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A REVIEW ON CUTTING EDGE TECHNOLOGIES IN CROP PESTS AND DISEASES DETECTION

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Abstract
Agriculture is one of the most prominent sources in contemporary society. In agriculture, different crops are yielded in every region of the world to substantially expand the country's income and production and provide surplus sustenance to people. However, factors like weeds, pests, diseases, and other things may have an extreme impact on the development and crop yield. Due to these factors, farmers struggle to monitor the crop and timely detect crop damage. This review focuses on detecting crop pests and diseases using cutting-edge technologies such as image processing, machine learning, and deep learning. These technologies have shown significant promise to transform numerous sectors due to their robustness for feature learning on enormous image datasets. Moreover, these technologies have given accurate results based on image datasets to detect crop pests and diseases, which is helpful to farmers in implementing remedies.
Keywords: Crop Pests and diseases, Image Processing, Machine Learning, Deep Learning, Performance Metrics, classification algorithms

Introduction

Crop pests and diseases are substantial issues to yield quality. It has a deleterious effect on agronomy development and also on agronomists. Diseased crops traditionally have visible dots or damage on their foliage, stalks, blossoms, or plant yields [1]. Most pests and diseases have been identified, and symptoms have been shown on the leaves [2]. According to the Food and Agricultural Organization, pests and diseases create enormous losses of more than 40% for agricultural development, costing around \$200 billion annually [3]. Agronomists recognize pests and diseases based on previous experience and use pesticides extensively to improve the quality of agricultural production and the lifespan of crops. However, heavy pesticide usage causes environmental pollution and grievous human health issues[4]. Sometimes agronomists without proper knowledge may make mistakes and misuse pesticides throughout the recognition approach. So, identifying pests and diseases has become a pivotal topic and is also time-consuming in the contemporary era [1]. To confront the above impediments, researchers use sophisticated technologies such as image processing, machine learning, and deep learning in agriculture to detect pests and diseases and avoid unnecessary damage [5-6].

The rest of the paper is laid out in the following sections: Section 1 describes the technologies exploited in crop pests and diseases. Section 2 gives a background on crop pests and diseases.

Section 3 provides the methodologies of existing research. Section 4 describes the performance metrics to measure the model. Section 5 elaborates on the drawbacks of the current work and finally gives the conclusion of the work.

Technologies Exploiting in Crop Pests and Diseases

Detecting crop pests and diseases based on technologies and predominantly image features incorporates accumulating image datasets from different sources[6-7]. These images are captured using cameras, sensors, and other devices that operate in various spectrum bands and are available on multiple public repositories such as internet sources.[8] Each pest and disease dataset is described systematically, including parameters such as imaging equipment and setups, picture range, format and intensity, annotation type, implementations, and possible constraints. The data is organized chronologically and alphabetically to facilitate further process of detection. Finally, image datasets play a vital role in the image analysis channel and in obtaining precision results for the affected crop [9].

Image processing is a vital technology for research to solve the issues of earlier diagnosis and detection of crop pests and disease detection [10-11]. An image cquisition is the primary process for retrieving infected crop images from various sources in image processing. It converts an optical image (natural world data) into a computational array that can be manipulated on a machine using image processing algorithms. It applies various enhancement methods to improve image quality or obtain accuracy using processing algorithms[8,12]. The contiguous process is image restoration, restoring and evaluating the innovative infected crop images by obliterating a blur, noise, and ambiguity from the image [13]. It employs numerous color model images, namely RG, HSI, and CMYK emphatically characterizing the colors of the pests and diseases of the crop [14]. Morphological processing operates on images to differentiate pests and diseases based on their shapes and sizes. Image segmentation is to classify pests and diseases into different segments, which predicts the image's labels and detects the objects of the image [15]. After the images have been segmented, it is represented by the specific features for processing during pattern recognition or adequate during image compression[16]. In computer vision, image classification is a critical and challenging problem to classify infected crop images based on classification algorithms and texture methods [17]. Therefore, image processing technology will benefit agronomists by allowing them to detect infected leaves quickly and affordably.

Machine Learning and Deep Learning are sophisticated technologies to detect crop pests and diseases together with image processing. It performs the various algorithmic rules that allow systems the competence to enhance and develop based on past observations instantaneously-feeding infected crop images as input to solve pest and disease problems. After the image dataset has been taken, the features of the images are extracted from the image segmentation and fed into supervised or unsupervised algorithms. The steps such as training, testing, and validation are performed based on the categories of algorithms [18],[19]. Finally, the targeted images would give accurate classification and detection to predict crop pests and diseases.

Furthermore, Deep Learning is part of Machine Learning, and the functioning of the biological mind influences the input layers, weights, hidden layers, and output layers. Each crop pests and diseases image features are taken as a single node in the input layer. Forward and Backward propagation is employed for the updation of weights. When the process is done would get better accuracy [20],[21]. It has diverse architectures that have been applied to significantly enhance the precision of pests and diseases for recognition and detection, so that hazard and restraint care can be carried out in the future [11],[22].

Fig:1 Workflow to evaluate the Images

Background

Various crops have been developed in agriculture to provide surplus food and needs to humans worldwide. Crops like Kharif, Rabi, and Zaid crops should be decided in multiple seasons. However, in every season, biological parameters have frequently attacked the crops due to climatic conditions, insufficient availability of nutrients to destroy productivity, and losses to agronomists. Yield is defined as potential, attainable, or actual based on various factors due to biotic and abiotic stresses [23]. The biotic stresses are living organisms responsible for infecting foliage, stalks, blossoms, or plant yields. Fungal pests can be necrotrophic (destroy host cells by secreting toxins) or biotrophic (feed non-living host cells). They can cause vascular wilts, leaf spots, and plant cankers[24]–[26]. Nematodes consume plant materials and are mainly responsible for soil-borne diseases that result in nutritional deficiencies, growth retardation, and wilting [27], [28]. Viruses, like bacteria, can cause systemic inflammatory damage, resulting in osmotic stress and stunted growth. [29]. Conversely, mites and insects harm plants by feeding (protruding and squeezing) on them or by laying eggs. Insects may also serve as carriers of different microbial pathogens [30].

Abiotic stresses such as moderate or medium temperatures, insufficient or extreme water, salt stress, toxic substances, and ultraviolet rays are detrimental to crop growth and expansion, resulting in significant crop productivity losses[31]. Crops in cool climates are subjected to frightening and cold circumstances, which seem highly stressful. Extreme weather has led to a rise in temperature, Carbon dioxide levels in the atmosphere, and irregular rainfall distribution, all of which occur to seed death prematurely and decrease their metabolic demands. The concurrent occurrence of stress is toxic material incorporated into agricultural soil, which harms the soil-crop system [32]. The most persistent is sodium chloride stress, exacerbated by increasing soil salinity of cultivable land. [33].

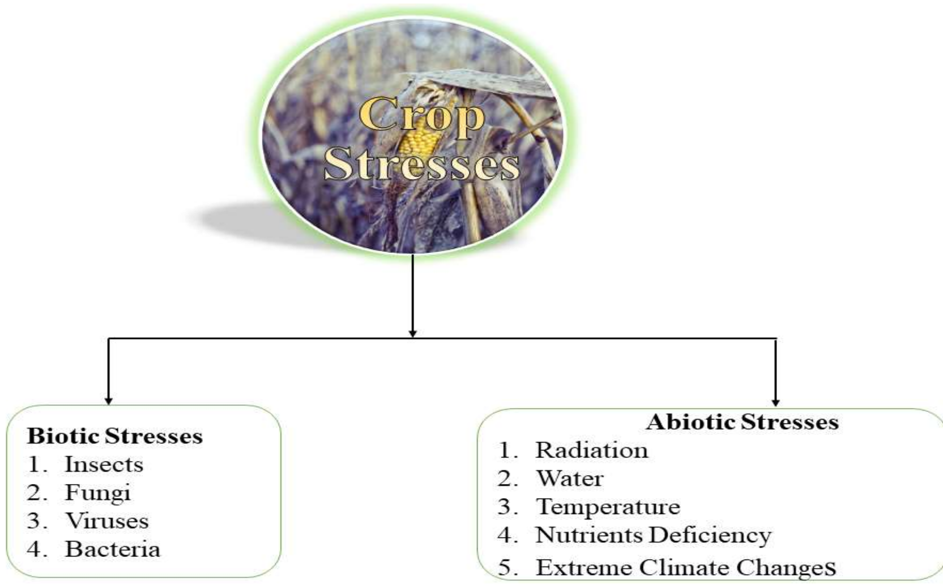

Fig 2: Different types of Crop Stresses

Related Work

The proposed work [34] segmented and classified tomato disease images with correspondent leaf masks using the Modified U-net and Efficient Bo, Efficient B4, and Efficient B7. Image datasets have been segregated into ten sections for feeding the models. The healthy leaf images were in one part, and the unhealthy diseased leaf images were in another region. Moreover, these harmful leaf-diseased images have been designated into five subsections: fungal, viral, mite, bacterial, and mold. Preprocessing has been performed to resize the images to 256 x 256 and 224 x 224 for various segmented and classified networks per image specifications. Similarly, training images were balanced using augmented methods to remove the imbalanced data. The visualization technique (Score-CAM) was also utilized to obtain and upgrade the network decisions with clear visualization. Furthermore, the Efficient B7 approach performed superior for two and six classifications compared to other techniques. In contrast, the Efficient B0 approach performed excellently for ten classifications. Ultimately, the models achieved higher accuracy by assessing the pre-trained models.

In this research, the authors [35] proposed the improved Yolo v3 model to accomplish multi-scale object detection by using different image resolutions, to achieve an efficient detection of tomato pests and diseases (below Table-1) with accuracy and speed. It combines different layers to increase the filters that conserve the computational task and running speed. In this model, the input size was modified during the learning phase, allowing the predictive algorithm to alter the various ranges for location and category prediction. The prior box dimension in the custom-made tomato datasets was calculated using the K-Means algorithm to acquire the desired cluster center for detecting pests and diseases. Moreover, SSD, Faster R-CNN, Yolo v3, and improved Yolo V3 models were comparatively analyzed to assess the validity, accuracy, and stability and were used as the evaluation metrics. The improved Yolo V3 accomplishes the finest detection in terms of accuracy and speed.

The authors proposed [36] that detecting and recognizing rice pests and diseases using a framework that includes a non-consecutive VGG16 and Inception-V3 has been adopted and fine-tuned. Moreover, MobileNet, NasNet Mobile, and Squeezenet are effective internal representation consecutive methods contrasted with the multi-step convolution neural network framework and utilized 3 X 3 filters. Meanwhile, the original images were rescaled for frameworks that contain 299 x 299 x 3 and 224 x 244 x3 as a slice of the augmentation task. An image datasets of nine groups was then segregated into seventeen subsections with pre-trained weights. The performance of these modeling techniques on real-world datasets has been demonstrated with distinct learning approaches such as baseline Training, Fine Tuning, and Transfer Learning applied. These learning approaches configured the layers, weights, and dense layers to obtain a good result. Finally, Fine Tuned VGG16 delivered the best outcome and showed efficiency.

In this proposed model [37], the authors specified Hybrid Deep CNN Transfer Learning to classify and identify rice plant diseases. In this work, three varieties of disease images have been preprocessed using a geometric transformation procedure to yield the Resilient Distributed Dataset accuracy. The image data of size 224 x 224 x 3 was trained on the network, which includes convolution, max-pooling, dense layer using activation functions, and sigmoid. Moreover, the techniques were carried out in various epochs, and the efficiency has based on the accuracy and no of epochs.

The work proposed [38] that a fine-tuning-based transfer learning approach can diagnose hot pepper pests and diseases. The authors used pre-trained VGG16, VGG19, and ResNet50 techniques that rely on ImageNet datasets to extract the convolutions in the vector space. The size of the kernel was 3 x 3, utilized with the dimensions applied by filters while utilizing a stride value of one in the ConvNet and the stride value of 2 in the pooling layer. Meanwhile, residual blocks efficiently conducted the updated layers using short connections. Transfer Learning was involved in the pre-trained models to fine-tune the new layers by adding them to the prior layers, and these were trained by adding the new dataset images. The KNN algorithm classified the unlabelled data and utilized the Bray-Curtis distance to improve the throughput of pests and disease images, equivalent to the labeled input images. Therefore, the image datasets from different varieties of hot pepper pests and diseases found a high accuracy outcome.

The authors examined [39]that pests and diseases in chili the traditional method were contrasted to the deep-learning-based models for extracting features. Images of chili leaves with five diseases, two pest attacks, and one wholesome leaf have been captured. Six traditional feature-based methods and six deep-learning feature-based frameworks have been used to evaluate possible pests and disease features from chili image data. Three Machine Learning classifiers have consumed the input images, such as the Support Vector Machine, Random Forest, and Artificial Neural Network, to detect pests and diseases. According to the evaluation results, the deep learning feature-based approach outperformed the traditional feature-based approach, successfully classifying the classes using the classifiers.

In this proposed paper, the authors specified [40] that visual representation in disease identification techniques was examined and displayed. In this experiment, the U^2 net has been used effective unsupervised neural network for detecting important and relevant objects. From the original input, a pre-trained model produced a correlated obscured image. It accomplished the binary execution between the input and segmented images by using the obscured image to identify whether the coffee crop was healthy or unhealthy. The guided methods for diagnosing coffee disease after visualization to recognize classification errors.

In this exploration, the authors proposed [41] stages such as semantic segmentation to calculate the severity of the crop and classification of the lesion symptom. In this work, they have applied semantic architecture such as UNet and PSPNet. The UNet model is classified into an expansive path and a contractive path for upsampling and downsampling, which are concatenated with the feature convolutions to increase the depth and dimensionality of an image. The PSPNet model has been employed to segment complex scenes and determine similar objects, reducing incorrect classifications. Resnet has been used in this model to extract the features. Resnet has been used in this model to extract the features. The distinct sub-regions have been gathered using the pyramid pooling module, which employs the activation map and the average pooling operation. Finally, the result undergoes the upsampling and is added to the activation map through a last convolution step by providing the pixel prediction to identify the salient manifestation of coffee pests and diseases.

This research article [42] employed image processing and deep learning techniques on creating an end-to-end framework for identifying the pests and diseases infection in coconut trees. In this study, coconut tree pests and diseases image datasets have been captured and resized to 64*64 for further processing, bringing the 39,000 images approximately using an Image Data Generator. Disparate segmentation algorithms such as Thresholding, Watershed, and K-means clustering have been utilized to quickly identify the anomalous frontiers in manually accumulated images of coconut trees. Furthermore, hand designed CNN classification model has been trained, validated, and tested with segmented images to detect infections by employing the input layer, convolution layer, max pooling layer, flatten layer, fully connected layer, and output layer. According to an empirical study, K-means clustering outperformed other segmentation approaches, and on the other hand, hand designed CNN model achieved better accuracy.

In this paper [43], the authors focused on pests, nutrient deficiency, and diseases of coconut trees. The most advanced machine learning and image processing techniques were used to monitor coconut leaves after applying pesticides and fertilizers. Image processing steps were employed for capturing and preprocessing images and detecting objects. The dataset was preprocessed to increase precision and simplify its structure. Canny edge detection, Sobel edge detection, and the Laplacian approach may all be used to segment data. K-means algorithms may assist in detecting nutritional deficiencies, while edge detection technology was used to identify pests. To achieve a higher level of accuracy, features were extracted from the supplied data and converted into the specified set of characteristics. Furthermore, the afflicted leaf characteristics were fed into the SVM and CNN algorithms for training and testing to detect pests, diseases, and nutritional deficiencies. Eventually, techniques were effective, efficient, and precise enough to diagnose diseases in incipient phases.

In this proposed work, the authors specified [44] that Gaussian Mixture Model determined the dispersion of colors in the background and foreground regions were evenly dispensed. Subsequently, a Markov random field (MRF) was developed on the GMM labels. The MRF cost function was evaluated predicated on the connected regions with the same label, and a graph cut optimization splits vertices into backgrounds and foregrounds for cotton leaf diseases. Furthermore, they suggested Yolox Model with a customized Spatial Pyramid Pooling (SPP) layer to efficiently retrieve pertinent features at various scales from training data and accomplish this by stringing together multistep features gathered from lower to higher scales. Numerous skip connections were also implemented to improve network convergence and detection precision, and a regression loss function based on IoU was also implemented. A dataset containing cotton plant images with co-occurring diseases and their escalating severity levels was compiled. In conclusion, this approach was able to identify disease symptoms that appeared similar and overlapped more accurately.

In this work, authors [45] employed meta-deep learning to diagnose numerous cotton leaf diseases reliably. In the first step, they collected datasets and discarded the noises from images. The annotation technique was demonstrated in the following step. The data augmentation technique was carried out to increase the size of the dataset after annotation. Furthermore, the Machine Learning model, CNN, and transfer learning models were used to train the datasets. The convolution layers, a dropout layer, a max pool layer, and the softmax layer had seven layers to diagnose besides. After that, VGG-16, InceptionV3, and Resnet-50 were also used as pre-trained models for training the models. After the training of many models, stacked ensemble learning was used to integrate the models, and a final model was then applied. To conclude, the classification accuracy was enhanced by the layered model.

In this research approach, the authors [46] introduced DeepLabV3+ to segment the sugarcane leaves along with detached the leaves background. Labelme software was used to assign labels to the leaves, resulting in a mask map and measured accuracy against a baseline of manually categorized pictures. Supervised and deep convolution generative adversarial networks were employed for data augmentation such as contrast brightness transformation, increase noise ,and geometric transformation. Eventually, background-removed datasets with data augmentations were used, and diverse Deep Learning networks were utilized by comparing the networks to acquire the classification accuracy of the sugarcane crop.

According to the proposed research[47], white leaf disease is a severe disease that hurts the crop. Deep learning techniques have been employed to find the disease. These include a collection of RGB images from an unmanned aerial vehicle (UAV), image processing, image labelling, model tuning, and prediction. At the same time, farmers acted as the ground truth in identifying the diseases, and red color tags were placed before the photographs were gathered. Agisoft Metashape 1.6.6 created RGB orthomosaics for examination during picture pre-processing. ENVI 5.5.1 tiled training, testing, and validation of RGB orthomosaic images. In the next stage, augmentation methods such as random rotation, flip, blur, and brightness were employed to create more images to improve the model. Moreover, labeling was used to label the picture datasets used for training and testing. A bounding box was used to identify the affected plants accurately, and the annotations were verified by specialists using image interpretation. The prediction box location and category were gathered from the pictures and matching labels during model development. Ultimately, multiple performance measures assessed object-detecting models.

The authors proposed [48] that a deep residual neural network has been used to detect pest signs in winter wheat canopies. Images captured by a conventional RGB camera were used to compile a massive database of annotations. After that, the image classifier was trained using original, unprocessed camera images tiled into image patches, and the image classifier was evaluated at various phases of a disease epidemic. In this case, the ResNet-18 architecture was used, which stacks several residual blocks, each of which comprises eight residual blocks. A residual block comprises a shortcut connection that uses the identity function x and a stack of convolution layers whose output F(x) is added to the identity mapping to make the residual block's output F(x)+x. Eventually, the picture classifier achieved good accuracy at the patch level. The image classifier on the picture level, a sliding window with a long stride length, was used to allow for quick test performance. Even at the outset of the Pst epidemic, accuracy was attained less when the disease spread was relatively low (0.5%). However, detection of medium accuracy may be achieved in the first phase of the Pst pandemic, with 2 to 4% of Pst disease spreading.

The authors employed [49] the deep learning techniques known as improved RetinaNet to recognize the wheat spider mites. Firstly, field photography and tagging create wheat spider mite photos, and the dataset is augmented via data augmentation and image segmentation. Furthermore, the size of wheat spider mites varies widely, with bigger ones having roughly 100*100 pixels and smaller ones having 20*20 pixels or fewer. After that, RetinaNet uses ResNet created pyramid shaped feature maps to add a detection head, particularly for tiny objects in FPN, and modify the pyramid structure to gain additional information for the identification of wheat spider mites. The approach for generating anchors is optimized and improved to increase the identification of microscopic wheat spider mites. Extensive experiments have confirmed the efficacy of the enhanced model and image split, and the mAP has been enhanced.

In this proposed work [50], peanut diseases have been identified using Machine Learning methods with the combined output of deep learning techniques. Data augmentation methods were employed to obtain the multiple image datasets for training and testing by ensemble techniques such as AlexNet, VGG, ResNet, DensseNet, Inception, Random Forest, Support Vector Machine, and Logistic Regression. In this work, authors used K-fold cross-validation to make predictions on test samples without using the training samples known as out-of-field predictions, in a ratio of 4:1 as training and testing sets. Moreover, K was set to five, and machine learning techniques were used as the meta-model, whereas deep learning techniques were used as the base model. After that, ensembled techniques randomly, and finally, ResNet-50 achieved the highest accuracy by ensembled with logistic regression. While the DenseNet-121 achieved the next highest accuracy after being ensembled.

In this research article [51], authors quickly and correctly found and diagnosed diseases on peanut leaves. A data balance algorithm was proposed to solve the data distribution tilt, the needed data was balanced using the upsampling data technique, improving the network's capacity for generalization, and deep transfer learning was employed to generate a recognition model to improve generalization by removing the original network output layer, re-adding the normalization and pooling layers, modifying the fully connected layer, and introduced regularisation constraint strategies based on the lightweight convolutional neural network. It enabled the immediate on-site diagnosis of single leaf healthy, black spot disease, brown spot disease, net spot disease, and mosaic disease. The lightweight convolutional neural networks, MobileNet V2, Xception, and NasNetMobile, were trained and deployed using the self-built peanut leaf disease dataset. According to comparative trials, the average macro accuracy for peanut leaf disease identification has been achieved with high accuracy.

The authors proposed that [52] various convolution neural networks have been employed to identify disparate pests automatically in mango crops. An image dataset has been taken to implement the data augmentation process, such as rotation and reflection, to diminish overfitting, neither compromising nor altering the overall qualities of the picture in the neural network process. Moreover, this model splits the data into training and testing based on k-fold data validation. Finally, the ResNet model was proposed and comprised of diverse layers, such as convolution, activation, pooling, and fully connected to identify the pests with the highest reliability when compared to other models.

Image Datasets	**Devices**	**Category**	**Before annotation Image datasets**	**Annotation and Cropping Techniques Applied**	**After Annotation Image Datasets**	**URL**
Tomato [34]	Not Mentioned	RGB	18161	Not Mentioned	No Annotation Values	https://github.com/spMohanty/PlantVillage-Dataset
Tomato [35]	Smart Phone	RGB	15000	Bounding Box	1,46,912	Not Available
Rice [36]	Not Mentioned	RGB	1426	Not Mentioned	No Annotation values	https://drive.google.com/open?id=1ewBesJcguriVTX8sRJseCDbXAF__T4akK

Rice [37]	Not Mentioned	RGB	119	Not Mentioned	No Annotation values	Not Available
Red Pepper [38]	Not Mentioned	RGB	23868	Image Cropping	15,435	https://facebook.github.io/react-native/docs/getting-started. https://docs.expo.io/versions/latest/. https://flask-doc.readthedocs.io/en/latest/. https://redis.io/.
Chilli [39]	Smart Phone	RGB	974	Not Mentioned	No Annotation values	Not Available
Coffee [40]	Not Mentioned	RGB	1560	Not Mentioned	No Annotation Values	Not Available
Coffee [41]	Smart Phone	RGB	1747	Mask Annotation	2722	https://facebook.github.io/react-native/docs/getting-started. https://docs.expo.io/versions/latest/. https://flask-doc.readthedocs.io/en/latest/. https://redis.io/.
Coconut [42]	Digital SLR Camera	RGB	1564	Not Mentioned	No Annotation Values	Not Available
Coconut [43]	Digital Camera	RGB	Not Mentioned	Not Mentioned	No Annotation Values	Not Available

Cotton [44]	Smart Phone	RGB	1112	Bounding Boxes	Not Mentioned Annotation Values	Not Available
Cotton [45]	Smart Phone	RGB	2385	Annotaion Implemented	Not mentioned annotation values	Not Available
Sugar cane [46]	Not Mentioned	RGB	790	Not Mentioned	No Annotation Values	Not available
Sugar cane [47]	Drone Camera	UAV Derived-RGB	1680	Bounding Box	Not Mentioned Annotation Values	https://github.com/facebookresearch/ detr.git https://github.com/woctezuma/detr.git https://github.com/facebookresearch/ detectron2
Wheat [48]	DSLM camera ILCE-6000, APS-C type sensor chip, 50 mm lens attached (SEL50 F18), 16 mm lens	RGB	2772	Patch annotation	20371	Not Available

Wheat [49]	Camera or Mobile Phones	RGB	1959	Not Mentioned	No Annotation Datasets values	https://github.com/tzutalin/labelImg
Peanut [50]	Mobile Phone	RGB	2000	Cropping	6029	Not Available
Peanut [51]	C7070WZ camera, Sony DSC-HX30V camera, CMOS sensor camera, Canon EOS Kiss X5, (digital video camera	RGB	1215	Not Mentioned	No Annotation Values	Not Available
Mango [52]	Mendely.com	RGB	510	Not Mentioned	No Annotation values	Not Available

Table:1 Different Types of Devices, Categories, and Annotations

Article-No	**Crop**	**Pests and Diseases names**	**No of Images**	**Processing Methods**	**Algorithms used**	**Accuracy**
34	Tomato	Fungi, Bacteria, Mold,	18161	Classification	Efficient B0	99.95%, 99.12%, 99.89%

		Viruses, Mite, Early Blight, Septoria Leaf Spot, Target Spot, Leaf Mold, Bacterial Spot, Late Bright Mold, Tomato Yellow Leaf Curl Virus, Tomato Mosaic Virus		Segmentation Augmentation	Efficient B4 Efficient B7	
35	Tomato	Early blight, Late blight, Yellow leaf, curl virus, Brown spot, Coal pollution, Gray mold, Leaf mold, Navel rot, Leaf curl, disease Mosaic, Leaf miner, Greenhouse whitefly	15000	Bounding Box dimension Clustering	Improved Y3 Model, K means	92.39%
36	Rice	False Smut, Brown Plant Hopper (BPH), Bacterial Leaf Blight (BLB), Neck	1426	No Traditional Processing Techniques	VGG16 Inception V3	93.3%

		Blast, Stemborer, Hispa Sheath Blight and/or Sheath Rot, Brown Spot, Others				
37	Rice	Leaf Blast, Brown Spot, Leaf Smut	119	Preprocessing	Hybrid Deep CNN Transfer Learning	90.8%
38	Hot or Red Pepper	Aculops, Baccarum Latus, Slug, Speculum, Spodopteralitura, Stali, Tabaci, Thrips, Thunberg, Anthracnose, Bacterial spot, Canker, Gray mold, Leaf spot, Pepmov, Powdery mildew, TSWV, White leaf spot	23868	Preprocessing	VGG-16, VGG-19, RESNET-50, KNN	97.87%
39	Chilli	aphids-infestation, whitefly-infestation, bacterial leaf spot, Cercospora	974	Acquisition, Preprocessing, Segmentation	SVM InceptionV3 DenseNet201	92.10 %

		leaf spot, CMV, CVMV, chiLCV				
40	Coffee	Robusta coffee leaf	1560	Segmentation	CNN U^2 net	98%
41	Coffee	Healthy Leaf, Leaf Miner, Rust, Brown Leaf Spot, Cerspora Leaf Spot	1747	Semantic Segmentation, Augmentation	Unet, PSPNet	99.53 %, 99.31%
42	Coconut	Healthy, Stem Bleeding, Pest Infection by RPW, Leaf Blight	1564	Segmentation	Hand Designed CNN model	96.94%
43	Coconut	Pests, Nutrient deficiency, Diseases	Not Mentioned	Acquisition Preprocessing, Segmentation, Feature Extraction,	SVM, CNN	93.54%, 93.74%
44	Cotton	Leaf Curl, Sooty mold stress	1112	Preprocessing	Improved SPP-based YOLOX-s	73.13(mAP for Training) 3.27(mAP for Testing)
45	Cotton	Healthy, Leaf Spot, Nutrient Deficiency, Powdery Mildew,	2385	Enhancement, Preprocessing, Annotation, Augmentation	CNN, VGG16, Inception V3,Resnet50	98.53%

		TargetSpot, Leaf Curl				
46	Sugarcane	Red Rot, Ring Spot, Rust, and Healthy	790	Segmentation (DeepLab V3+), Augmentation (Supervised, DCGANS)	MobileNet V3 Large, Alexnet, Resnet, Densenet	Images Produced by DCGAN accuracy is 99%
47	Sugarcane	White Leaf Disease	1680	Acquisition, Preprocessing, Annotation	YoloV5, YoloR, Faster R CNN, DETER	95%,92%,93%, 79%
48	Wheat	Stripe rust	2772	Splitting, Augmentation	Deep ResNet	95%
49	Wheat	White Spidermite	1959	Enhancement, Labeling, Augmentation	Improved RetinaNet Model	81.7%
50	Peanut	Scorch, Leaf Spot, Rust, Simultaneous Rust, and Scorch	2000	Data Augmentation, K-Fold Cross-validation	ResNet-50, DenseNet-121	97.59%, 90.50%
51	Peanut	Healthy state, Black Spot Disease, BrownSpot Disease, Net Spot Disease,	1215	Data Balance Algorithm, Enhancement	MobileNet V2, Xception and NasNetMobile	97.8%, 99.0%, 97.4%

		and Mosaic Disease				
52	Mango	Apoderus javanicus, Aulacaspis tubercularis, Ceroplastes rubens, Cisaberoptus kenyae, Dappula tertia, Dialeuropora decempuncta, Erosomyia sp., Icerya seychellarum, Ischnaspis longirostris, Mictis	510	Augmentation, Preprocessing	ResNet-50	99.72%

Table:1 Crop Pests and Diseases with Techniques, Algorithms, and Accuracy

Performance Metrics

The existing research employed performance metrics designated as classification problem metrics to measure the model performance. There are two sorts of classification problems: binary classification, which has just two classes, and multi-class classification, which has more than two classes [53]. Distinct classification metrics such as accuracy, precision, recall, specificity, and more, measured the performance of various models in the previous works. The importance of classification metrics is stated in the following way.

1. Accuarcy – It is one of the metrics for categorisation performance that is most often utilized and generated as the number of accurate forecast values divided by the total no of forecast values [53]

$$Acc = \frac{TP+T}{TP+TN+FP+F}$$

2. Precision – The ratio between the accurate positive forecast and the sum of the positive forecast [53]

$$Prec = \frac{TP}{TP+FP}$$

3. Recall/Sensitivity- The other name is designated as the true positive rate. The ratio between the accurate positive forecast and the sum of positive samples [53]

$$RC = \frac{TP}{TP+FN}$$

4. Specificity - The other name is designated as the true negative rate. The ratio between the accurate negative forecast and the sum of negative samples [53]

$$SP = \frac{TN}{TN+}$$

5. F-Score - The test's accuracy is gauged by the F-score. It is determined based on accuracy and recollections. [54]

$$F - Score = \frac{2*Prec*RC}{Prec*RC}$$

In the related work, numerous deep learning models, including Efficient, Yolo, VGG, Inception, Dense Net, and others, have been observed and compared using various crop pests and diseases. This study will now contrast the various deep learning models to determine which model has provided the best performance metrics. In existing research, the authors focused on various performance metrics by observing the various existing research EfficientB7 model obtained the highest accuracy, precision, sensitivity, and specificity f1-score. In contrast, the Improved Yolox model obtained the lowest accuracy and precision. The remaining deep learning models also obtained fewer performance metrics compared to Efficient B7 as shown in Table 4.

Models	**Accuracy**	**Precision**	**Recall/Sensitivity**	**Specificity**	**F1-Score**
EfficientB7(two Classes) [34]	**99.95**	**99.94**	**99.77**	**99.95**	**99.95**
EfficientB7(Six Classes) [34]	**99.12**	**99.91**	**99.81**	**99.11**	**99.10**
EfficientB4(ten Classes) [34]	**99.89**	**99.45**	**99.94**	**99.44**	**99.14**
ResNet50 [37]	**97.87**	**99.16**	**-**	**-**	**-**
SVM with (Inception + DenseNet) [39]	**92.10**	**91.17**	**90.76**	**-**	**-**
Resnet50 [41]	**97.07**	**96.85**	**96.69**	**-**	**-**
Improved Yolox [44]	**73.13**	**74.02**	**-**	**-**	**-**
Transfer learning [45]	**98.53**	**98.70**	**98.50**	**-**	**98.68**
MobileNetv3 [46]	**99.00**	**99.25**	**99.00**	**99.75**	**99.00**
YoloV5 [47]	**95.00**	**92.00**	**93.00**	**-**	**-**

ResNet [48]	**95.00**	**96.00**	**99.00**	**-**	**98.00**
ResNet50 [50]	**97.59**	**95.30**	**95.20**	**-**	**-**
Xception [51]	**99.00**	**99.00**	**99.20**	**-**	**99.20**
InceptionV3 [52]	**88.68**	**-**	**80.52**	**99.23**	**-**

Demerits Of Existing Research Employed

A few limitations have been discovered after studying the existing studies of agricultural pests and diseases. The first limitation is that the outcome of the proposed work has not been up to the expected standard, and more research needs to be conducted on multiple environmental variables. In addition, datasets have not made any progress on the identical class of pests and diseases, nor can they be split based on their growth periods. The accuracy and detection of pests and diseases have not been improved, and optimization methods and model tweaks have not been employed [34-35]. The second limitation is that, in classifying the pests and diseases, the symptoms were overlooked and incorrectly interpreted. More dataset samples were not gathered, and efficiency was reduced.

Additionally, more symptoms were not included to assess the system's ability to discriminate color features [36-39]. The third limitation is that the image annotations have not been appropriately employed whereas segmentation techniques have not been examined. Detecting pests and disease severity levels has not been up to standard and also not considering the various features such as soil type and water level [40-43]. The fourth limitation is that the authors have not identified the multiple diseases on a single leaf and also accelerate training and testing speed by making lightweight models in contrast with precision, and confidence values were not improved [44-45].

Conclusion

The crop pests and disease detection purpose is to develop the crop yield for farmers by initiating the state of art technologies. These technologies employed robust algorithms to advance the detection of damages in the crop influenced by pests and diseases. This review mainly focused on segmentation algorithms, preprocessing techniques, and classification algorithms to predict pests and diseases. Different crops such as rice, tomato, cotton, and related papers were collected to obtain the outperformed algorithm. Efficient B7 outperformed to obtain the highest accuracy compared to other algorithms, same as other performance metrics. In all the existing research papers, RGB image datasets were employed to predict pests and diseases for precision agriculture. Eventually, the demerits of the existing papers are also mentioned in this paper. In the future, we will accumulate hyperspectral and multispectral image datasets for predicting pests and diseases, and other challenges in agriculture. We anticipate this work will get more beneficial to farming societies as well as promote more research understanding relevant to the cutting-edge technologies discussed in this paper.

Acronyms	Definitions
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
SP	Specificity
RC	Recall
Prec	Precision
RGB	Red Green Blue
HSI	Hue Saturation Intensity
CMYK	Cyan Magenta Yellow Black

Table 5: List of Acronyms and Definitions

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