma, G. P. S., & Davuluri, R. L. (2023). ResNet-based modified red deer optimization with DL-CNN classifier for plant disease identification and classification. *Computers and Electrical Engineering*, 105, 108492.

https://doi.org/10.1016/j.compeleceng.2022.108492

[65] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016, August). "Why should I trust you?" Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1135–1144).

[66] Rinu, R., & Manjula, S. H. (2021). Plant disease detection and classification using CNN, 3878(3), 152–156. https://doi.org/10.35940/ijrte.C6458.0910321

[67] Rois-Díaz, M., Lovric, N., Lovric, M., Ferreiro-Domínguez, N., Mosquera-Losada, M. R., den Herder, M., Graves, A., Palma, J. H. N., Paulo, J. A., Pisanelli, A., Smith, J., Moreno, G., García, S., Varga, A., Pantera, A., Mirck, J., & Burgess, P. (2018). Farmers' reasoning behind the uptake of agroforestry practices: Evidence from multiple case-studies across Europe. *Agroforestry Systems*, 92(4), 811–828. https://doi.org/10.1007/s10457-017-0139-9

[68] Rumelhart, D. E., McClelland, J. L., & PDP Research Group. (1986). *Parallel distributed processing, Volume 1: Explorations in the microstructure of cognition: Foundations*. The MIT Press.

[69] Salih, T. A., Ali, A. J., & Ahmed, M. N. (2020). Deep learning convolution neural network to detect and classify tomato plant leaf diseases, 7, 1–12. https://doi.org/10.4236/oalib.1106296

[70] Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2017). Grad-CAM: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 618–626).

[71] Shi, T., Liu, Y., Zheng, X., Hu, K., Huang, H., Liu, H., & Huang, H. (2023). Recent advances in plant disease severity assessment using convolutional neural networks. *Scientific Reports*, 13(1), 1–13. https://doi.org/10.1038/s41598-023-29230-7

[72] Singh, S., St, V., & Kingdom, U. (2020). Plant disease classification using convolutional neural network, 2(1), 119–133.

[73] Skendžić, S., Zovko, M., Živković, I. P., Lešić, V., & Lemić, D. (2021). The impact of climate change on agricultural insect pests. *Insects*, 12(5). https://doi.org/10.3390/insects12050440

[74] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, 2016. https://doi.org/10.1155/2016/3289801

[75] Suresh, A. (2023). Crop disease prevention and detection using a hybrid of CNN and SVM. ISSN no: 1869-9391.

[76] Sun, Y., Ning, L., Zhao, B., & Yan, J. (2024). Tomato leaf disease classification by combining EfficientNetV2 and a Swin transformer. *Applied Sciences*, 14(17), 7472.

[77] Tan, L., Lu, J., & Jiang, H. (2021). Tomato leaf diseases classification based on leaf images: A comparison between classical machine learning and deep learning methods. *AgriEngineering*, 3(3), 542–558. https://doi.org/10.3390/agriengineering3030035

[78] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, 161, 272–279.

[79] Tudi, M., Ruan, H. D., Wang, L., Lyu, J., Sadler, R., Connell, D., Chu, C., & Phung, D. T. (2021). Agriculture development, pesticide application and its impact on the environment. *International Journal of Environmental Research and Public Health*, 18(3), 1–24. https://doi.org/10.3390/ijerph18031112

[80] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., … & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30.

[81] Wang, G., Sun, Y., & Wang, J. (2017). Automatic image-based plant disease severity estimation using deep learning. *Computational Intelligence and Neuroscience*, 2017. https://doi.org/10.1155/2017/2917536

[82] Wani, J. A., Sharma, S., Muzamil, M., Ahmed, S., Sharma, S., & Singh, S. (2022). Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: Methodologies, applications, and challenges. *Archives of Computational Methods in Engineering*, 29(1). https://doi.org/10.1007/s11831-021-09588-5

[83] Woo, S., Park, J., Lee, J. Y., & Kweon, I. S. (2018). CBAM: Convolutional block attention module. In *Proceedings of the European Conference on Computer Vision (ECCV)* (pp. 3–19).

[84] Wspanialy, P., & Moussa, M. (2020). A detection and severity estimation system

for generic diseases of tomato greenhouse plants. *Computers and Electronics in Agriculture*, 178, 105701. https://doi.org/10.1016/j.compag.2020.105701

[85] Wu, Q., Zhang, K., & Meng, J. (2019). Identification of soybean leaf diseases via deep learning. https://doi.org/10.1007/s40030-019-00390-y

[86] Yadav, S., Sengar, N., Singh, A., Singh, A., & Dutta, M. K. (2021). Identification of disease using deep learning and evaluation of bacteriosis in peach leaf. *Ecological Informatics*, 61, 101247. https://doi.org/10.1016/j.ecoinf.2021.101247