Neural Networks for Pest Diagnosis in Agriculture: A Global Literature Review

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***Abstract*—Agricultural pests severely reduce global crop yields. To mitigate these losses, pest identification systems based on artificial intelligence have gained importance. This review analyzes worldwide advances in the use of neural networks for agricultural pest diagnosis, covering studies from 2007 to February 2024 retrieved from the Scopus database. Data were processed in Minitab 19 and spreadsheets, and keywords were mapped with VOSviewer. Results show that India and China lead scientific output, with research focused on corn, tomato, rice, and wheat. The most common architectures are ResNet, YOLO, and VGG-16/19, achieving performance metrics of up to 99 %. The review highlights the strong relationship between economic development and the adoption of neural networks. These findings provide researchers, agricultural engineers, and policymakers with a global perspective to guide future AI-based pest management strategies and support automation, especially in developing countries.**

Keywords*—Neural networks; pests; agriculture; developing countries

I. Introduction

Agriculture is fundamental to human health and population growth [1]. The world population is expected to reach 9.7 billion by 2050; therefore, food production must increase by 70% by 2050 [2]. But food production suffers from the environmental impact of chemicals [3]. In the world, the most important crop is soybean, and it is estimated that the crop has occupied 6% of the world's arable land since the 1970s [4].

Likewise, during the last decades, crops such as rice have become a staple food consumed by the majority of people around the world [5]. Asia is the center of rice production and produces more than 90% of the world's rice [6]. Another important commodity is maize, and it is widely grown [7], globally. 13% of malnourished children and 900 million poor households prefer maize as a staple food [8]. On the other hand, in the horticultural industry, tomato is recognized worldwide as one of the most cultivated vegetables and has a high nutritional value [9].

The increasing global demand for food production poses significant challenges to farmers in protecting their crops from harmful pests [10], with pests destroying up to 40% of global crop production each year [11]. Farmers suffer huge economic losses as income depends on the number of healthy crops they produce [12]. So, overcoming this problem becomes a major challenge, as agriculture is the most important economic branch in many countries [13].

In recent times, the application of artificial intelligence (AI) has become widespread in a number of areas, most notably its role in plant pest and disease identification [14]. Intelligent deep learning (DL) techniques have gained great popularity and have been widely adopted, especially in situations where human work cannot provide the speed and efficiency needed to analyze data on time and cover large areas in the field of monitoring [15].

AI and DL, especially image processing and convolutional neural networks (CNNs) are effective tools to apply in various tasks within the agricultural industry, such as leaf counting, leaf segmentation, and yield prediction [16], to enable farmers to effectively deal with plant leaf stress [17]. In recent agricultural research, techniques based on AI, DL, and CNN have shown great promise [10]. For example, in pest management for coconut crops [18], the deep learning model, VGG16, showed high precision and accuracy in diagnosing diseases, contaminated leaves, and insect infestation, demonstrating the potential for early disease detection. In studies to detect pests in maize [10], the MobileNet-SSD-v2 deep learning model was used with an overall relative error rate of 0.1579, which demonstrates high potential in real-time pest monitoring. The PlaNet model used in research [19] to diagnose diseased and healthy leaves achieved 97.95% accuracy. For pakcoy pest management [20] used known convolutional neural networks, such as MobileNetV2, GoogLeNet, and ResNet101, where the accuracy rate of tests reached 98 % as in the research of [9] that identified pests in tomato, using a convolutional neural network model based on GoogleNet, AlexNet, and ResNet-50c, and obtained an accuracy of 96.99%. While in the research of [21], they proposed a lightweight and effective agricultural pest detection model for small pests, called YOLO-Pest, which achieved 91.9% detection accuracy. On the other hand, research to identify agricultural pests [22] adopted the latest developments YOLOv3, YOLOv3-Tiny, YOLOv4, YOLOv4-Tiny, YOLOv6, and YOLOv8 for detection, where YOLOv8

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achieved a substantial mean average precision (mAP) of 91.9% in pest diagnosing.

Although several studies reported high accuracy and even strong mAP values, these metrics must be interpreted with caution. Accuracy alone does not capture whether infestations are systematically missed (low recall) or whether false alarms lead to unnecessary pesticide use (low precision). Therefore, integrating precision, recall, and mAP in model evaluation is essential to assess their real-world applicability in agriculture.

Based on the above, the objective of this research was to determine the advances of neural networks for pest diagnosis in agriculture through a global literature review.

The remainder of this paper is organized as follows. Section II describes the materials and methods, including the literature search strategy, data processing, and keyword analysis. Section III presents the results and discussion, highlighting global trends, key crops, and the most frequently applied neural network architectures for pest diagnosis. Section IV provides the main conclusions and outlines recommendations for future research and the practical adoption of artificial intelligence in agricultural pest management.

II. Materials and Methods

The bibliography consulted goes back to 2007, up to February 2024. Boolean operators were applied, using the following terms: “neural networks”, “pests” and “agriculture”. All the research was carried out through a search in the Scopus database, due to its capacity to compile open access texts, after a rigorous peer review [23] and 289 scientific articles were found and 129 studies were rescued and used for this study (Fig. 1).

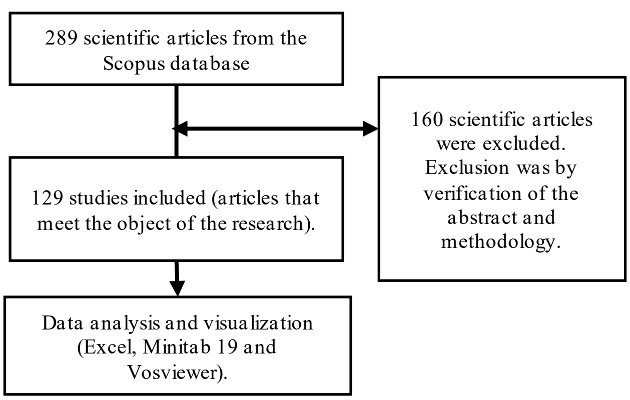


Fig. 1. Flowchart of scientific literature selection.

Publications from 2007 to February 2024 in all languages were considered. Titles, abstracts, methodology and main results were reviewed to select articles of interest. As well as the geographical scope was worldwide. Papers, such as book chapters, conference papers, and letters to the editor were excluded. Gray literature was also excluded because it did not pass peer review [24]. In addition, inconclusive studies and duplicates were not taken into account (Fig. 2).

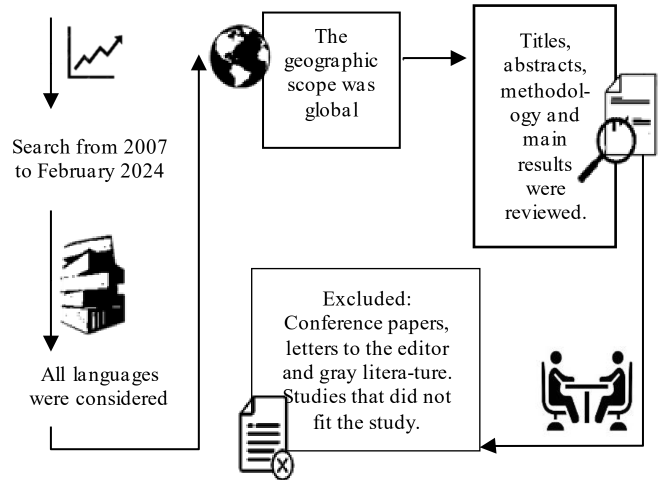


Fig. 2. Exclusion and inclusion process.

A. Data Analysis

The data were downloaded in CSV format and processed in Minitab 19 and spreadsheets to facilitate the determination of the distribution of studies by year and country. Keyword analysis was performed with VOSviewer version 1.6.19, a tool widely used in the scientific community to represent and visualize bibliometric networks. VOSviewer employs several colors to help understand and discover keyword relationships [25].

III. Results and Discussion

Fig. 3 shows the distribution of articles according to affiliation and country of origin, showing that the country’s leading the studies related to the application of neural networks in agriculture are India (40 articles) and China (35 articles). These results are related to the advances in agriculture in India where approximately 62% of the population lives in rural areas and depends directly or indirectly on agriculture, being the main source of income. India's agricultural sector contributes almost 18% of India's GDP and ranks second in the world in production of agricultural products [26, 27]. However, the scarcity and lag in data availability in developing economies have necessitated artificial neural network (ANN) modeling techniques for price prediction in developing economies [28]. Likewise, in China, the agricultural industry generates jobs for more than 300 million farmers, and in recent years, the use of artificial neural networks (ANNs) has been applied in the agricultural sector [29–31]. In developing countries, agriculture plays a key role in the economy and provides rural inhabitants with higher incomes and job opportunities [32].

The evolution of publications per year is also evident; the growth occurred since 2016, highlighting 45 articles in the year 2023 (Fig. 4A), evidencing a breakthrough in the application of deep learning techniques to the identification of plant diseases and pests, given that they are one of the greatest threats to food security [33, 34].

The largest amount of scientific production is focused on research on corn, tomato, rice, wheat, apple, citrus, grape, and cotton crops are the crops that predominate in neural network studies for pest diagnosis in agriculture (Fig. 4B).

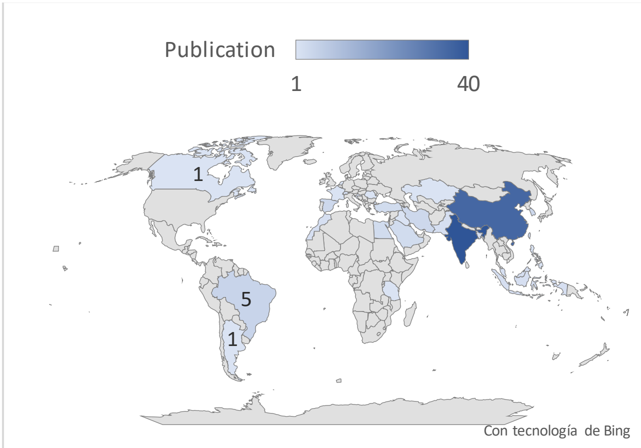


Fig. 3. Distribution of scientific production by country.

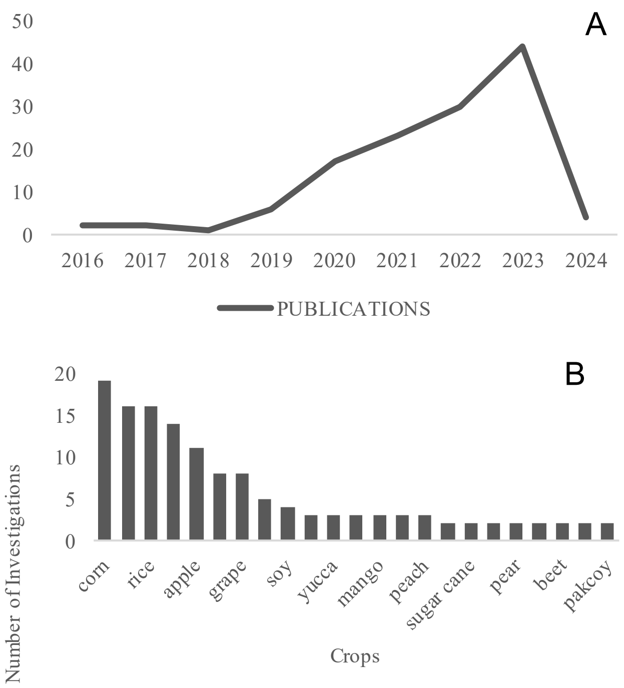


Fig. 4. Evolution of publications with respect to agricultural crops.

In Fig. 5, it is evident that the three most used neural network architectures in the explored studies are ResNet and versions, YOLO and versions, and VGG-16, 19. The neural network architectures with GoogleNet were the ones that evidenced fewer studies, although these are based on the construction of a deeper model to achieve greater accuracy and, at the same time, keep it computationally efficient [35].

Beyond their frequency of use, each architecture offers specific advantages that explain their adoption in agricultural applications. ResNet is valued for its ability to train deep networks effectively while mitigating vanishing gradient issues, making it suitable for complex image classification tasks [9, 49, 85, 165]. YOLO stands out for its speed and real-time object detection, which is essential for pest monitoring directly in the field [21, 22, 55, 70]. VGG-16/19, although computationally heavier, remains relevant for its high accuracy and robustness in image recognition [9, 49, 124]. GoogleNet, with its inception modules, provides efficiency with fewer parameters, which is particularly advantageous in environments with limited computational resources [9, 35]. These differences help explain why researchers select certain models depending on the crop, available resources, and the practical requirements of the study.

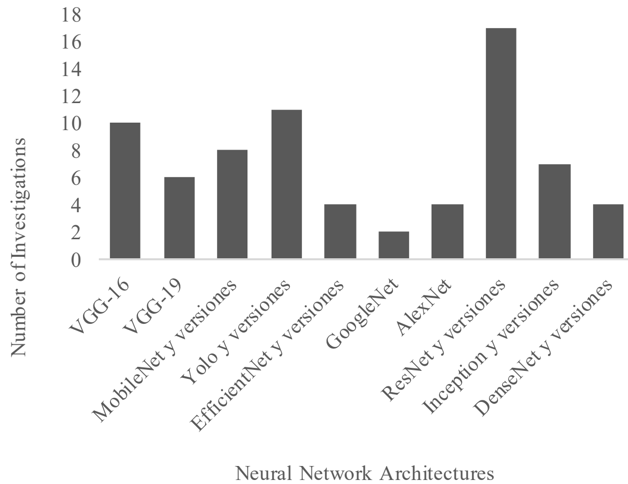


Fig. 5. Known neural network architectures used in research.

The keyword co-occurrence is related to the emerging theme regarding global agriculture, with the keywords "Convolution neural networks, image processing, and Deep learning (Fig. 6). The network of co-occurrence of words indicates the relationship of the emerging studies in the world, due to the interest in improving agricultural productivity and promoting economic growth through nondestructive alternative techniques in pest recognition [36–38].

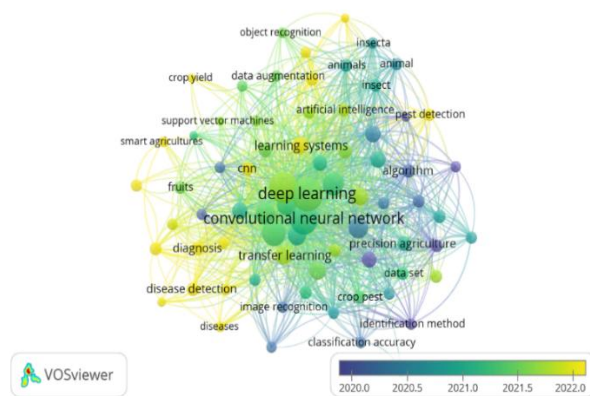


Fig. 6. Map of the keyword concurrence network.

Beyond the bibliometric visualization, these keyword clusters reflect concrete agricultural challenges. The prominence of terms such as deep learning and convolutional neural network highlights the reliance on high computational resources and large annotated datasets [30, 38]. However, such requirements are difficult to meet in developing countries, where data scarcity, limited infrastructure, and high implementation costs restrict practical adoption [13, 14]. In these contexts, farmers often cannot afford advanced computing systems or generate sufficient labeled images, which limits the transfer of research advances to the field [29,171]. Therefore, the co-occurrence network not only maps research priorities but also underscores the urgent need for cost-effective, data-efficient, and locally adaptable AI models to ensure wider adoption in agriculture.

Table I shows the related studies according to the quartile of the journal models/Neural Network Architectures, crops evaluated, and the performance metrics of the models, where it is evident that the studies are focused on neural networks to detect pests and diseases in maize crops, based on improved GoogLeNet and Cifar10 models for the recognition of leaf diseases [39]. The highest recognition accuracy found was 95.3%; however, it is limited to the number of diseases in maize [40]. As well as its evaluation yield of each year of corn, will serve as a basis for making accurate decisions about harvesting and marketing of corn grain in real time, minimizing possible losses of profitability.

Tomato is one of the most popular and appreciated vegetables among Asians, and worldwide, it is the second most consumed vegetable [41]. Moreover, tomato is not only served as a vegetable, but also serves as a sauce, jam, etc. and is used in the processing of different types. But it is affected by different pests; in that sense, to identify tomato pests, have selected image datasets from repositories there are convolutional neural network (CNN) models to deal with this problem [42]. In this regard, several studies using images of common tomato pests have classified pest categories [43]; therefore, continuous monitoring is necessary for early disease detection [44]. Another crop widely studied by CNN models is rice and wheat; this may be related to the fact that rice is one of the most important agricultural products in the world; this crop is the staple food for more than half of the world's population [45, 46]. Approximately 160 million hectares are planted annually and produce 750 million tons of rice [47]. Given the scarcity of water for agriculture, the increase in food demand, and future drought scenarios, it is essential to design new technologies that contribute to lower water consumption [48].

On the other hand, we have the application of Model Fuzzy Modified Faster Fuzzy Region based CNN (MGAN MFRCNN with Fuzzy) on leaves of diseased and healthy banana plants [49] attacked by banana leaf spot disease [50]. It is important to predict leaf disease symptoms at an early stage and to develop an automatic detection technique. Considering that India is at 19% production, followed by Brazil with 15% and Ecuador with 12%. China produces 10% and the review shows only one research, which indicates that studies are just beginning to focus on this important sector.

For the assessment of potato leaf diseases, several machine learning techniques have been developed, among them is the multilevel deep learning model, where the potato leaves are extracted from the potato plant image using the YOLOv5 image segmentation technique. Where it is extracted, the potato leaves from the potato plant image are used using the YOLOv5 image segmentation technique. In this study, the widely used deep learning hierarchical CNN (HDLCNN) model is evidenced for data sets of diseased and healthy potato plant leaves. This is because of the great trend, given the crops are affected by various diseases caused by pests and pathogens such as viruses, bacteria and fungi [51], hence, the material used for this type of work is images taken from healthy and infected leaves of the plant and the accuracy has reached up to 98.9% with no signs of overfitting [52].

It was found that the CNN model was also used to identify major diseases in grape crops. As well as an automatic method to monitor pests based on a CNN with a dataset of 177 images with apple moth, however, researchers mention that CNN models have several difficulties in identifying crop diseases due to morphological and physiological changes in crop tissues and cells, because some studies already report a lightweight CNN model called GrapeNet for identification of different symptom stages of specific grape diseases [53].

TABLE I GENERAL CHARACTERISTICS OF THE SCIENTIFIC PRODUCTION NEURAL NETWORKS FOR PEST DIAGNOSIS IN AGRICULTURE

Quote	Quartile	Neural Network Model	Dataset	Crop(s)	Pest(s)/Disease(s)	Performance Metrics
[18]	Q1	VGG-16	Kaggle	Coco	Whitefly	Accuracy: 95.71%
[54]	Q1	VRFNet (Visual Regenerative Fusion Network)	D0, IP102	Multiple crops	Insects (varied age, size, shape, color)	Accuracy: D0 = 99.12%; IP102 = 68.34%
[10]	Q2	MobileNet-SSD-v2-Lite	2,605 images	Corn crops	Ladybugs, beetles (Coccinella sp., Anoxia villosa)	mAP: 0.8923; Relative error: 15.79%
[55]	Q1	Improved Pest-YOLO	Pest24 (25,378 images)	Leaves of various crops	24 pest classes	mAP: 73.4%; Recall: 83.9%
[56]	Q2	FDPRC-Net (Feature Pyramid Dilation Residual CNN)	Mixed (Wang, Xie, Tomato pests)	Tomato	Mixed pest classes	Accuracy: Tomato = 98.12%, Wang = 97.43%, Xie = 93.98%, Overall = 93.46%
[57]	Q3	CNN (ABC-CNN + Adam optimizer)	Kaggle	Tomato	Key tomato pests	Accuracy: 99.33%; MAE: 0.007; MSE: 0.007
[19]	Q1	CNN (PlaNet)	PlantVillage, Kaggle	corn, apple, grape, etc.	Leaf diseases (spot, rust, scab)	Accuracy: 97.95%; AUC: 0.9752; F1-score: 0.9686
[58]	Q1	HCNet (Hierarchical Complementary Network)	IP102	—	Diverse insect species	Accuracy: 75.36%

[59]	Q4	CNN (new proposed model)	19,046 images	Rice and wheat	Green caterpillar, A. Tridens, rice bug, etc.	Accuracy: 99%
[60]	Q1	CSLSNet (proposed CNN model)	PlantVillage	Tomato	Early blight, mosaic virus, yellow virus	Accuracy: 90.08%
[20]	Q3	MobileNetV2	1,226 labeled images	Pakcoy cultivation	Leafminers, cabbage butterflies, powdery mildew	Accuracy: 98%
[61]	Q1	Cotton LeafNet (CNN-based)	22 types of cotton leaf disease images	Cotton crops	Leaf diseases, bacteria, fungi, viruses, nutrient deficiency	Accuracy: 99.39%
[62]	Q1	ITF-WPI intermodal feature fusion model	10,598 image and text samples	Goji berry	Wolfberry pests (WPIT9K)	Accuracy: 97.98%, F1-Score: 93.19%
[63]	Q1	RetinaNet with R50-FPN and R101-FPN	400 melon leaf images	Melon leaves	Leafminers	mAP: 92.36%, Recovery Rate: 92.70%
[64]	Q2	MGAN-MFRCNN (CNN + Fuzzy logic)	Healthy and diseased banana leaf images	Banana crops	Xanthomonas, Sigatoka	Accuracy: 98%, F1-Score: 96%
[65]	Q1	LSTM-CNN	4,447 pest and disease instances	Apple	Apple pests and diseases	Accuracy: 99.2%
[66]	Q2	Mask R-CNN	Fall armyworm (FAW) insect dataset	Corn	Fall armyworm detection	mAP: 94.21%
[67]	Q2	HGS-DCNN (Optimized CNN with preprocessing)	Augmented pest dataset with variable ages, colors, etc.	Various	Insect detection across variability	Accuracy: 99.1%, F1-Score: 97.80%
[68]	Q3	MIL-CNN (Multi-instance learning CNN)	12,000 images	Cotton crops	Whitefly detection	Accuracy: 98.13%
[51]	Q1	HDLCNN (Hierarchical Deep Learning CNN)	Dataset of diseased and healthy potato leaves	Potato	Major potato diseases	Accuracy: +4%; Precision: +6%; Recall: +3%; F1-score: +3.5%; Specificity: +4.5%; Sensitivity: +1%; PSNR: +2% (vs. VGG-INCEP, Deep CNN, RF, SNN)
[69]	Q3	Improved YOLOv5 (lightweight algorithm)	Dataset with 15 species of agricultural pests	Various crops	Insects (various ages, colors, shapes, sizes)	Accuracy improved by 4.3% over YOLOv5n; mAP@0.5: 95.3%
[70]	Q1	YOLOv5s (basic architecture)	7737 images from IP102 dataset	Leaf crops	Insects (various ages, colors, shapes, sizes)	Accuracy: 98.1%; Recall: 97.5%; mAP@0.5:0.95 = 88.1%
[71]	Q1	EfficientNetB7 and VGG16	600 leaf images from different species	Red beans, black beans, mango, cranberry, chickpea, lima bean, soybean	Healthy and diseased leaves	Accuracy: 96%–98%
[72]	Q1	Perceptron + Fuzzy Logic; ANN; CBR	~600 images	Sugarcane	Eye spot, leaf scald, yellow leaf, pokkah boeng	Eye spot: SEN 85.12%, SPEC 84.96%, Acc 83.72%; Scald: SEN 85.16%, SPEC 84.85%, Acc 83.42%; Yellow leaf: SEN 85.95%, SPEC 84.26%, Acc 83.41%; Pokkah Boeng: SEN 85.76%, SPEC 84.28%, Acc 83.72%
[73]	Q1	Mask R-CNN R50 FPN3; Fast R-CNN; InceptionV3	1000 image samples	Olive	Fungi and *Aceria oleae*	Training accuracy: 90%; Validation accuracy: 85%
[9]	Q3	GoogleNet, AlexNet, ResNet-50	PlantVillage dataset	Tomato	Bacterial spot, early blight, leaf mold, Septoria leaf spot	Accuracy: 96.99%

[74]	Q2	Smart Farm Software with Sigmoid Sorting	900 training images, 890 test images	Rice	*Chilo suppressalis*	Accuracy: 88%–92%; Recall: 91%
[75]	Q1	Three-Scale Care CNN (TSCNNA)	21,000 pest images	Corn, cabbage	Corn borer, cabbage moths, larvae, cabbage blight	Accuracy: 93.16%
[76]	Q3	15-layer Augmented CNN	Kaggle rice dataset	Rice	Leaf charcoal, bacterial leaf blight, brown spot	Accuracy: 95%
[77]	Q4	Decision Tree (DT), CNN, ResNet, Attention-based CNN	Dataset of 18,000 images	Common plants	Whitefly	DT: 81%, CNN: 96%, ResNet: 97.5%, Attention-CNN: 98% (Accuracy)
[78]	Q2	Deep Neural Network (DNN)	Dataset of 430 images	Apple trees	Apple moth	Accuracy > 99%
[22]	Q2	YOLOv3, YOLOv3-Tiny, YOLOv4, YOLOv4-Tiny, YOLOv6, YOLOv8	Dataset of 9,875 images	Various crops	Thistle caterpillars, red beetles, citrus psylla	YOLOv8: mAP = 84.7%, Loss = 0.7939
[79]	Q1	YOLOv3 Optimized, ResNet50, VGG16	IP102 dataset	Various crops	Multiple pests including rice leaf caterpillar, rice leaf roller, rice stalk fly	Accuracy = 96%, F1 Score = 84%
[80]	Q2	GPA-Net (Pyramidal CNN with Graphical Attention)	IP102 dataset	Cassava leaves	Multiple agricultural pests	Accuracy = 99%
[81]	Q1	VGG19 Classifier	Dataset of 862 images	Various crops	Codling moth larvae (Spodoptera frugiperda)	Accuracy = 99%
[21]	Q1	YOLO-Pest	Teddy Cup dataset and IP102	Various crops	Creatonotus, Nilaparvata, Staurophora celosia	mAP@0.5 = 91.9%
[82]	Q1	Custom CNN model	Dataset of 5,000 images	Potato crops	Sana, black dandruff, scabies, blackleg, pink rot	Accuracy = 99%–100% across disease classes
[83]	Q3	MLP Neural Network	Dataset of 300 images	Apple tree leaves	Black spot, Alternaria, Minoz blight	CC index = 0.976, RMSE = 0.098
[84]	Q1	Multi-image fusion recognition method	IP102, DO, and ETP datasets	Rice, corn, wheat, beet, alfalfa, citrus, tomato, mango	Leaf roller, caterpillar, wireworm, bactrocera tsuneonis	Accuracy = 88.7%
[85]	—	R-CNN, ResNet	Full dataset (images & videos of diseased and healthy leaves)	Tea, apple trees	Leaf diseases	Accuracy = 99.2%
[86]	Q3	RDODL-APDC, NestNet, MobileNet-v3	Dataset of 7,222 grape and 7,771 apple disease images	Apple, grape plants	Scab, Black Rot, Rust, Cedar Apple, Leaf Blight	Apple disease accuracy = 95.8%, Grape = 97.19%
[87]	Q1	EfficientNetV2	PlantVillage, IP102	Various crops	Leaf spots, rust, late blight, cucumber mosaic virus, tomato mosaic virus, etc.	Accuracy = 99.71%
[88]	Q4	ResNet50	1,221 images	Grenada crops	Bacterial blight, anthracnose, fruit spot, fusarium wilt, fruit borer	Accuracy = 98.55%
[89]	Q4	VGG16, ResNet50, AlexNet, EfficientNetB2, EfficientNetB3	41,763 images	Tomato leaves	Tomato pests and diseases	Accuracy = 99.85%
[90]	Q2	Enhanced CNN (VGG16-based)	1,003 wheat images	Winter wheat	Aphid, powdery mildew, leaf rust, linear rust	Accuracy = 96.02%

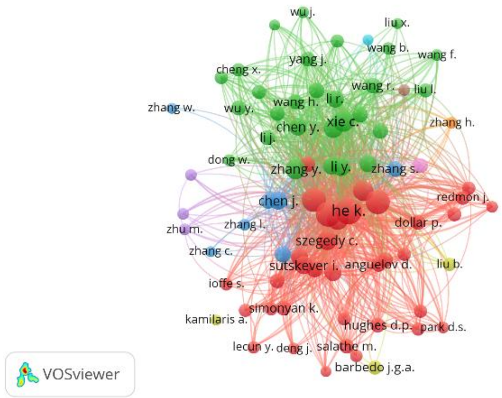
[91]	Q1	YOLOv7	IP102	Corn	Corn borer, budworm	mAP@0.5:0.95 = 96.69%, Accuracy = 99.95%
[92]	Q2	Hybrid CNN + GAN	Xie2	Various crops	Green-horned caterpillar, stink bug, Helicoverpa, etc.	Performance gain: AlexNet = +3.75%, ResNet50 = +2.74%, ResNet101 = +1.54%, GoogleNet = +1.76%, VGG16 = +1.76%, VGG19 = +2.74%, Simple CNN = +2.14%
[93]	Q2	ANN (Model 1: PMD, Model 2: VMD)	400 images	Apple trees	Blister moth	Model 1: Accuracy = 98%, Model 2: Accuracy = 94%
[1]	Q3	VGG16, VGG19, InceptionV3, MobileNetV2-mod	Corn image database (augmented)	Corn	Budworm	VGG16 = 96.17%, VGG19 = 97.15%, InceptionV3 = 99.23%, MobileNetV2-mod = 99.13%
[94]	Q1	YOLOv5s (modified)	1,565 images	Various crops	Ants, grasshoppers, palm weevils, shield bugs, wasps	Precision = 0.018, Recall = 0.015, mAP = 0.011
[95]	Q2	Custom CNN (convolution + clustering, batch normalization layers in series and parallel)	598 citrus images (Citrus Leaves Prepared)	Citrus leaves	Black spot, canker, greening	Accuracy = 96%, F1-score = 95%, Precision = 96%, Recall = 95%
[96]	Q1	CNN with fine-tuned ResNet50	1896 images of oranges	Orange	Black spot	Accuracy = 99.5%, F1-score = 100%
[97]	Q1	ADM (Anomaly Detection Model), DIM (Disease Identification Model), LPDM (Leaf Powder Distinction)	~9000 tomato leaf images	Tomato leaves	Leaf mold and powdery mildew	ADM Acc = 97.4%, DIM Acc = 93.63%, LPDM Acc = 98.7%
[98]	Q1	VGG19	2892 rice leaf images (Kaggle dataset)	Rice	Hispa, brown spot, leaf blight, NPK deficiency	Accuracy = 91.8%
[99]	Q1	Fine-tuned Inception-v3	IP102 dataset	Various crops	Parasitic insect pests (e.g., rice leaf caterpillar, rice roller, Apolygus lucorum, etc.)	Accuracy = 67.88%
[100]	Q1	Hybrid CNN (transfer learning and fine-tuning)	PlantVillage dataset	Tomato crops	Bacterial spot, early blight, late blight, leaf mold, Septoria leaf spot, spider mites, target spot, TYLCV	Accuracy = 98.1%
[101]	Q2	OplusVNet (CNN13 + VGG16)	2071 citrus images	Citrus	Canker, leaf miner, rust scab, rusty wall, citrus scab, etc.	Accuracy = 99%
[102]	Q1	Optimized MobileNetV2	IP102 dataset	Various crops	Insect pests (e.g., rice leaf caterpillar, rice roller, Apolygus lucorum, etc.)	Accuracy = 71.32%
[103]	Q2	Faster R-CNN, Mask R-CNN, YOLOv5	Baidu AI insect dataset, IP102	Rice, wheat, corn	Military armyworm, Asian rice borer, brown planthopper, rice borer, English grain aphid, rice gall midge	YOLOv5 >99%, Faster/Mask-RCNN >98%
[104]	Q2	New CNN model built from scratch	Plant Village dataset	Grape crops	Main grape diseases	Accuracy = 99.34%; F1 score = 0.9934
[105]	Q2	Hybrid deep learning model	Dataset with most common crop pests	Various plants	Insects of different ages, colors, sizes, and shapes	SSIM = 0.99; MAE < 0.2; AP = 89.67%
[106]	Q2	CNN with image mosaic	Dataset of 58,349 images of beetle-bitten leaves	*Brassica chinensis*	Flea beetle (*Phyllotreta undulata*)	99.7% detection of bitten leaves

[107]	Q3	Deep learning architecture with minimal parameters	Kaggle dataset	Yucca plants	Cassava bacterial blight (CBB), brown streak (CBSD), cassava green mite (CGM), cassava mosaic (CMD)	Accuracy = 90%
[108]	Q2	Classic ResNet50 network	Dataset of 900 images	Corn husks	*Spodoptera frugiperda*	Validation accuracy: ResNeSt50 = 98.77%, ResNet50 = 97.59%, EfficientNet = 97.89%, RegNet = 98.07%
[109]	Q2	CNN with majority voting ensemble and early merger ensemble	Turkey PlantDataset (4,447 images)	Apples, peaches, pears, cherries, etc.	*Aphis spp.*, *Eriosoma lanigerum*, *Monilia laxa*, drying symptom, *Parthenolecanium corni*, *Erwinia amylovora*	Accuracy: Majority voting = 97.56%, Early merger = 96.83%
[17]	Q1	Two-stage CNN: semantic segmentation + symptomatic lesion classification	BRACOL dataset	Coffee leaves	Leaf miner, brown leaf spot, *Cercospora* leaf spot, rust, general leaf spot	Accuracy > 97%
[110]	Q1	Faster R-CNN with MobileNetV3 backbone	Dataset of 36,000 images	-	*Popillia japonica*, *Cetonia aurata*, *Phyllopertha horticola*	Accuracy = 92.66%
[111]	Q3	Tuned CNN	Dataset of 4,868 images	Cucumber leaves	Spider, leaf miner, downy mildew, powdery mildew	Accuracy = 98.19%
[112]	Q4	Ensemble CNN (VGG-19, ResNet-50, InceptionV3)	Dataset of 18,345 images	Tomato and cotton	Bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, bacterial blight, curly top virus, *Fusarium* wilt	Accuracy = 97.9%
[113]	Q3	Ensemble Learning (VGG16 + VGG19 + Xception, transfer learning)	PlantVillage (grape leaves)	Grape	Black Rot, Black Measles (Esca), Leaf Blight	Accuracy: 99.82%; Precision/Recall/F1 = 1.00
[114]	Q1	CNN + Transfer Learning (ResNet50, DenseNet121, InceptionV3)	Custom image dataset (field-collected tomato leaves)	Tomato	Early blight, Late blight, Septoria leaf spot	Accuracy: 98.7%; Precision: 98.5%; Recall: 98.6%; F1-score: 98.5%
[115]	Q2	Modified Capsule Network (MCapsNet)	~2000 images	-	Mucolycid worms, corn borers, moths, caterpillars, ladybugs, aphids, cotton bollworms, cicadas	Accuracy = 87.52%; Recovery = 78.30%
[5]	Q2	RDD_CNN Model	4398 images	Rice leaves	Brown spot disease, bacterial blight, stemborer	Accuracy = 98.47%
[116]	Q2	Enhanced EfficientNet	IP102 dataset	-	Various pests	Accuracy = 69.45%; F1 score = 63.06
[103]	Q1	Multi-branch CNN (Mb-CNN)	1100 images (aphids)	Wheat, corn, rapeseed	Aphids	MAE = 10.22; MSE = 12.24
[117]	Q4	ResNet50, ResNet18, Inception-V3	1493 images	Pomegranate	Bacterial blight, anthracnose, fruit blotch, wilt, fruit borer	ResNet50 = 97.92%; ResNet18 = 87.5%; Inception-V3 = 78.75%
[118]	Q4	Super-Resolution CNN (SRCNN)	54,343 images	Apples, tomatoes, grapes, corn, potatoes	Apple scab, black rot, bacterial spot, citrus greening, etc.	Accuracy = 99.175%
[119]	Q2	Enhanced MobileNet-V2	3503 images (Kaggle)	Apple, cassava, corn, cotton	Rust, apple scab, cassava brown streak, corn rust, etc.	Accuracy = 92.20%

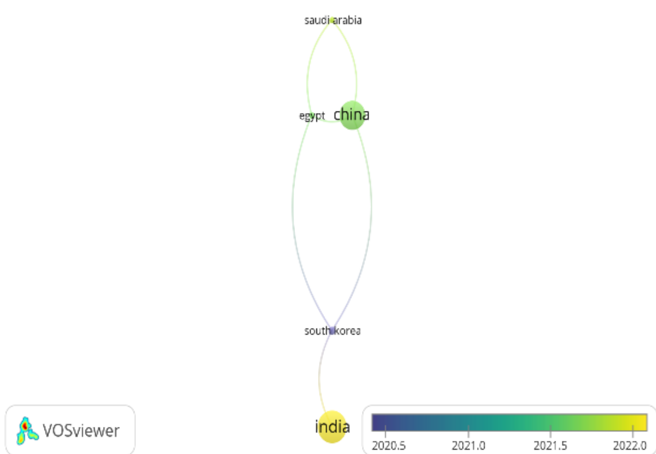
[12]	Q4	CNN segmentation model	2424 images	Tomato leaves	Tuta absoluta	Min. confidence = 70% in 5 seconds
[120]	Q1	Big data + deep learning	52,322 images	Pear leaves	Leucoptera malifoliella	Accuracy = 91.3–99.5%; F1 = 0.69–0.93
[121]	Q1	Mask R-CNN (ResNet backbone)	2500 images	Strawberry	Angular leaf spot, anthracnose, gray mold, powdery mildew, etc.	Accuracy = 82.43%
[122]	Q1	Lightweight CNN (SimpleNet)	568 images	Wheat	Glume spot scab	Accuracy = 94.1%
[123]	Q1	Faster R-CNN	IP102 dataset	-	Aphids, cicadellidae, linseed budworm, flea beetles, mites	Accuracy = 99.0%
[124]	Q2	Deformable VGG-16 (DVGG-16)	>2000 images	-	Rice borers, moths, caterpillars, bollworms, bugs, locusts	Accuracy = 91.14%
[125]	Q4	DL + RMSProp, Adam, SGDm	8000 images	Citrus crops	Snail infestation	Accuracy = 98.73%
[126]	Q1	InceptionResNetV2	Kaggle dataset	Rice leaves	Leaf blight, brown spot, bacterial blight	Accuracy = 95.67%
[127]	Q1	DNN-SAR (Optimization method)	2326 images	Rice	*Cnaphalocrocis medinalis*, *Scirpophaga incertulas*	Accuracy = 98.29%
[128]	Q1	GoogleNet and ResNet50	60,659 images	Cotton leaves	Cotton leaf diseases	GoogleNet = 86.6%; ResNet50 = 89.2%
[129]	Q2	Cascade approach CNN	Greenhouse image dataset	-	Flies, midges, thrips, whiteflies	F1 = 0.92/0.90; Count accuracy = 0.91/0.90
[130]	Q1	Deep learning + computer vision	841 images	Grape leaves	Mildew, spider mite	Accuracy = 94%; F1 = 0.94
[131]	Q1	Hand-designed CNN + MobileNet + InceptionResNetV2	1564 images	Coconut palms	Hemorrhagic stem disease, leaf blight, red palm weevil	CNN = 96.94%; MobileNet = 82.10%; InceptionResNetV2 = 81.48%
[132]	Q3	AlexNet	4344 images	Rice	Borer, brown leafhopper, leaf folder, green leafhopper	Accuracy = 96.9%
[133]	Q3	YOLOv5	5000 images	-	Ambrosia, amaranth, bromo	Accuracy = 82–92%
[134]	Q3	Custom DL model	3000 images in wheat fields	Weeds	*Capsella*, *Chenopodium*, *Sinapis arvensis*, *Tripleurospermum*	Accuracy = 98%
[135]	Q4	DenseNet201	859 images	Tomato crops	Major tomato pests	Accuracy = 94.87%
[136]	Q2	VGG-19-based model	3199 images	Peach	Multiple bacterial and fungal diseases	Accuracy = 94%
[137]	Q2	ResNet-50 tuning	3549 images	Rice	*Leptocorisa acuta*, *Locusta migratoria*, etc.	Accuracy = 95.01%
[138]	Q1	Tiny-YOLOv3	~5000 images	Longan	*Tessaratoma papillosa*	mAP = 89.72–95.33%
[139]	Q3	CNN architecture	Plant Village + Digipathos	Various crops	Multiple fungal and bacterial diseases	Accuracy = 99.85%
[140]	Q1	Seq-RNN	Plant Village	Bell pepper	Bacterial spot, other bell pepper diseases	Performance = 98.17
[141]	Q1	New CNN model	CPAF dataset, 73,635 images	-	Insects and larvae	Accuracy = 92.26%
[142]	Q1	Faster RCNN ResNet-50	IP102 + Bugwood	-	Diverse insects (e.g., ants, grasshoppers)	Accuracy = 94%
[143]	Q1	BridgeNet-19	12,561 images	Citrus	Citrus pests (e.g., psyllid, aphids, cicada)	Accuracy = 95.47%

[144]	Q1	ResNet-18 CNN	4753 images	-	*Drosophila suzukii* (fruit fly)	AUC = 0.506–0.603
[145]	Q3	DenseNet121-based CNN	Dataset of 66 pest species	-	66 pest species incl. *Spodoptera*, *Chilo*, *Leptocorisa*	ID rate = 93.9%; False alarm = 8.2%
[146]	Q1	Proposed CNN model	1600 images	Cotton	*Aphis gossypii*, *Anthonomus grandis*, *Helicoverpa* spp.	Accuracy = 98%
[147]	-	Proposed CNN	4300 images	Mango	*Capsid bug*, *Cecid fly*, *Fruit fly*, *Leaf hoppers*	Accuracy = 88.75%
[148]	Q1	ResNet50-based	1747 images	Coffee	Leafminer, rust, cercospora	Symptom class. >97%; Severity = 86.51%; Biotic rating = 95.24%
[149]	Q4	AlexNet	IP102 dataset	Multiple crops	*Xylotrechus*, *Ampelophaga*, etc.	Accuracy = 89.33%
[150]	Q3	DenseNet169	859 images	Tomato	*Tuta absoluta*, *Bactrocera*, *Bemisia tabaci*	Accuracy = 88.83%
[151]	Q3	R-CNN and Mask R-CNN	1239 images	Bell pepper	Whitefly, thrips, mites	R-CNN = 89%; Mask R-CNN = 81%
[152]	Q1	WRN (Wide ResNet)	>36,000 samples	Tomato, potato, grape, apple, corn	Typical crop diseases	Accuracy = 85–99%
[153]	Q1	New CNN architecture	>100,000 images	Wheat, rice, corn, barley, rapeseed	Various plant diseases	BAC = 0.98
[154]	Q1	CFN	2200 images	Wheat, corn, canola	Aphids	Accuracy = 76.8%
[155]	Q1	CNN (NBAIR + Xie1/Xie2)	Diverse datasets	Rice, wheat, corn, soy, sugarcane	10+ pests	Accuracy = 96.75%
[156]	Q1	Transfer Learning CNN	2 weed types	Weeds	*Sisymbrium sophia*, *Veronica persica*	Accuracy = 98.92%
[157]	Q1	Weakly DenseNet-16	12,561 images	Citrus	Medfly, psyllid, stink bug, canker	Accuracy = 93.33%
[158]	Q1	Residual neural system	8178 images	Wheat	*Septoria*, *Tan spot*, *Rust*	Balanced accuracy = 0.87
[159]	Q3	CNN (Real-time monitoring)	Grain pest dataset	Wheat	*Sitophilus oryzae*, etc.	Accuracy > 90%
[160]	Q1	CNN + augmentation	4400 images	Wheat, rice	*Sawfly*, *Aphid*, *Mite*, *Leafhopper*	mAP = 81.4%
[161]	Q2	CNN (Morphological analysis)	280 images	Rice	*Chilo spp*, *Gryllotalpa*, etc.	Accuracy = 81.82–94.44%
[162]	Q1	AlexNet, VGGNet, ResNet	10,000 images	Soybean	Defoliation estimation	MSE = 4.57
[163]	Q1	VGG16	687 images	Rice	*BPH (Brown grasshopper)*	Accuracy = 95%
[164]	Q1	Faster R-CNN, R-FCN, SSD	5000 images	Tomato	Leaf miner, mold, whitefly, etc.	FRCNN: 0.413–0.906; R-FCN: 0.7545–0.9492; SSD: 0.762–0.8841
[165]	Q1	Residual CNN	555 images	Corn, wheat, soy, canola	5 insect pests	Accuracy = 98.67%
[166]	Q1	CNN whitefly ID algorithm	3185 images	-	*Bemisia tabaci*, *Frankliniella occidentalis*	Precision: 0.92–0.96; F1: 0.94–0.95
[167]	Q1	CNN moth detector	177 images	-	Apple moth	AUC increased from 0.931 to 0.934

CNN: Convolutional Neural Network; VGG16: CNN with 16 depth layers; YOLO: You Only Look Once, real-time object detection; ResNet: Residual Neural Network; Inception: CNN with multi-scale filters; EfficientNet: Scalable CNN; MobileNet: Lightweight CNN; DenseNet: Densely Connected CNN; Mask R-CNN: Region-based CNN for detection and segmentation; LSTM: Long Short-Term Memory; GAN: Generative Adversarial Network.



(A)



(B)

Fig. 7. Behavior of co-citation of articles by authors (7A) and countries (7B).

Fig. 7 shows the co-citation of the evaluated articles, this indicates a strong co-occurrence relationship that occurs when two items from the existing literature are cited [168], among them are the articles of Yang, Zhang, Wang, Chen and Xie. While in the country's co-citation is led by India and the most emerging citations is led by India and China. These results are related to the advancement of smart agriculture and have actively responded to climate change achieved sustainable breakthroughs [169–171]. This indicates that new technologies should be incorporated in all countries, especially in developing countries in order to close research gaps [172].

A. Comparison with Previous Research

The trends identified in this review are consistent with earlier bibliometric and application-oriented studies on artificial intelligence in agriculture. For example, recent analyses have also highlighted India and China as leading contributors to neural network-based pest detection, reflecting their rapid adoption of AI technologies in agriculture [26, 27, 169, 170]. Similar dominance of ResNet and YOLO architectures was reported in global surveys of deep learning for plant disease diagnosis, where these models achieved high accuracy across multiple crops [35, 39, 55, 70, 91]. However, our findings reveal an even stronger concentration of research in Asia than those reports, while Latin America and Africa remain underrepresented, echoing the gaps in agricultural automation noted in previous works [173–175]. These comparisons reinforce the need for international collaboration and targeted funding to expand AI-driven pest management research in developing regions.

IV. CONCLUSION

The studies of neural networks in the diagnosis of pests show that the countries of India and China lead in the publications, focused on corn and rice crops, the most used neural network architectures in the studies explored were ResNet and versions, YOLO and versions, VGG-16 showing a great performance, this is related to the keywords that stand out are "Convolution neural networks, image processing and Deep learning". In that sense, this review provides emerging research information, evidencing that there is a dire need to implement these advanced and innovative technologies, such as AI. By adopting these advanced technologies, farmers will improve their farming practices. The advancement of such advanced technologies will lead to sustainable agriculture.

Future research should also address the geographic imbalance identified in this review by promoting studies in underrepresented regions such as Latin America and Africa, and by conducting comparative evaluations of different neural network architectures under diverse climatic and cropping conditions to identify the models with the best cost-benefit ratio for real-world implementation. Likewise, collaborative initiatives among researchers, policy makers, and local farming communities would foster technology transfer and the practical adoption of AI-based pest management in smallholder and resource-limited agricultural systems.

Data Availability: The data used to support the findings of this study are available from the corresponding author upon request.

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