Chapter 2

CHAPTER 2

LITERATURE SURVEY

Leaf diseases and pest detection have been the subject of a great deal of study for ages. This chapter provides a concise summary of the most recent findings in the fields of agricultural pest detection using AI models and pesticide/fertilizer recommendation systems, leaf disease detection using image processing with ML algorithms, and DLwith transfer learning algorithms. The issue of leaf disease diagnosis and pesticide prescription also has a significant knowledge gap because of this.

2.1 PREAMBLE

Energy from plants has grown in importance as a means to combat climate change. One of the main threats to the economy is the spread of diseases that affect various crops. Bacteria, viruses and fungi are some of the pathogens that can lead to illness. Infections caused by different pathogens typically exist themselves with distinctive signs and symptoms, including localized lesions. When recognizing a pathogen, which is typically targeted by disease-specific lesions, symptoms become crucial. Historically, this approach to disease diagnosis has been widely employed. Developing countries like India, where a significant portion of the population still depends on agriculture for survival, have an urgent need to update their antiquated agricultural practises.

Monitoring with the naked eye is an outdated method that necessitates additional time to diagnose the disease and also requires expertise, so open analysis of the disease does not yield acceptable outcomes. It's also difficult to find a sufficient number of qualified individuals. Agricultural productivity, crop quality, and the agricultural economy are all directly affected by plant diseases, making research into efficient techniques of plant disease detection essential. To aid in the early diagnosis of leaf diseases and associated pests, image processing has emerged as a valuable tool, including several pre-processing and enhancement procedures. The automatic detection of diseases and pests is made possible by AI algorithms that learn from a large training set of images.

There remains potential for improvement in the detection accuracy of leaf diseases and pests, despite the fact that image processing and AI models may help. The challenges of early detection of leaf diseases and pests are investigated.

The rest of the chapter discusses various state-of-the-art studies associated with the different image processing algorithms and AI models in leaf diseases and pest detection, as well as pesticide/fertilizer recommendation systems in agriculture.

2.2 LITERATURE ON MACHINE LEARNING MODELS FOR LEAF DISEASE DETECTION

Many researchers, first focusing on improving leaf disease pictures using image processing methods, then developing various ML models for leaf disease diagnosis. This section provides a critical analysis of a selection of research.

Detection of plant leaf diseases (Singh & Misra 2017) was performed based on the image segmentation and soft computing methods. At first, input leaf inputs were subjected to pre-processing in order to remove any undesirable distortions. After cutting the leaf picture, the desired image area was produced, and then the image was smoothed using a filter. Then, the threshold was chosen to mask the green coloured pixels and the masked pixels in the borders were omitted to segment the important sections by genetic algorithm. Furthermore, the collected portions were used in a classification system for leaf diseases. But its performance depends on the selection of threshold values.

Optimized weighted segmentation and feature selection approaches were proposed (Sharif et al., 2018) for the recognition and classification of citrus illnesses in agricultural settings. First, a weighted segmentation optimization was used to manually extract the citrus lesion sites. Then, different features such as colour, surface and symmetric features were merged. Also, the relevant features were picked by an ensemble PCA rate, entropy and covariance vector. Further, Multi-class SVM (M-SVM) was applied for categorizing the diseases of citrus plants. But it was not suitable for large-scale datasets because of high computation burden.

Plant disease identification (Sun et al. 2018) was presented using image processing method such as multiple linear regression. The threshold for segmenting photos of leaf diseases was determined using an enhanced histogram segmentation approach. Features such as color, texture, and form were extracted by combining regional development with factual color picture analysis. Additionally, leaf illnesses were identified using a multiple linear regression classifier. Though it was simple and automated, it achieved very less accuracy.

ML and digital image processing methods were offered for disease detection in leaves (Ramesh et al., 2018). Initially, colour, form, and texture were extracted using the Histogram of Oriented Gradients (HOG) feature extraction technique. After that, the random forest classifier was used to assign labels to these characteristics. But it has a low degree of accuracy.

Bacterial foraging optimizer-based Radial Basis Function Neural Network (BRBFNN) is an innovative technique for detecting and labelling the region of interest (ROI) of various diseases on crop plants (Chouhan et al., 2018) has been created. First, the region expanding approach was used to do feature extraction by searching for and clustering together seed points with shared characteristics. Then, the RBFNN was trained by initializing the optimal weight values, which are chosen by the bacterial foraging optimizer to enhance the convergence speed and model efficiency. But its efficiency was not satisfactory since it relied only on fungal diseases.

Leaf diseases in plants may be identified and categorized using K-means and SVMs (Oo & Htun, 2018). Pre-processing, feature extraction, segmentation, image capture and classification are all part of the process. Images of diseased leaves were collected and processed beforehand to improve their clarity. The images were then divided into ROIs using K-means clustering. Grey Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) are two features that were extracted from the segmented images. Diseases of the plant leaves were also identified using SVM, including Bacterial Blight, Cercospora Leaf Spot, Powdery Mildew, and Rust. But it was not fit for large-scale datasets.

A novel technique (Khan et al. 2019) was presented for apple disease detection and classification. First, a hybrid technique including 3D box filtering, de-correlation, a 3D Gaussian filter, and a 3D median filter was used to enhance the spots on the apple leaves. After the lesion areas were segmented using the robust correlation-based technique, the findings were fine-tuned using a fusion of Expectation Maximisation (EM) segmentation. Afterwards, distinct features were retrieved from the segmented images, then fused by the comparison-based parallel fusion. In addition, a genetic approach was used to choose the characteristics that were ultimately categorized using a one-vs-all M-SVM. But the computational cost was high for large-scale datasets.

A novel framework based on the combination of Simple Linear Iterative Cluster (SLIC) and SVM has been developed (Sun et al., 2019) to improve the extraction of the tea plant leaf infection saliency map in complicated situations. Super-pixel blocks were identified using SLIC, essential samples were identified using the Harris method, and the fuzzy salient area contour was derived using the convex hull technique. The conspicuous and contextual super-pixel blocks' 4D texture properties were then retrieved. The SVM used to assign labels to the super-pixel blocks ultimately generated the classification map. Saliency maps of pictures of sick leaves were obtained by recreating the super-pixel segments that had previously been identified using morphological and numerical algorithms. But its computational complexity was high for large-scale datasets.

Using an image processing and ML technique, Jaisakthi et al. (2019) proposed a system that can automatically identify illnesses in grapevines. The grabcut technique was first used to segment the picture of the leaf. Next, using global thresholding and semi-supervised techniques, the contaminated region of the resultant picture was extracted. In addition, SVM, AdaBoost, and random forests were used to extract and categorize the features. But these classifiers provide low performance for the dataset with noise and were not suitable for high-dimensional dataset.

To divide the ROIs, researchers at UC San Diego developed a unique fuzzy set extended from neutrosophic logic-based segmentation (Dhingra et al., 2019). After then, fuzzy membership factors were used to distinguish between these images. The divided regions served as the basis for extracting the characteristics used by several ML classifiers to identify diseased leaves. However, these classifiers did not do very well in terms of accuracy.

Mango leaf infections were categorized into many groups (Pham et al., 2020). Wrapper-based attribute choice technique employing an Adaptive Particle-Grey Wolf metaheuristic (APGWO) was used to determine which features were crucial. In order to differentiate between unhealthy and healthy leaves, these features were input into a Multi-Layer Perceptron (MLP). However, this is only possible after careful adjustment of the MLP's settings, such as its layer count, hidden node size, and activation function.

Using image analysis and a Back-Propagation Neural Network (BPNN), Zhu et al. (2020) presented a technique for the automated identification of grape leaf diseases. Denoising the contaminated pictures was accomplished with the use of wiener filtering and the wavelet transform. Segmentation utilising the Otsu method was used to identify affected areas of grape leaves, and morphological approaches were used to enhance the lesion shape. The whole lesion edge was then extracted using the Prewitt operator. Diseases on grape leaves were detected using a three-tiered BPNN. However, there were only slight differences in the morphological aspects of the various lesions, making a definitive distinction between them impossible based on a limited number of parameters.

Artificial Bee Colony (ABC)-based feature selection and SVM have been investigated for their potential in disease identification and classification in grape leaves (Andrushia and Patricia, 2020). To begin, noise and background details were removed from the input images through a pre-processing step. Later, color, texture, and shape characteristics were extracted. The optimum feature set for grape foliar disease diagnosis was selected using the ABC technique, and then input into a SVM classifier. But it did not support the detection of other leaf diseases, results in poor generalizability.

An automated approach for distinguishing between early blight and late blight on potato leaves has been created using the graph-cut algorithm (Hou et al. 2021). Otsu thresholding was first used to remove foreground seeds, whereas color statistical thresholding on the a* and b* components was used to isolate background seeds. To get rid of the backdrops that are the same color as the affected area, it iteratively eliminated the superpixels that border the outline of the leaf if their entropies are distant from those of the primary section of the leaf. Subsequently, the L*a*b* channels were used to extract color characteristics from the improved ROI, while the local binary pattern scheme was used to recover texture characteristics. In addition, many classifiers were used, including the KNN, SVM, ANN, and random forest, to locate the potato disease. But the feature extraction was difficult under irregular illumination, overlapping leaves, etc.

For the plants Jatropha Curcas L. and Pongamia Pinnata L., a leaf disease segmentation and classification system based on computer vision methods has been created (Chouhan et al., 2021). To begin separating the disease area from the leaf images, an Adaptive Linear neurone (ADALINE) was utilised. ADALINE is a superpixel clustering-based hybrid neural network. In order to identify leaf illnesses, several ML algorithms retrieved and categorized data based on color, shape, and texture. But the network parameters such as the connection weights between the layers were not optimized, which may influence the classification performance.

To automatically detect illnesses in tea leaves using image processing algorithms, a novel framework was created (Mukhopadhyay et al., 2021). First, photos of tea leaves were clustered using the Non-dominated Sorting Genetic Algorithm (NSGA-II) to identify the infected area. The segmented pictures were then put via PCA and M-SVM to choose the best characteristics and identify the various diseases. But its accuracy was not satisfactory due to the class imbalance problem.

A recognition of foliar diseases on corn leaves (Phan et al. 2022) was presented using a Simple Linear Iterative Clustering (SLIC) segmentation that generates superpixels, where a group of pixels defining the ROI on a corn leaf. Then, different pre-learned DL structures were applied to detect diseased areas related to various superpixel classes like healthy, background, etc. But it needs to utilize images of larger sizes for further enhancing the detection of multiple diseases per image. Table 2.1 summarizes the aforementioned models based on their strengths and weaknesses.

Table 2.1 Comparison of Leaf Disease Detection Models based on Machine Learning

Author & Year	Models	Benefits	Limitations	Dataset Used
Singh & Misra (2017)	Image pre-processing, clipping, clipping, smooting filter, genetic algorithm based segmentation and soft computing.	Early detection of leaf diseases in plants is possible.	Its performance depends on the selection of threshold values.	Bacterial disease on rose leaves, bacterial disease on bean leaves, sunburn disease on lemon leaves, early scorch disease on banana leaves, and fungal disease on bean leaves.
Sharif et al. (2018)	Optimized weighted segmentation, ensemble PCA and M-SVM	It can achieve better accuracy.	It was not suitable for large-scale datasets because of the high computation burden.	Plant Village and Citrus Image Database of Infested Scales, as well as a combined collection of images of citrus diseases, are two such examples.
Sun et al. (2018)	Improved histogram segmentation, multiple linear regression	It can be simple and suitable for small-scale datasets.	It achieved very low accuracy.	Images inside and outside the training libraries
Ramesh et al. (2018)	HOG feature extraction and random forest classifier	It can be economically efficient.	Its accuracy was not efficient.	300 leaf samples from both normal and infected parts of the field in the rural region of Panpoli village, Tamilnadu
Chouhan et al. (2018)	Region growing method and BRBFNN	Better sensitivity and specificity.	Its accuracy was not satisfactory since it relied only on fungal diseases.	Common rust, cedar apple rot, late blight, leaf curl, leaf spot, and early blight are just some of the fungal diseases shown in these 270 pictures from the Plant Village collection.

Author & Year	Models	Benefits	Limitations	Dataset Used
Oo & Htun (2018)	Pre-processing, feature extraction and SVM	It achieved better detection accuracy.	It was not fit for large-scale datasets.	Bacterial blight, Cercospora leaf spot, powdery mildew, and rust leaf disease on chile, grape, rice, soybean, wheat, rose, cotton, apple, mango, etc.; 560 picture samples taken; four classes.
Khan et al. (2019)	EM segmentation and one-vs-all M-SVM	It achieved better accuracy.	The computational cost was high.	Images of both healthy and sick apple leaves, collected from the Plant Village collection.
Sun et al. (2019)	Combined SLIC and SVM	It can achieve higher accuracy.	Its computational complexity was high for large-scale datasets.	Tea anthracnose, Tea brown blight, Tea netted blister blight, Exobasidium vexans Massee, and Pestalotiopsis theae are only a few of the 1308 samples infected with these five prevalent illnesses.
Jaisakthi et al. (2019)	Grabcut method, SVM, AdaBoost and random forests	It achieved better performance while using small-scale datasets.	These classifiers provide low performance for the dataset with noise and were not suitable for high-dimensional datasets.	5675 grape leaf images from the Plant Village website
Dhingra et al. (2019)	New fuzzy set extended form of neutrosophic logic-based segmentation	It can be most effective for small-scale datasets.	The accuracy of these classifiers was not highly effective.	Images of basil leaves from the herbs garden at Punjab Agriculture University Ludhiana, including both healthy and sick specimens of Ocimum sanctum, Ocimum tenuiflorum, Ocimum basilicum, and Ocimum gratissimum.

Author & Year	Models	Benefits	Limitations	Dataset Used
Pham et al. (2020)	APGWO and MLP	It has a simpler network structure, resulting in faster performance.	It requires to fine-tune the MLP parameters: the number of layers, hidden nodes and the activation factor.	Anthracnose, Gall midge, Powdery mildew, and Healthy Mango Leaves are the four categories for which 450 photographs were gathered in Vietnam.
Zhu et al. (2020)	Otsu method, Prewitt operator and three-level BPNN	It achieved high classification accuracy.	The variances between the morphological characteristics of different lesions were small and so they cannot be completely differentiated by a few features.	60 samples of grape disease leaves including leaf spot, Sphaceloma ampelinum de Bary, anthracnose, round spot, and downy mildew, were obtained from a farm in Zhengzhou City, Henan Province
Andrushia and Patricia (2020)	ABC feature selection and SVM	Better accuracy and reliability.	It did not support the detection of other leaf diseases, resulting in poor generalizability.	A total of 350 images of diseased grapes, healthy grapes, grape esca, grape black rot, and grape leaf blight from the Plant Village dataset
Hou et al. (2021)	Otsu thresholding, KNN, SVM, ANN and random forest	It can achieve the highest overall accuracy.	The feature extraction was difficult under irregular illumination, overlapping leaves, etc.	There were a total of 2840 images of potato leaves, categorized as either "healthy," "moderately affected," "severely affected," "generally affected," or "infected."

Author & Year	Models	Benefits	Limitations	Dataset Used
Chouhan et al. (2021)	ADALINE-based segmentation and ML classifiers	It achieved higher average specificity, sensitivity and classification accuracy.	The network parameters such as the connection weights between the layers were not optimized, which may influence the classification performance.	There are a total of 133 images of healthy Jatropha Curcas L. leaves and 124 images of sick leaves, while there are a total of 322 images of healthy Pongamia Pinnata L. leaves and 276 images of diseased ones.
Mukhopadhyay et al. (2021)	NSGA-II-based image clustering, PCA and M-SVM	It reduced pre-processing complexity and execution overhead.	Its accuracy was not satisfactory due to the class imbalance problem.	Both diseased and healthy tea leaves, including those affected by red rust, red spider, thrips, helopeltis, and sunshine burn, were examined.
Phan et al. (2022)	SLIC segmentation	It can effectively detect diseased areas with the highest overall accuracy.	It needs to utilize images of larger sizes to further enhance the detection of multiple diseases per image.	Corn leaf images from the Plant Village and CD&S datasets

2.3 LITERATURE ON DEEP LEARNING BASED LEAF DISEASE DETECTION

For the purpose of identifying leaf diseases, several scientists have created unique DL models using transfer learning. Some of them are briefly discussed here. Sladojevic et al. (2016) proposed a new technique to disease categorisation in plants based on the DCNN. Initially, leaf photos were obtained independently for each plant disease. The captured pictures were then pre-processed so that the leaf region of interest (ROI) could be obtained, and augmentation was used to correct for any remaining distortions. A DCNN was then trained to identify normal and unhealthy leaves. But it was time-consuming and labour-intensive due to the independent processes.

DL model (Ferentinos 2018) was suggested for plant disease recognition and diagnosis. The author utilized the CNN model to recognize healthy and diseased leaf images. But its performance was degraded while the image quality was poor or blurry. A segmentation of corn leaf disease (Wang & Zhang 2018) was presented using Fully Convolutional Network (FCN). To begin, pre-processing and data improvement strategies were used to obtain training and testing datasets. The input image's dimensions were then sampled using the FCN, and the resulting feature map was obtained. Deconvolution was used to rebuild the segmented image, and the result was acquired by pixel-by-pixel classification of the upsampled feature map. But its accuracy was not effective and needs to recognize multiple leaf diseases.

An automated framework (Khan et al. 2018) was developed to segment and identify fruit crop diseases using correlation coefficient and DCNN features. The procedures included in this system are those of identifying diseased areas, extracting features from them, and classifying them. First, input picture was enhanced by hybrid method to segment the sick regions. In order to extract the characteristics of certain illnesses, next turned to VGG16 and AlexNet. A parallel feature fusion procedure was used to integrate the features, and the genetic algorithm was used to determine which characteristics were most important before an M-SVM classifier was used to make the final determination. But it needs more features to improve the recognition accuracy.

A symptom-wise recognition scheme (Ma et al. 2018) was presented for cucumber leaf diseases depending on DCNN model. To begin, images of cucumber leaves showing illness signs were split from their clutter-filled backgrounds using an image segmentation technique. Next, the DCNN was taught to distinguish between diseases using the segmented images as input. However, it is not capable of early, simultaneous recognition of numerous disease types.

Instead of analyzing a whole leaf image, a plant infection detection system (Barbedo 2019) was built employing specific lesions and spots and a pre-learned CNN like GoogLeNet. But the number of images related to every infection differed highly because of the symptoms characteristics. Multiple tiny lesions or spots caused huge image collections, resulting in degrading overall model performance.

The Plant Disease Diagnosis and Severity Estimation Network (PD2SE-Net) was developed by Liang et al. (2019) as a computer-assisted network for estimating the severity of plant diseases; it makes use of the residual architecture and shuffle modules. This PD2SE-Net model's hyperparameters were also optimized for speed. The PD2SE-Net model relied on a combination of the ResNet50 base model and shuffle units for its functionality. However, overfitting might be an issue if the dataset is broken into classes in a way that isn't intended.

Research into plant disease classification using enhanced CNNs was conducted (Hang et al., 2019). These CNNs combine the structure of inception modules such the squeeze-and-excitation module with the global pooling layer. The characteristics of the convolutional layer at various sizes were combined using the inception structure. Additionally, the FC layer was omitted in favor of global average pooling in order to reduce the total number of hyper-parameters. But it was difficult to categorize similar diseases since most of the areas in such diseased leaves were very identical.

A Multilayer CNN (MCNN) (Singh et al. 2019) has been presented for classifying the Anthracnose fungus in mango leaves. First, the well and diseased mango leaf images were acquired. After that, a normalised histogram was used to do preliminary processing, and the mid square scheme was used to reformat the images to standard dimensions. After training and testing, the MCNN-based ternary classifier was used to determine which leaf was diseased. However, the employment of the softmax function rendered its compatibility with the classification of numerous disorders ineffective.

Highly facilitated DCNNs may be built using a Neuroph Studio model (Sibiya and Sumbwanyambe 2019) since convolution and pooling attribute mining are already included into the Neuroph files. In order to detect and categorize maize leaf diseases, a DCNN with 50 hidden layers was built. Back-propagation was also used in the learning process. However, it only takes RGB images into account, despite the necessity to evaluate the CNN's performance on grayscale images as well.

The RGB hyperspectral images (Nagasubramanian et al. 2019) was translated into the HSV colour space and partitioned the charcoal rot tissue using thresholding. Diseased soybean stem tissue was classified using the 3D-DCNN, which extracted features simultaneously across spatial and spectral coordinates. However, it was ineffective in terms of categorization. A method was created for automated recognition and classification of leaf spot disease in sugar beetroot leaves using a modified Faster Region-based Convolutional Neural Network (FRCNN) (Ozguven and Adem 2019). However, in order to prevent the misclassifications, the CNN parameters must be optimized.

Multilateral Funding Increased The Cucumber Leaf Disease Identification CNN (GPDCNN) (Zhang et al. 2019) disease detection on cucumber leaves by combining dilated convolution and global pooling. The input image's multi-scale features were first extracted and combined using multi-scale convolutional kernels. The FC layer was then utilized to diagnose plant ailments. However, it must improve productivity by making use of probabilistic graphical frameworks. Tomato leaf infections may be identified using a DL-based ToLeD model (Agarwal et al., 2020) that consists of three convolution, three max-pooling, and two FC layers. But its accuracy was less because of the lower quantity of images.

Yu et al. (2020) introduced a unique method based on the ROI-aware DCNN for detecting illnesses in apple leaves. Before the VGG network could be used to categorize the leaf illnesses, two sub-networks, including an encoder-decoder network, had to be developed to partition the images that were input into distinct regions. After that, they were sent to a fresh training set that included class information according to leaf disease categories and ground truth images, where they were taught autonomously. After the two networks were fused and trained together, the projected ROI feature map was overlaid on top of the original source picture. The last step in the process of detecting leaf infections was applying a stacked feature map to the sub-network. On the other hand, its accuracy was not satisfactory.

It was recommended that the Convolutional Neural Network (CNN) (Hasan et al. 2020) be used to detect and categorize grape leaf illnesses. There were three stages to this system: acquisition, attribute training and categorization. First, image pre-processing was performed for enhancing the image regularity. After after, the images were used to teach the CNN about the many illnesses that might affect grape leaves. However, it was less accurate.

In order to identify and quantify the stress generated by the biotic agents on coffee leaves, Esgario et al. (2020) proposed an approach that is both effective and practical. Included is a multi-tasking strategy that makes use of both data augmentation and CNN. However, this approach has certain limitations, chief among them the fact that the dataset only includes the most significant biotic pressures that coffee plants face.

To detect grape leaf diseases, a novel Dense Inception CNN (DICNN) was created (Liu et al., 2020). Images of sick grape leaves were gathered and then processed using a data augmentation technique to generate enough training images. To improve the generalisation efficacy, digital image processing technology was used to simulate the images in several scenarios. Then, a disease detection in grape leaves using DICNN; it has deep separable convolution, an Inception architecture, and a dense connection strategy. However, its significant temporal complexity might be attributed to the Inception architecture's many convolutional layers.

Many photos of sick grape leaves were generated for use in training the recognition models, thanks to a unique Leaf GAN model (Liu et al., 2020). At first, images of sick grape leaves were made using a producer with progressively more complex layers. When it came to distinguishing between original and replicated infected images, the differentiator turned to the dense connectivity approach and image regularization. Finally, the training process was stabilized with the help of the deep regret gradient penalty scheme. However, accurate identification during training necessitates the use of many types of images.

A maize leaf feature improvement approach (Lv et al. 2020) was designed to boost the maize features under the complex situations. Then, a whole new DNN was created for disease detection in maize leaves, and it relied on AlexNet's centralized network architecture. This model's attribute mining performance was enhanced by combining dilated and multi-scale convolutions. Overfitting was avoided by using batch regularization to improve dependability. Adabound optimization and the Parametric ReLu (PReLU) activation factor were employed to improve convergence and accuracy. However, it must concurrently categorize additional types of maize pests and illnesses.

The MobileNetv2-YOLOv3 model has been reported for early disease detection of tomato gray leaf spot (Liu and Wang, 2020). The MobileNetv2 was used as the main network to facilitate the switch to mobile devices. To improve the model's generalizability, the pre-learning approach of transfer learning was used. To improve the effectiveness of regression box for detecting tomato gray leaf spot, researchers substituted the Intersection Over Union (IoU) loss function with the Generalized Intersection Over Union (GIoU) loss function. But meteorological elements were essential for developing a multi-data fusion model to effectively improve early diagnosis of leaf diseases.

The Dual-Attention and Topology-Fusion with Generative Adversarial Network (DATAGAN) was developed (Dai et al., 2020) to enhance the quality of low-resolution images of leaves. The number of parameters was also reduced by using the weight sharing technique. As an added step, the resulting high-resolution images of leaf diseases were input into several pre-learned DCNN models for classification. But the spatial correlation across the image series should be learned for increasing the detection accuracy.

Grape and mango leaf disease identification by transfer learning using DL was reported (Rao et al., 2021). They used pre-learned CNN model such as AlexNet to recognize diseases in grape and mango leaf images. However, image quality had an effect on performance, and a recommendation system was required to advise the best course of action to eliminate the threat.

Automated and reliable leaf disease recognition model (Chowdhury et al. 2021) was presented using EfficientNet to categorize the segmented tomato leaf images into healthy and different kinds of tomato leaf diseases. However, its efficiency should be analyzed under more diverse circumstances. The identification of viral infections in the leaves of the Vigna

Mungo plant was demonstrated using a DL-based method that is both effective and non-destructive (Joshi et al., 2021). At first, the acquired picture collection of Vigna Mungo leaves belonging to several classes were segmented and supplemented. Then, a CNN named VirLeafNet was trained over the course of several epochs using different leaf pictures to distinguish between uninfected, mildly infected, and severely infected leaves. However, the dataset was very limited and the efficiency was less since it considered only viral diseases.

A technique for recognizing multiple fungi diseases of wheat shoots (Genaev et al. 2021) was presented using EfficientNet-B0 structure with transfer learning. However, due to the similarity between the visual signs of rust illnesses and those of other diseases as septoria and powdery mildew, cross-misclassification between these diseases sometimes occurred.

To identify tomato leaf diseases, a DL-based segmentation and classification of leaf images (Shoaib et al. 2022) was created. First, various U-Net designs were utilized to elect the best segmentation model by evaluating the segmented model mask with the images of ground truth masks. Then, InceptionNet was used to classify segmented tomato infected leaf images into different classes. It needs to integrate recommendation systems to further increase the crop yields by controlling leaf infections.

Predicting the disease class that would harm grape and tomato leaves was the primary motivation for the investigation of transfer learning for multi-crop leaf disease image categorisation (Paymode and Malode 2022). In order to identify characteristics and classify them as either healthy or sick, the Visual Geometry Group (VGG) model was developed. A thorough study of leaf images, however, requires the use of sophisticated CNN architectures.

An efficient DL model (Akbar et al. 2022) was developed for categorizing bacteriosis in peach leaves. Initially, healthy and bacteriosis peach leaves were acquired and pre-processed based on the image resizing, noise elimination, image enhancement, etc. Then, such images were given to the new LightWeight CNN called LWNet to categorize images into healthy and bacteriosis. But this model considered a limited number of labelled training images and may not be appropriate for infections that have not been observed before.

The above-studied models are summarized based on their benefits and limitations in Table 2.2.

Table 2.2 Comparison of Leaf Disease Detection Models based on Deep Learning

Author & Year	Models	Benefits	Limitations	Dataset Used
Sladojevic et al. (2016)	Pre-processing, augmentation and DCNN	It can automatically classify and detect leaf diseases.	Its accuracy was not satisfactory.	A database of 4483 images of healthy and diseased leaves for peach, apple and grape
Ferentinos (2018)	CNN	It achieved the best success rate in identifying corresponding leaf diseases.	Its sensitivity and specificity were degraded while the image quality was poor or blurry.	The 87848 images in this public collection include 25 plant species and 58 types of [plant, disease] pairings.
Wang & Zhang (2018)	FCN	Common corn leaf disease images may be segmented using this method..	Its accuracy was not effective and needs to recognize multiple leaf diseases.	Six common illnesses are shown here, including corn leaf spot, tiny spot disease, leaf spot disease, brown spot disease, streak disease, and round spot disease, among 750 images of corn leaves.
Khan et al. (2018)	VGG16, AlexNet, parallel feature fusion and M-SVM	It can achieve a higher sensitivity.	It needs more features to improve the recognition accuracy.	Plant village and CASC-IFW datasets
Ma et al. (2018)	DCNN (ShuffleNetV2)	Its robustness and accuracy were efficient.	It cannot recognize multiple types of diseases simultaneously.	Four types of diseases may affect cucumbers, and this collection of 1184 images shows them all: anthracnose, downy mildew, powdery mildew, and target leaf spots.

Author & Year	Models	Benefits	Limitations	Dataset Used
Barbedo (2019)	GoogLeNet	It can be effective for detecting severely affected leaf diseases.	Multiple tiny lesions or spots can degrade the overall model performance.	A total of 1575 images and 46409 images of various crop diseases for each plant/disease pair before and after subdivision, respectively
Liang et al. (2019)	PD^2SE-Net using ResNet50	It enhanced detection accuracy.	An overfitting problem can occur because of the undesired splitting of classes in the dataset.	A dataset including 9 different plant species in both healthy and disease classes
Hang et al. (2019)	Enhanced CNN	It can reduce the training time and the number of training parameters.	It was difficult to categorize similar diseases since most of the areas in such diseased leaves were identical.	Leaf illustrations representing 10 different plant diseases
Singh et al. (2019)	MCNN-based ternary classifier	It achieved a higher classification accuracy.	Because it used the softmax function, it was inefficient at classifying various disorders.	Using live, in-the-moment photography, researchers at India's Shri Mata Vaishno Devi University were able to acquire 1070 images of both healthy and diseased Mango tree leaves.
Sibiya and Sumbwanyambe (2019)	Neuroph Studio model for DCNN	It achieved satisfactory accuracy and feasibility.	While evaluating the CNN's effectiveness with grayscale images, it only takes RGB images into account.	100 colour images of disease and healthy leaves of maize crop
Nagasubramanian et al. (2019)	3D-DCNN	It has better classification accuracy.	Its F1 score was not high.	There are 111 hyperspectral images of stems in a collection, 64 of which depict healthy stems and 47 depicting sick ones.

Author & Year	Models	Benefits	Limitations	Dataset Used
Ozguven and Adem (2019)	FRCNN	Its overall correct classification rate was satisfactory.	In order to prevent misclassification, the CNN parameters must be optimized.	155 images of sugar beet leaves were used to create the dataset; 38 were of healthy leaves, 20 had moderate illness, 35 had severe disease, and 62 had a mixture of mild and severe disorders.
Zhang et al. (2019)	GPDCNN	Convergence may be hastened and the recognition rate raised with its help.	The use of probabilistic graphical frameworks is required to improve productivity.	Real-world cucumber diseased leaf image dataset
Agarwal et al. (2020)	ToLeD model	It has less complexity.	Its accuracy was less because of the lower quantity of images.	Images of tomato diseases from plant village dataset
Yu et al. (2020)	ROI-aware encoder-decoder network and VGG	It can reduce the complexity.	Its accuracy was not satisfactory.	Apple leaf images provided by the Apple Research Institute in South Korea
Hasan et al. (2020)	CNN	Less computation time and complexity.	Accuracy was less.	Kaggle dataset includes 1,000 images of healthy, Black Rot, Esca, and Leaf Blight grape leaves.
Esgario et al. (2020)	Multi-task method using data augmentation and CNN	It can be more robust and accurate.	The dataset only included the most significant biotic stressors experienced by coffee trees, which limited its usefulness.	A total of 1747 images of coffee leaves including healthy leaves and diseased leaves, were collected in different regions in Brazil

Author & Year	Models	Benefits	Limitations	Dataset Used
Liu et al. (2020)	DICNN	Improved robustness and recognition performance were attained.	The Inception architecture's great temporal complexity may be attributed mostly to the enormous number of convolutional layers it employs.	A total of 7669 images of grape leaves are either infected with anthracnose, brown spot, mites, black rot, downy mildew, leaf blight, or are otherwise healthy.
Liu et al. (2020)	Leaf GAN	It can effectively improve the detection accuracy.	Effective identification during training necessitates the use of many types of images.	The Plant Village dataset was mined for a total of 4062 images of grape leaf diseases, comprising 1180 Black rot images, 1383 Esca measles images, 1076 Leaf spot images, and 423 healthy leaf images
Lv et al. (2020)	Combined Dilated and Multi-Scale convolution (DMS)-robust AlexNet	It achieved high accuracy and strong robustness.	Concurrently identifying and classifying maize pests and diseases is essential.	The majority of the 7193 maize leaf disease images gathered from the Plant Village collection fall into the following categories: common rust, grey leaf spot, northern leaf blight, zinc deficiency, round spot, autumn army worm, and healthy.
Liu and Wang (2020)	MobileNetv2-YOLOv3	It detected gray leaf marks on tomatoes in real time while maintaining a high degree of accuracy.	A multi-data fusion model for effective early leaf disease detection required weather components.	A total of 2385 tomato gray leaf spot images

Author & Year	Models	Benefits	Limitations	Dataset Used
Dai et al. (2020)	DATAGAN	It achieved better accuracy by using high-resolution leaf images.	Improving detection accuracy requires training on the spatial correlation between images in a sequence.	Plant Disease Recognition Competition of the 2018 AI Challenger DIV2K Dataset and 1350 Crop Leaf Disease Images
Rao et al. (2021)	AlexNet	It achieved the maximum detection accuracy.	A recommendation system was required to advise on the best course of action to take since poor the image quality was hindering performance.	The Plant Village collection contains 8438 images of sick and healthy grape and mango leaves.
Chowdhury et al. (2021)	EfficientNet	It has the highest classification accuracy.	Its efficiency should be analyzed under more diverse circumstances.	A total of 18161 tomato leaf images for healthy and different disease classes
Joshi et al. (2021)	VirLeafNet	All classification of leaf images was done automatically, without any destruction, and in real time.	The dataset was very limited and the efficiency was less since it considered only viral diseases.	A total of 433 images of Vigna mango leaves are divided into three groups: healthy, mildly diseased, and severely infected.
Genaev et al. (2021)	EfficientNet-B0	It achieved better accuracy and reduced the degeneracy of training data.	Due of the similarity in appearance, rust infections and others like septoria and powdery mildew were sometimes misdiagnosed as one another.	This 2414-image set depicts several wheat fungal infections.

Author & Year	Models	Benefits	Limitations	Dataset Used
Shoaib et al. (2022)	U-Net and InceptionNet	It achieved the maximum detection accuracy.	It needs to integrate recommendation systems to further increase crop yields by controlling leaf infections.	Including both healthy and sick tomato leaf images, the 18161-image Plant Village dataset is available for analysis.
Paymode and Malode (2022)	VGG	It achieved better accuracy.	A thorough study of leaf images requires the use of sophisticated CNN architectures.	A total of 54303 images of crop leaves from 152 crop solutions representing 38 crop classes and 19 crop categories were included in the Plantvillage collection.
Akbar et al. (2022)	LWNet	It can be more effective and achieve maximum classification accuracy.	It considered a limited number of labeled training images and may not be appropriate for infections that have not been observed before.	A dataset consists of 10000 peach leaf images including 4500 Bacteriosis and 5500 healthy images

2.4 LITERATURE ON PEST DETECTION USING ARTIFICIAL INTELLIGENCE TECHNIQUES

Some academics had focused on detecting pests using DL models. A detailed review of some studies is presented in this section. Using a saliency map and DCNN training, Liu et al. (2016) presented a method for the automated detection and identification of pests in agricultural settings using visual data. After that, bounding box was extracted, resized and utilized to create a huge dataset named PestID. Such dataset was considered to learn image characteristics and categorize pest classes. But its accuracy was not effective since it needs to consider a finer search in the saliency maps. In a complicated setting, a pest identification model was demonstrated using deep residual learning (Cheng et al., 2017). To distinguish the pests from the farm's complex backdrop, they employed CNNs and deep residual learning models. However, when CNN's depth was increased, accuracy was sacrificed.

A reliable DL-based identifier (Fuentes et al. 2018) has been developed to recognize the real-world tomato crop illnesses and insects. Together with VGG and ResNet, this model used the FRCNN, R-FCN, and SSD (Single Shot Multibox Detector). In addition, a strategy for improving learning efficiency and decreasing mistakes via picture magnification, label notation of nearby objects, and global label notation were also presented. However, because of the low number of photos available, many of the few labels that had significant pattern shifts were incorrect.

For accurate CNN-based pest localization and identification in agriculture, an efficient data augmentation strategy has been proposed (Li et al., 2019). Images were rotated at different angles and cropped into numerous grids as part of a data augmentation strategy used during the learning stage. In the evaluation phase, researchers employed the test time augmentation technique, which allows the trained multi-scale model to make clear inferences from input pictures of varying resolutions. Moreover, such recognition outcomes from various image scales were concatenated by non-maximum suppression to obtain a final solution. However, training efficiency was degraded due to the random image augmentation that creates more uncontrollable noise and affects image quality.

A region-based end-to-end channel-spatial attention with the CNN model called PestNet (Liu et al. 2019) was developed to identify and categorize large-scale multi-class pests. At first, a new Channel-Spatial Attention (CSA) was integrated with the CNN to extract and enrich features. Using extracted feature maps from pest images, an area Proposal Network (RPN) was developed to provide area suggestions as potential pest sites. When it came time to classify pests and determine their bounding boxes, the FC layer was replaced with the Position-Sensitive Score Map (PSSM). Furthermore, region-of-interest (ROI) context data was employed to supplement the recognition accuracy of pest traits. In contrast, the mean precision was less due to the low-quality images that contain noise and occlusions.

An efficient DCNN framework with transfer learning (Thenmozhi and Reddy 2019) was designed for categorizing crop pests. Categorisation was performed using a transfer learning technique that made use of pre-learned versions of DCNN models including AlexNet, ResNet-50, ResNet-101, VGG-16, and VGG-19. To improve detection efficiency, however, finer-grained characteristics from insect photos were required. A crop pest detection technique based on the CNN (Li et al. 2020) was presented to precisely detect various crop pests. First, the crop pest dataset was acquired and then a modified GoogLeNet structure was adopted to classify the pest classes. However, this model needs more computing power and training period.

A new deep residual network model (Alves et al. 2020) was designed for cotton pest's categorization in field-based images. A new RGB cotton field ground-truth dataset and the ResNet34* model to automatically classify major pests (primary and secondary) from images were presented. But it needs to enlarge the pest dataset by adding new samples and more classes of insects related to other types of crops to further improve the precision. A few-shot cotton pest detection scheme (Li and Yang 2020) was presented, in which the CNN was used to capture feature vectors of pest images. The CNN feature extractor was trained by the triplet loss to separate multiple pest species and guarantee the model robustness. But its accuracy was not satisfactory and the execution speed was less due to the more network parameters.

An improved YoloV3-based CNN model (Liu et al. 2020) was developed that utilizes the image pyramid to merge features of multiple levels and obtain feature maps of multiple scales for detecting tomato diseases and pests. Also, Then, the object box size was grouped and the number of anchor box was increased to get additional edge details of the object. However, the precision of detecting leaf disease and pest images was less due to the limited low-quality images of various kinds of diseases and pests.

In order to detect diseases and pests in rice plant photographs, Rahman et al. (2020) introduced a unique training scheme called two-stage training that use the Simple CNN model. However, in order to further enhance the detection effectiveness, it must include meteorological and soil data with photos of the affected plant portions. Recognition and categorization of soybean pests (Tetila et al. 2020) was presented based on the DL models using UAV images. They used several fine-tuning and transfer learning techniques to research a wide variety of deep-learning architectures including InceptionV3, ResNet50, VGG16, VGG19, and Xception. However, the low-resolution pest photos hindered sensitivity.

Data augmentation model (Kusrini et al. 2020) has been presented for automated categorization of pests in mango farms. The network's deep features were extracted using an augmented version of the VGG16 architecture. The 2-layer FC network then used these extracted characteristics to learn how to categorize pests in mango crops. But its overall classification accuracy was less due to the low-quality pest images, which impacts the training of the deep-learning model.

Ayan et al. (2020) used a genetic algorithm-based weighted ensemble of DCNNs to classify agricultural pests. They employed transfer learning to improve and retrain the VGG-16, VGG-19, ResNet-50, Inception-V3, Xception, MobileNet, and SqueezeNet DCNN architectures they had previously learned. The detection efficiency was further improved by training an ensemble of the three best-performing CNN models (Inception-V3, Xception, and MobileNet) using a sum of maximum probability approach. Next, researchers used a weighted voting system based on an ensemble of similar models, with individual vote weights set by a genetic algorithm.However, the accuracy was less for large-scale datasets that comprises more than hundred classes.

The integration of multi-scale context-aware information representation was offered as the foundation for automated in-field pest detection (Wang et al., 2020). They came up with a novel method of pest detection using cascading mobile vision dubbed DeepPest. To begin, a context-aware attention network was built to first classify pest photos into crop types based on retrieved multi-scale contextual information from the images. In order to create the super-resolved feature map, a multi-forecast pest detection framework was developed to combine contextual information about the pests from low- and high-level convolutional layers. These crop pest images were also used to train the model. When just a few images of pests were used throughout training, however, its effectiveness decreases.

Automated acoustic detection of a cicadid pest in coffee plants was performed by Escola et al. (2020). They developed a new algorithm, which is executed in a low-cost real-time platform for identifying the acoustic of cicadas in plantations. This algorithm included the bark scale, wavelet-packet transform, paraconsistent feature extraction and SVM classifiers. But it has a high complexity and less accuracy for large-scale datasets. A ResNet model was presented (Tian et al. 2020) to recognize diseases and pests on the citrus plants. But its accuracy was not efficient since it needs a larger number of samples for effective training.

Early identification of tea foliar infections and pest damages in real-time field situations was shown (Lee et al., 2020) to be possible using the FRCNN, which identifies the sites of the lesion on the leaves and the origins of the lesions, i.e. pests. But the performance was not effective due to the limited number of samples. Also, the main problem was more precise detection of multiple infections and pests concurrently. A knowledge-based crop pest identifier (Rodríguez-García et al. 2021) was developed to detect various overlapping pests related to the diseases in almond tree, olive tree and grape vine. However, other factors like soil, weather, etc., were essential to increase the detection performance and yield quality.

Wheat mite identification and counting in wheat fields using a three-stage DL model was described (Chen et al., 2021). Initially, actual image dataset was split into small one. Then, CNN was used to process the input image and provide a group of feature maps. The RPN was provided with such feature maps in order to generate many rectangular goal suggestions, each of which was assigned an object score. Then, the two FC levels, a box-regression layer and a box-classifier layer, were fed one 256-dimensional vector containing these suggestions to calculate probability scores for the locations and the wheat mite population. However, identifying photos with fewer than 50% wheat mites proved challenging.

The CNN model comprising four convolutional layers and a FC layer was built (Naufal et al. 2021) to detect various species of insects in the sweetcorn field in Thailand. But it has a less accuracy since it failed to detect a few insects like aphids, thrips, etc. Field testing of a crop pest detection technique (Chen et al. 2021) based on an attention-embedded lightweight network was described. Using the pre-learned MobileNetv2 as a backbone network and including the attention approach and a Classification Activation Map (CAM) in the CNN network improved the learning ability for insect photos with crowded backgrounds. Two-stage transfer learning and an improved loss function were also used. Although it is able to identify the locations of the pests, the model accuracy was negatively impacted by false positives in the attention map.

The Convolutional Rebalancing Network (CRN) has been developed (Yang et al., 2021) to classify large, imbalanced datasets of rice pest and disease data. A convolutional rebalancer, an image enhancer, and a feature concatenation unit made up this network. To extract features from images of rice pests and illnesses, a convolutional rebalancing unit was deployed; this unit used instance-balanced sampling, while reversed sampling was employed to enhance feature engineering for classes with less training images. Then, an image augmentation unit was constructed to increase the learning data. Also, a feature concatenation unit was used to boost the categorization efficiency by merging the image features learned by earlier layers. But the accuracy was degraded when increasing the number of attention maps in the CRN.

The automated insect pest monitoring system used an Online Semi-Supervised Learning (OSSL) model (Rustia et al. 2021). In OSSL, insect image recognition was accomplished by unsupervised pseudo-labelling and semi-supervised classifier model training. There are three main phases to the pseudo-labelling algorithm: image tagging, label reconfirmation, and sample cleaning. However, due to differences in the number and quality of insect image samples recorded from each farm, the average F1-score was low.

There is now a method for accurate pesticide spraying thanks to the use of DL on an embedded drone to identify fruit tree pests (Chen et al., 2021). They used a drone equipped with a sensor to locate the pest and then trained a neural network to recognize T. papillosa in the orchard and pinpoint its position in real time. The locations of these pests were used to plan the most efficient route for the agricultural drone to spray insecticide. But it did not consider weather factors that may influence the model efficiency.

An image detection of crop diseases and pests (Xin and Wang 2021) was developed using DCNN model. Initially, an enhanced 3D panoramic image synthesis scheme was applied according to the coordinate ascending inverse mapping. Then, the location of ROI in all images was recognized by the YOLO-v4 model. In addition, the inverse mapping technique of coordinate elevation was derived from the pixel coordinate system using the calibration parameters of the insect cameras and the other conditions. The absolute predicted location was obtained by combining and filtering the prediction locations. But the model performance was affected by the visual quality of images.

A CNN ensemble called PlantDiseaseNet (Turkoglu et al. 2022) was developed for plant disease and pest recognition. Two categorization frameworks were presented depending on deep feature extraction from pre-learned CNNs. Various classical CNNs were modified and combined to extract deep features. Then, such features were given to the SVM classifier to get final results. However, there were not enough data points to properly train the DL model.

Recognition of crop diseases and insect pests (Wang 2022) was presented using DL-based model. Initially, crop images were acquired and preprocessed based on the nearest neighbor interpolation scheme. After that, the improved AlexNet was designed by tuning the FC layer to recognize both crop diseases and pests precisely. But the recognition time was high and the accuracy was less due to the limited number of images. A combined YOLOv5 and GhostNet (Zhang et al. 2022) was designed by substituting the convolution kernel with a linear operation to recognize orchard pests. However, the average precision was decreased since a few feature details were missed while adding the GhostNet in the backbone part.

A crop pest image identification technique (Liu et al. 2022) has been built utilizing transfer learning and CNN models. At first, a geometric operation was applied on the crop pest image in order to expand the dataset's sample size. After that, such samples were trained by the AlexNet, VGG-16 and ResNet-50 models to recognize crop pests. But the model performance depends on the network parameters like convolutional kernel size, pool size, training rate, epoch, etc. A recognition of field pests in the complex background (Zhang et al. 2022) has been achieved based on the rotation detection scheme. But its accuracy was not satisfactory due to the limited number of samples collected at constrained circumstances, whereas the efficiency was needed to improve by collecting samples of multiple pests in more complex conditions.

A Multi-Scale Attention Learning Network (MS-ALN) has been developed (Feng et al. 2022) for pest detection. By using the MS-ALN, discriminative areas were localized and region-based feature representation was learned. In order to create multi-scale images, the MS-ALN uses target localization, attention detection, and attention removal to link two feature extraction sub-nets in close proximity. By using the attention removal unit to randomly reduce the discriminative area, occlusions may be avoided while the target localization and attention recognition units are utilized to pinpoint the discriminative regions and eliminate complicated backdrops, respectively. Next, the feature extraction sub-network was followed in all of its branches by the parameter-shared classification sub-network in order to identify pests. Misclassification of minor pests is simple for the MS-ALN to make, and thus reduces its detection accuracy.

For the purpose of identifying pests and illnesses of fruits like Longan and lychee, a recognition model has been created (Zhu et al., 2023). Before anything else, a knowledge graph of lychee and Longan-related illnesses and pests was established.

After that, an embedded system with VGG16 network was trained by the created knowledge graph for recognition. But its accuracy was not satisfactory and it was expensive.

To identify litchi leaf illnesses and pests, an improved Fully Convolutional One-Stage (FCOS) object identification technique was developed (Xie et al. 2023). Our knowledge of litchi leaf diseases and pests was enhanced by adding the Central Moment Pooling Attention (CMPA) method on top of the G-GhostNet-3.2 backbone network. Adding the width and height dimensions of an actual target improved the models' ability to generalize for future targets. An enhanced localisation loss function was used to locate the specific location of leaf diseases and pests. However, the accuracy was impacted by a few missed recognitions in the recognizing phase.

A novel pest recognition model using enhanced YOLOv5m (Dai et al. 2023) has been developed. To aid in the extraction of more generalised information from pest images, the YOLOv5m network was first supplemented with the SWin Transformer (SWinTR) and new Transformer (C3TR) techniques. Residual Spatial Pyramid Pooling (ResSPP) was later included into the foundation in order to extract even more features. To transfer the global features from the feature map to the recognition phase, the feature fusion phase transforms the three output necks C3 into SWinTR. To further enhance the network's feature fusion capability, a Weight Concat (WConcat) was included into the fusion feature. But it has a high complexity and less accuracy.

Table 2.3 provides an overview of the aforementioned models in terms of their advantages and disadvantages.

Table 2.3 Comparison of Pest Detection Model based on Artificial Intelligence

Author & Year	Models	Benefits	Limitations	Dataset Used
Liu et al. (2016)	DCNN	It achieved better mean accuracy precision and less runtime.	Its accuracy was insufficient since it did not take into account a more nuanced search in the saliency maps.	Over 5,000 images of 12 common paddy field pest bug species were obtained from Google, Naver, and FreshEye's image search databases.
Cheng et al. (2017)	CNN	It achieved the highest classification accuracy.	Complexity was high while increasing the depth of CNN.	10 classes of crop pest images
Fuentes et al. (2018)	Integration of FRCNN, R-FCN and SSD with VGG and ResNet	It can handle complicated situations from a plant's environment in order to identify pests and illnesses.	Few labels having huge motif changes were often inaccurate owing to a lack of sufficient pictures, leading to a high rate of false positives.	5,000 images of tomato illnesses and pests, taken from farms around the Korean Peninsula.
Li et al. (2019)	Data augmentation and CNN	It achieved better mean average precision for pest detection.	Training efficiency was degraded due to the random image augmentation that creates more uncontrollable noise and affects image quality.	Four different types of pests (wheat mites, wheat aphids, wheat sawflies, and rice planthoppers) are represented in this data collection.
Liu et al. (2019)	PestNet	It can be suitable for large-scale datasets.	The mean precision was less due to the low-quality images that contain noise and occlusions.	More than 80,000 images were used to name and categorize 580,000 pests into 16 different groups for the 2018 Multi-class Pests Dataset.

Author & Year	Models	Benefits	Limitations	Dataset Used
Thenmozhi and Reddy (2019)	Pre-trained DCNNs	It can achieve the highest classification accuracy.	Better detection performance required more fine-grained characteristics extracted from insect photos.	Insects from the NBAIR (40 classes), Xie1 (24 classes), and Xie2 (40 classes) datasets.
Li et al. (2020)	Modified GoogLeNet	It achieved better accuracy and robustness.	This model needs more computing power and a training period.	All all, there are 5,629 images here; the vast majority came via the Bing image search, while the remaining 650 were gathered via web crawling. More than 400 images belong to the pest category, and over 1000 belong to the snail group.
Alves et al. (2020)	ResNet34*	It achieved the greatest accuracy and f-measure.	In order to increase precision, the pest dataset should be expanded to include data on more crop kinds and insect families.	The database contains 1,600 images from the field and is evenly split between 15 pests and 1 control.
Li and Yang (2020)	CNN	It achieved low complexity cost and running time.	Its accuracy was not satisfactory and the execution speed was less due to the more network parameters.	National Bureau of Agricultural Insect Resources (NBAIR) dataset
Liu et al. (2020)	Improved YoloV3	Tomato diseases and pests can be promptly located, and their classification determined.	The precision of detecting leaf disease and pest images was less due to the low-quality images.	15000 images of tomato diseases and pests

Author & Year	Models	Benefits	Limitations	Dataset Used
Rahman et al. (2020)	Simple CNN	It achieved higher accuracy with reduced model size.	To further enhance detection effectiveness, it should include meteorological and soil data with images of the affected plant portions.	There are a total of 1426 images of rice diseases and pests from Bangladeshi paddy fields that have been collected by the Bangladesh Rice Research Institute (BRRI).
Tetila et al. (2020)	Pre-trained DCNN models	It achieved better accuracy and generalizability.	The sensitivity was not good due to the low-resolution pest images.	A set of 5,000 images in 13 pest classes
Kusrini et al. (2020)	VGG16	It can reduce the required computational time.	The trained deep-learning model's overall classification accuracy suffered by the low-quality pests images.	There are 510 unique images included in a collection, all of which were taken on mango fields in Indonesia.
Ayan et al. (2020)	Pre-trained DCNNs	Small-scale datasets may be used effectively for early identification and categorisation of pests.	More than a hundred class instances reduced accuracy for big datasets.	D0 dataset with 40 classes
Wang et al. (2020)	DeepPest	It may make the model more reliable and effective in identifying pests.	When just a few images of pests are used during training, it performs less well.	In-Field Pest in Food Crop (IPFC) dataset
Escola et al. (2020)	SVM	It improved accuracy.	It has a high complexity for large-scale datasets.	Database of 1366 recordings of the cicadid pest in coffee plants

Author & Year	Models	Benefits	Limitations	Dataset Used
Tian et al. (2020)	ResNet	Less complexity.	Its accuracy was not efficient since it needed a larger number of samples for effective training.	510 diseased or insect-infested pomelo leaves
Lee et al. (2020)	FRCNN	It could help growers identify the origins of problems on tea leaves in near-real time.	The performance was not effective due to the limited number of samples.	Images of sick tea leaves date back to 1822, and they may be traced back to a variety of pests such as the leaf miner, tea thrip, tea leaf roller, and tea mosquito bug.
Rodríguez-García et al. (2021)	Knowledge-based crop pest identifier	It achieved the highest accuracy.	Other factors like soil, weather, etc., were essential to increase the detection performance and yield quality.	Almond tree, olive tree, and grape vine have a combined 212 symptoms caused by 75 distinct pests and diseases.
Chen et al. (2021)	CNN and RPN	It achieved better recognition accuracy.	It was complex to recognize the images having lower than 50% wheat mites.	546 images, which contain more than 1000 wheat mites
Naufal et al. (2021)	CNN	Less complexity and can be effective for images with no background.	It has less accuracy since it failed to detect a few insects like aphids, thrips, etc.	5568 images of eight sweet corn pests
Chen et al. (2021)	Attention-embedded lightweight network	It improved the average accuracy of identifying plant pests.	The attention map's false positives reduced the model's accuracy.	A total of 5629 images of spiders, insects, and other pests were culled from the public database and organised into 10 different groups.

Author & Year	Models	Benefits	Limitations	Dataset Used
Yang et al. (2021)	CRN	It may serve as a vital resource for the effective management of rice diseases and pests.	When more attention maps were added to the CRN, accuracy suffered.	Using freely available plant image datasets (Flavia, Swedish Leaf, and UCI Leaf) and pest image datasets (SMALL and IP102), a large, heterogeneous collection of rice pests and diseases (18391 pictures) was compiled.
Rustia et al. (2021)	OSSL model	It can achieve better accuracy.	Due to differences in the number and quality of insect image samples obtained from each farm, the average F1 score was low.	There were a total of 2174 images of insects and 1876 images of other animals.
Chen et al. (2021)	Tiny-YOLOv3	It may help farmers track pests in their fields and take preventative measures in real time.	It did not consider weather factors that may influence the model efficiency.	700 images of T. papillosa collected from the wild and online in various stages and instars
Xin and Wang (2021)	YOLO-v4	It has better recognition accuracy.	The visual quality of the images has an effect on the model's performance.	640 still images of pests and illnesses in agricultural crops
Turkoglu et al. (2022)	PlantDiseaseNet	It achieved better accuracy.	Insufficient data prevented a more thorough training of the DL model.	The Turkey-Plant-Dataset contains unrestricted photos of 15 different types of plant diseases and pests.

Author & Year	Models	Benefits	Limitations	Dataset Used
Wang (2022)	AlexNet	Its complexity was less.	Recognition time was high and the accuracy was less due to the limited number of images.	A total of 1200 images of Yulu fragrant pear leaf pests
Zhang et al. (2022)	Combined YOLOv5 and GhostNet	It has high feasibility and less detection time.	The average precision was decreased since a few feature details were missed while adding the GhostNet in the backbone part.	2500 pest images in 7 classes collected from web crawler
Liu et al. (2022)	Pre-trained DCNNs	Improve crop quality and output while decreasing pesticide usage with this revolutionary tool.	Model performance depends on the network parameters like convolutional kernel size, pool size, training rate, epoch, etc.	Image Database for Agricultural Diseases and Pests (IDADP)
Zhang et al. (2022)	Rotation detection	It has a low detection speed and rotation detection time.	Its accuracy was not satisfactory due to the limited number of samples collected under constrained circumstances.	Pest dataset pest Rotation Detection (PRD21)
Feng et al. (2022)	MS-ALN	It is able to solve issues associated with occlusion and complicated backdrops.	It can easily misclassify small pests, which impacts the detection accuracy.	IP-102 dataset, comprising more than 75000 images of 102 common agricultural pests

Author & Year	Models	Benefits	Limitations	Dataset Used
Zhu et al. (2023)	VGG16	It may be utilized for real-time illness and pest detection.	Its accuracy was not satisfactory and it was expensive.	Knowledge graph of lychee pests and diseases
Xie et al. (2023)	FCOS object recognition scheme	It may help with the goal of instantaneous and accurate leaf disease detection.	A few missed recognitions during the identification stage had an effect on the overall accuracy.	Diseases and parasites such as the litchi leaf mite, litchi sooty mould, litchi anthracnose, mayetiola sp., and litchi algal spot are all represented in this data collection.
Dai et al. (2023)	Enhanced YOLOv5m	Accuracy and reliability in identifying plant pests may be improved.	It has a high complexity and less accuracy.	Dataset with 1309 pest images in different classes

2.5 LITERATURE ON RECOMMENDATION SYSTEMS IN AGRICULTURE

A few scholars had experienced in developing pesticide or fertilizer recommendation systems in agriculture. In-depth review of some pesticide recommendation systems to control leaf diseases and pests is presented in this section.

A pesticide residue monitoring (Ferentinos et al. 2013) was performed by a new ANN combined with a bioelectric cellular biosensor. As the amount of data points increased, however, so did the complexity of the ANN. A content-based paddy leaf disease diagnosis and treatment prediction model was developed making use of K-means clustering and the SVM (Pinki et al., 2017). The first step in isolating the damaged region in a paddy leaf image was using K-means clustering. Colour, texture, and shape were then isolated for further analysis. The SVM classifier learns these properties to classify paddy leaf diseases. Once a disease was identified, a predicted cure was suggested based on the severity of the condition, helping farmers choose the most effective pesticides. However, this model did not do well when attempting to categorize several illnesses at once.

In order to categorize leaf disease images and advise on pesticides based on leaf disease, the CNN with several layers was provided (Kosamkar et al., 2018). They used two different stages: training and testing. During training, image acquisition, preprocessing and CNN-based training were performed. During testing, image acquisition, preprocessing, categorization of leaf diseases and recommendation of pesticides were performed. But other factors that impact the plant leaves were needed to increase the accuracy.

By optimising sigmoid kernels in M-SVM, the agricultural fertiliser recommendation system (Suchithra and Pai, 2018) was given. With the help of the genetic algorithm and particle swarm optimisation, a unique sigmoid kernel SVM classifier was constructed to provide recommendations for the multiclass soil nutrients on rice fields. But it cannot be effective for huge quantity of data since its training time was high and it did not learn more deep characteristics from the data.

A soil fertility analysis and fertilizer recommendation system (Pratap et al. 2019) has been presented to find the soil nutrient richness and predict the fertility of a given soil sample. According to these outcomes, the system can recommend the category of fertilizer to be utilized by the farmers. But its accuracy was less due to the limited data and training ability.

Model-based balanced nutrient necessities for barley output in northern Ethiopia were provided (Mesfin et al., 2021). This made it possible to create a system for recommending fertiliser based on a given location. The ideal ratios of nitrogen, phosphorus, and potassium for growing barley were predicted using a Quantitative Evaluation of Fertility of Tropical Soils (QUEFTS) model. Based on the predicted soil nutrients, a proper fertilizer was recommended to enhance yield quality. But it has a high complexity and requests other factors like weather changes to increase the recommendation efficiency.

For the purpose of determining the appropriate fertilizer, a prediction technique based on an Adaptive Neuro Fuzzy Inference System (ANFIS) has been developed (Kuzman et al., 2021). In order to anticipate the optimal fertilizers, this system can analyze the impact of environmental factors such as temperature, humidity, moisture, soil type, crop type, and soil nutrient. But its efficiency depends on the selection of appropriate fuzzy membership function. A voting-based ensemble classifier (Pragathi 2021) has been presented to recommend proper fertilizers based on the soil nutrients and weather factors. But it was not suitable for large-scale datasets.

A Nutrient Expert (NE)-based protocol (Amgain et al. 2021) was developed, which was a decision-making model depending on site-specific nutrient control to recommend an alternate fertilizer for enhancing rice productivity in Nepal. But its generalization was not effective since it considered the data collected from only specific locations. A new recommendation model using DL (JuhiReshma and Aravindhar 2021) was presented to predict the quantity of fertilizers for a banana crop based on the soil nutrients. However, its effectiveness was not measured so that its suggestion success rate could be compared to that of comparable models.

ML methods such as logistic regression, polynomial regression, and KNN were used to offer an optimization of pesticide spraying on crops in agriculture (Baghel et al. 2022). According to this system, the repetition of pesticides in agriculture was controlled.

But DL algorithms were needed to increase the optimization efficiency. A new hybrid statistical learning model (Grégoire et al. 2022) golf course pesticide consumption prediction model that incorporates SVM, random forest, and grasshopper's heuristic optimization approach. But weather factors should consider as input parameters to increase the efficiency of predicting pesticide usage on various weather conditions.

A novel model was created (Gao et al. 2023) by merging ML and swarm intelligence search techniques to select correct fertilizers. Predictions of crop production were made using a number of ML algorithms based on past data for maize, rice, and soybeans. These included random forest, extreme random tree, and extreme gradient boosting. Then, a significant model for making fertilization decisions based on the cuckoo search algorithm was included. But it did not consider weather factors and the accuracy was affected by the missing data or noise in the datasets.

An intelligent insecticide and fertilizer recommendation model (Thorat et al. 2023) was developed based on the DL. To determine the best pesticide to use, a picture of the pest was processed independently and in real time using a dual operator consisting of the Transition Probability Function (TPF) and a CNN. The goal function of the model was determined mathematically. In addition, a soil nutrient analysis was performed to provide fertilizer recommendations based on nutrient levels. But its accuracy was not sufficient and it needs weather factors to increase the recommendation efficiency.

The above-studied models are summarized in Table 2.4 based on their benefits and limitations.

Table 2.4 Comparison of Pesticide Recommendation Systems

Author & Year	Models	Benefits	Limitations	Dataset Used
Ferentinos et al. (2013)	New ANN with bioelectric cellular biosensor	It achieved a better overall success rate.	Adding more and more layers to the ANN made it more complicated as the amount of data.	Three different pesticide groups such as carbamates, pyrethroids, and organophosphates
Pinki et al. (2017)	K-means clustering and SVM	Based on illness severity, it may recommend pesticides.	Pesticide recommendations for many illnesses were labor-intensive.	Brown spot, leaf blast, and bacterial leaf blight: predictive measurement for paddy leaves
Kosamkar et al. (2018)	CNN	It achieved better accuracy.	Other factors that impact the plant leaves were needed to increase the accuracy.	Plant village dataset
Suchithra and Pai (2018)	New sigmoid kernel SVM	It can achieve better performance for small-scale datasets.	It cannot be effective for a huge quantity of data since its training time was high and it did not learn more deep characteristics from the data.	Method for recommending soil fertiliser types for paddy fields with several classes
Pratap et al. (2019)	Soil fertility analysis and fertilizer recommendation	It can predict the soil fertility and fertilizers to enrich the soil nutrients.	Its accuracy was less due to the limited data and training ability.	Soil samples, pH sensor values and moisture sensor values

Author & Year	Models	Benefits	Limitations	Dataset Used
Mesfin et al. (2021)	QUEFTS model	It achieved better prediction accuracy to recommend fertilizer based on crop requirements.	It has a high complexity and requests other factors like weather changes to increase the recommendation efficiency.	Soil data, yield and agronomic data
Kuzman et al. (2021)	ANFIS	Optimizing the crop production response in this way may help keep costs down.	Its efficiency depends on the selection of an appropriate fuzzy membership function.	Soil parameters
Pragathi (2021)	Voting-based ensemble classifier	It can be precise and accurate for a limited number of samples.	It was not suitable for large-scale datasets.	Soil nutrients
Amgain et al. (2021)	NE-based protocol	It was an effective tool to dynamically recommend fertilizers for rice.	Its generalization was not effective since it considered the data collected from only specific locations.	Yield data and soil nutrients
JuhiReshma and Aravindhar (2021)	DL model	It can recommend the amount of fertilizers with less complexity.	Its efficiency was not analyzed to comprehend the success rate of recommendation compared to the other models.	Soil nutrients for banana crop

Author & Year	Models	Benefits	Limitations	Dataset Used
Baghel et al. (2022)	Logistic regression, polynomial regression and KNN	It can reduce the impact of pesticides due to improper usage.	The optimization efficiency was not effective.	Crop data and pesticides sprayed on crops
Grégoire et al. (2022)	Hybrid SVM, random forest and grasshopper optimization algorithm	It can increase the model's sustainability.	Weather factors should be considered as input parameters to increase the efficiency of predicting pesticide usage in various weather conditions.	It has the potential to save expenses by enhancing the production responsiveness of crops.
Gao et al. (2023)	Random forest, extreme random tree, extreme gradient boosting and cuckoo search algorithm	It achieved the highest performance in optimizing fertilization.	It did not consider weather factors and the accuracy was affected by the missing data or noise in the datasets.	Yield data for maize, rice, and soybean crops
Thorat et al. (2023)	TPF and CNN	It can recommend fertilizers based on the soil nutrient values.	Its accuracy was not sufficient and it needs weather factors to increase the recommendation efficiency.	Soil nutrient analysis

2.6 RESEARCH GAP

Methods for detecting leaf diseases and pests may be broken down into two groups. Both visual analysis and automated systems can identify plant diseases. The following requirements are necessary for a visual examination are,

- It is difficult process since it demands constant manual monitoring and a knowledgeable botanical expert
- This technique employs the human eye and laboratory inspection to detect leaf diseases and pests
- The classification rate depends on how the technician detects the disease
- Identifying the precise disease type takes additional effort
- It is a complicated and time-consuming procedure

2.7 SUMMARY

To that end, this chapter provides a comprehensive review of the literature on pest detection using AI models, pest detection using DL with transfer learning models, and pest detection using image processing with ML algorithms, as well as pesticide and fertilizer recommendation systems in agriculture. In addition, the research gaps in those earlier studies are observed and discussed