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A Comprehensive Review of Deep Learning Technique for Crop Disease Identification

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Abstract: Agriculture is of utmost importance to the Indian economy. The production of main crops such as rice, maize, tomatoes, and potatoes go a long way to affect the livelihoods of the farmers. However, these crops are highly susceptible to many challenges most especially diseases that attack them; such maladies drastically reduce productivity. Early and rapid identification of such diseases are critical for initiating appropriate measures to contain potential losses. Deep learning techniques will be harnessed in this study involving feature extraction from digitized images of diseased plants for the accurate identification of maladies. Deep learning has also previously proven an efficient tool in handling very large datasets and finding patterns between normal and anomalous leaves. This review looks at different deep learning algorithms like VGG16, VGG19, RegNet50, EfficientNet etc. used in different studies and checks the accuracy, efficiency, and reliability of these models in detecting diseases in crops. The information learned from this review will help to find out the best deep learning algorithms for crop diseases detection. By better identifying and handling diseases, this study aims to increase productive crop farming in India which will help the sustainable growth of the agricultural sector.

Keywords: Crop Disease Detection, Convolutional Neural Networks, Image Classification, Deep Learning, Transfer Learning, Internet of Things.

I. INTRODUCTION

Traditional crop disease detection techniques rely on trained specialists conducting visual checks or laboratory analyses. These techniques may be time-consuming, need huge manpower [1] and are prone to human error. As farm operations grow in scale and there is a growing need for quick widespread monitoring, the drawbacks of these conventional means become starkly apparent. Deep learning, the new form of artificial intelligence, has been causing ripples in many sectors including agriculture recently. Deep learning methods, specifically convolutional neural networks (CNNs), have proved extremely effective in image classification and identification. The models are suited for crop disease detection due to their capability to identify sophisticated features from large sets of data. There are many benefits of using deep learning compared to traditional approaches in detecting diseases in crops. For example, algorithms are able to quickly and efficiently [2] process huge amounts of data, which allows for round-the-clock monitoring of checking crop health in large areas. Additionally, fundamental deep learning capabilities guarantee that detectors are not missing key elements, thereby enhancing accuracy and allowing them to detect possible crop diseases on time. Finally, deep learning technologies can be seamlessly integrated with other systems [3], like drones and satellite images for constructing all-encompassing scalable systems designed for disease monitoring.

The processes which typically occur when developing deep learning models for crop disease identification begin with obtaining a large quantity of labeled images featuring various disease symptoms and healthy plants. This data will be utilized as input to train the deep learning model. Following this is images preprocessing to work on getting them to a much higher quality standardization for consistency in format. Then, either a proper deep learning architecture is chosen or frequently designed depending on CNN [4] models that lead the research. And then train this trained dataset to identify and classify various kinds of disease symptoms. In the training process, the parameters of the model are tuned to reduce the discrepancy between its predictions and true labels. This occurs through a series of modifications using optimization algorithms and backpropagation. The trained model is then tested on an independent test dataset to determine how well it performs in terms of measuring accuracy, precision, and recall for the classification and identification of crop diseases. Using deep learning systems for disease detection in crops also has a number of challenges[5] like the requirement of high-performance computing hardware for both work stages: model generation and model use; creating simple interfaces for amateurs; fitting into current agricultural technology; fitting into current agricultural routines. Also, with changing conditions in the environment as well as variations in crop types is current research. The applications of deep learning in crop systems for detection of crop diseases exceed these limitations. Such systems enable early detection which would

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minimize pesticide use, maximize resource allocation, enhance pest control methods all of which enhances productivity with less environmental impact enhance food security.

The field of crop disease identification [6] with deep learning is progressing very fast. For example, in recent studies, an attempt has been made to fine-tune crop specific and disease specific pre-trained models using transfer learning. This may indicate that efficient detection systems can be developed even with small datasets. Moreover, deep learning combined [7] with hyperspectral imaging and Internet of Things (IoT) sensors are improving crop health monitoring systems. These multi-modal approaches not only strengthen visual assessments of plants but also consider their physiology and environment which plays a crucial role in understanding disease progression. This main aim of this review is to find the most impactful deep learning algorithms within problem solving frameworks tailored for farmers' difficulties in the field.

The paper is organized as follows. Section 2 presents overview of deep learning techniques. Section 3 presents the related work in the disease detection of crop/plant. Then, Section 4 explain the need for research. Following this, Section 5 shows the methodology used for review. Finally, conclusion is summarized in Section 6.

II. OVERVIEW OF DEEP LEARNING TECHNIQUES

A. Fundamentals of Deep Learning

Deep learning is a technical subfield of machine learning that uses multi-layered neural networks to learn complex patterns and representations from raw data directly. Such models excel in high-dimensional input tasks such as images and hence can be used as an extremely useful instrument for detecting crop diseases, when leaf images are used as the main input. Deep learning does away with manual feature engineering since it is able to automatically extract and optimize useful features while training. This feature is especially useful in agriculture, as disease symptoms are not fixed in shape, color, or texture, and identification by hand can be subjective and difficult. Specialist deep learning architectures are used in image-based detection tasks, which are optimized to process and analyze visual information quickly. Such architectures are able to recognize features like edges, textures, shapes, and objects based on their hierarchical nature. The most widely employed models for these purposes are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and more recently Transformer-based models with modifications for vision tasks. All of these architectures have something special to offer in image analysis, based on the type and complexity of the data to be analyzed.

B. Popular Architectures for Image-Based Detection

Specialist deep learning architectures are used in image-based detection tasks, which are optimized to process and analyze visual information quickly. Such architectures are able to recognize features like edges, textures, shapes, and objects based on their hierarchical nature. The most widely employed models for these purposes are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and more recently Transformer-based models with modifications for vision tasks. All of these architectures have something special to offer in image analysis, based on the type and complexity of the data to be analyzed.

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- Convolutional Neural Networks: CNNs are the most popular architecture for image classification, object detection, and segmentation. They are designed to learn spatial hierarchies of features automatically and adaptively with layers of nonlinear activation, pooling, and convolution. Convolutional layers employ filters to detect local patterns such as edges and textures, and deeper layers compose such patterns to create higherlevel features such as shapes and objects. Pooling layers reduce the spatial dimensions so that CNNs are computationally efficient while preserving the vital features. EfficientNet, ResNet, VGGNet, and AlexNet are among the well-known CNN-based models.
- Transformer-Based Models**:** Transformers, originally designed for natural language processing, have more recently seen use in image processing with transformation types like Vision Transformers (ViTs). The models utilize self-attention to rank the importance of different elements of the input data so that they can grasp longer-range relations better than CNNs. Vision Transformers divide an image into patches and handle them as word embeddings in NLP, enabling robust and flexible feature learning without convolutional layers. Vision Transformers have achieved competitive results on image classification, object detection, and segmentation tasks, particularly when it is fine-tuned on large datasets

C. Transfer Learning and Pretrained Models

Transfer learning is a method where a model trained on a particular task is copied and used as the initial model for a second related task. In deep learning, this frequently entails taking a pretrained model—having been trained on a big set such as ImageNet—as a feature extractor or fine-tuning it to a particular application. This method dramatically lowers the requirement of large amounts of labeled data and computational power, while frequently enhancing model accuracy

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and training efficiency. It is most useful in application areas where the collection of labeled data is costly or time-intensive. ResNet, Inception, and BERT (in NLP) are commonly applied in transfer learning workflows

III. REVIEW OF LITERATURE

Deep learning algorithms are being used as a fundamental tool in plant disease detection because of their capacity to process and analyze data efficiently. Deep learning models need large amounts of data to be trained. Data collection for plant disease detection in agriculture is confronted with numerous challenges because of the complexity of agricultural ecosystems and the variability of crops and diseases. Recent breakthroughs in deep learning have opened up exciting new possibilities for detecting leaf diseases. This section focuses at key studies and methods that have been used for crop disease detection.

A research study by Raouhi et al.[8] emphasized the difficulty in identifying these diseases using traditional methods, which are error prone and time consuming. The research explored different CNN architectures and optimizers for efficient olive disease detection. The models were tested using a database of 5571 olive leaf images consisting of healthy images. The results show that the MobileNet model with Rmsprop optimization performed best in detecting disease with 92.59% accuracy. Kundu et al. [9] highlighted the increasing disparity between the supply of maize and its output, mainly caused by its susceptibility to diseases like Turcicum Leaf Blight and Rust that have the potential to substantially reduce yields. They suggested an adapted deep learning architecture MaizeNet, from a real-world dataset, which was labeled by plant pathologists, to find diseases automatically, their severity to predict, and likely losses of the crop to estimate, with a remarkable accuracy of 98.50%. For identify the weeds in bell pepper field, Subeesh et al.[10] used deep convolutional neural networks (DCNNs) like AlexNet, GoogLeNet, InceptionV3, and Xception and achieved the highest accuracy of 97.7% with InceptionV3. To train the model with big datasets, Shabrina et al. [11] used the data augmentation techniques on plant leaves, such as image flipping, blurring and evaluated: ResNet101v2, CoAtNet-0, EfficientNetV2B0, and EfficientNetV2M. EfficientNetV2M achieved highest accuracy of 98.66%.

The mushroom disease detection model was deployed by Guragain et al.[12] to help farmers effortlessly upload images of suspected diseases into the IoT ecosystem. In return, they receive predictions about the disease along with useful recommendations. This model achieved an impressive accuracy of 98.33%. In similar way, generalized model developed by Azizi et al.[13] for categorizing strawberries into four classes: ripe, half-ripe, unripe and damaged, using a dataset of 800 confirmed images. Among the models tested, GoogleNet demonstrated the highest accuracy across various scenarios. The model achieved accuracies of 96.88% with original data, 97.50% with fundamental data augmentation, and an impressive 98.85% when using the LAS technique. Moreover, the model proposed by Dash et al. [14] utilized a comprehensive dataset consisting of 4988 images across four distinct classes of maize leaves: blight, common rust, gray leaf spot, and healthy. The experimental results are noteworthy, with the proposed model achieving a classification accuracy of 94.6%. For the classification task of Brassica napus and disease, Alom et al. [15] analyzed five contemporary CNN models: DenseNet201, VGG19, InceptionV3, Xception, and ResNet50 and the highest accuracy of 97% was achieved by DenseNet201. For multi-crop leaves, Md. M. Islam et al. [16] introduced deep transfer learning models like CNN, VGG-16, VGG-19, and ResNet-50 on a plant image dataset. ResNet-50 model emerged as the most accurate with 98.98%. Similarly for maize plants, Khan et al. [17] investigate deep transfer learning like VGGNET, Inception V3, ResNet50, and InceptionResNetV2. Among all these models, ResNet50 achieved the highest validation accuracy of 87.51%.

For classifying the local rice seed varieties in southern Tamil Nadu, India, Rajalakshmi et al. [18] proposed RiceSeedNet, a deep neural network. The proposed model demonstrates impressive performance, achieving a classification accuracy of 97% for 13 local rice seed varieties, consisting of 13,000 images representing. Rezaei et al. [19] proposed PMF+FA method which achieved high accuracy of 90.12% on the PlantDoc dataset, using as few as five images per class. Moreover, Li et al. [20] introduced a dual-branch deep neural network designed for identifying crop diseases. This innovative approach combined information from both the frequency and spatial domains to tackle challenges like background noise, differences in plant shapes, and variations in scale. As a result, it achieved an impressive accuracy of 96.7% on the corn test dataset. Similarly, for disease detection in jasmine plants, Shwetha V et al.[21] introduced the model which used MobileNetV3-based classifier. The classifier achieved an impressive 97% training accuracy, indicating its strong performance in recognizing disease symptoms.

A. et al. [22] introduced deep transfer learning model that can accurately spot various crop diseases just by analyzing images of plant parts like leaves, stems, and fruits. This model used several convolutional layers to pull out complex features from the images, such as texture and color differences. With an outstanding overall accuracy of 96.7% in classifying crop diseases, the CNN model proved its ability to identify and differentiate between healthy and infected plants. For Bell pepper plant leaf disease detection, Ranga et al. [23] analyzed five version of EfficentNet such as EfficientNetB4 to EfficientNetB7. Among those, EfficientNetB7 attained the highest accuracy of 98.12 %. Similarly for maize leaf disease identification, Sun and Huo [24] proposed a lightweight network EfficientNet model. By introducing the double pooling method, the overall feature distribution is smoothed while highlighting the important

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disease features. After the three improvements, the model achieved an average recognition accuracy of 98.32% of test dataset of maize leaves. Moreover, Askale et al. [25] analyzed models like VGG16, AlexNet and ResNet50 for maize dataset. VGG16 outperformed other models with highest accuracy of 95%. Table 1 shows the model analyzed, dataset used and the accuracy of models for each reviewed study.

B.

TABLE I EVALUATION OF TECHNIQUES AND METHODS

Sr. No.	Authors/ Year	Model(s) Analyzed	Plant/ Dataset	Accuracy	Future scope
1.	Raouhi et al. [8] /2022	MobileNet (RMS prop)	Olive plant leaves/Images taken under diverse real-conditions (Morocco)	92.59%	Studying the effects of data augmentation techniques on model performance in disease classification
2.	Subeesh et al. [10] /2022	InceptionV3	Bell pepper / Images from controlled environments or field	97.7%	Exploring the application of other advanced deep learning architectures.
3	Dash et al. [14] /2023	GA-SVM ANN SVM DenseNet201+SVM	Maize leaves/ Kaggle dataset	92.82% 94.4% 89.6% 94.6%	The model can be adapted for disease identification in other crops beyond maize.
4	Alom et al. [15] /2023	DenseNet201 VGG19 Inceptionv3 Xception ResNet50	Brassica Napus/ Images taken under diverse real-world conditions	97% 93% 95% 97% 65%	To study with data from separate metabolomics datasets from similar crops which can improve the accuracy of species.
5	Khan et al. [17] /2024	VGGNET, Inception V3, ResNet50, Inception	Fine-grained maize leaves/ Plant Village dataset	75.23 83.07 87.51% 77.60%	Integration of climate data can be done in real-time disease monitoring systems.
6	Rajalakshmi et al. [18] /2024	RiceSeedNet (Deep Neural Network)	Rice Seeds/ RiceSeed Image corpus	97%	Explore the integration of additional features such as soil quality and climatic conditions.
7	Rezaei et al. [19] /2024	ResNet50 and Vision Transformers	Multiple crops/PlantVillage, PlantDoc dataset	90.12%	Expanding and exploring the dataset to include a wider variety of plant diseases.
8	A. et al. [22] /2024	CNN	leaf images/ Images taken under diverse real-world conditions	96.7%	The expansion of crop species could significantly improve the model's accuracy and adaptability,
9	Ranga et al. [23] /2025	EfficientNet	Bell Papper	98.12%	Exploring the models for different plants and crops dataset
10	Askale et al. [25] /2025	VGG16, AlexNet, ResNet50	Maize leaf images/ Plant village and PlantDoc	95%, 91%, 72%	Exploring the wide range of dataset for crop disease detection

IV. NEED FOR RESEARCH

Agricultural research is essential to meet the increasing challenges of food security, population growth, climate change, and shrinking natural resources. Increasing population at the global level has created additional demands for food, which are exerted on agricultural systems to increase production with fewer resources. Research assists in bringing forward better crop varieties, effective farming practices, sustainable pest and disease management solutions, and improved soil and water conservation measures. Deep learning, a type of artificial intelligence, allows for the parsing of large and

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intricate agricultural data—ranging from satellite imaging to crop disease patterns—with great speed and accuracy. Through the use of deep learning in agricultural studies, more intelligent, data-informed solutions can be created that enable precision agriculture, conserve resources, and advance food security into the future. The goal of this research is to identify the best deep learning technique to tackle the challenge of recognizing harmful diseases in crops and determining the specific type of disease affecting them.

V. METHODOLOGY

To pinpoint the main issues, interviews, discussions, and distributed surveys were conducted to understand the current methods used by farmers, their limitations, and whether they had adequate knowledge about the solutions available after identifying the diseases affecting their crops. To find a suitable solution, a literature review was conducted, primarily focusing on deep learning techniques applied to crop and plant disease identification. Fig.1 shows the steps taken for conducting a literature review.

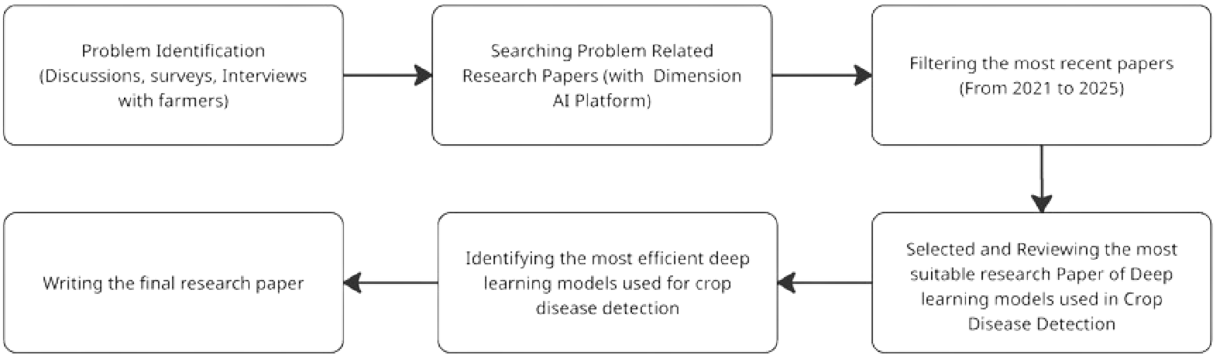

Fig. 1 Methods for Conducting a Survey

During this study, Dimensions [26] platform was used to search the total relevant papers for crop/ multi-crop disease detection with keywords like deep learning, CNN, convolutional neural network and transfer learning. From year 2021 to present, search results showed approx. 380 publications under the research categories: Information and Computing Sciences, Agricultural, Veterinary and Food Sciences, Data Management and Data Science, Machine Learning, and Crop and Pasture Production. Fig. 2 shows the number of publications on crop disease detection using deep learning techniques. After carefully looking at these papers, this study focused on the most important research papers based on factors like accuracy, the datasets used for crops, and the deep learning models used. Some of the crop datasets analyzed in the reviewed studies include rice, maize, tomato, potato and bell pepper.

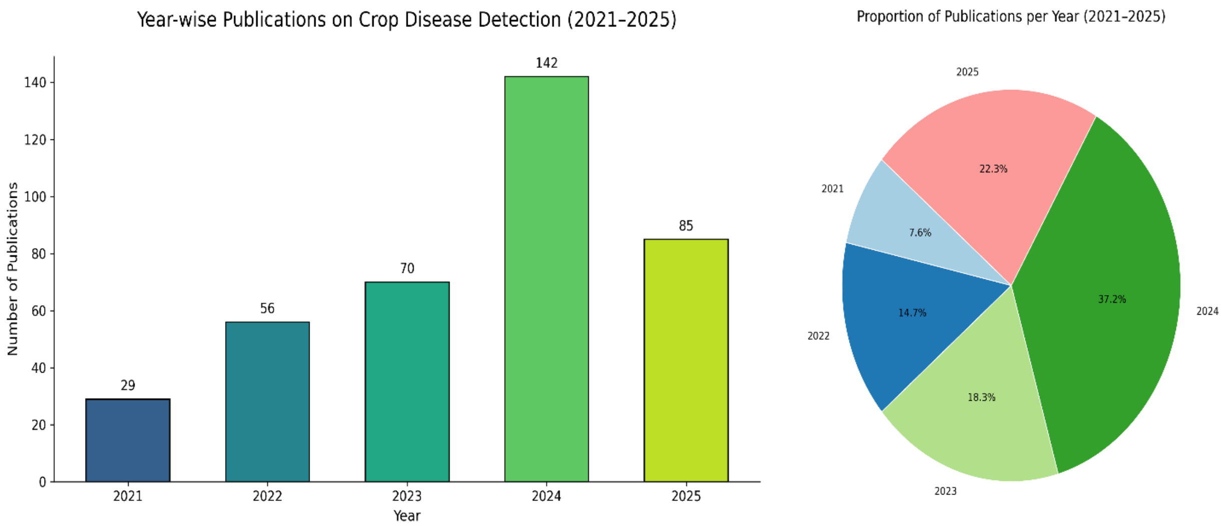

Fig. 2 Journal articles on crop disease detection

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VI. CONCLUSION

Crop diseases are a major threat to food security and agricultural productivity around the globe. These diseases stem from various pathogens like fungi, bacteria, and viruses, and can cause significant yield losses, lower crop quality, and create economic challenges for farmers everywhere. That's why early detection and proper diagnosis of such diseases are crucial, as these enable timely and effective management practices, which can reduce losses and encourage sustainable agriculture. This paper gives an overview of crop disease detection algorithms and their underlying methodologies. In light of the literature considered, deep learning algorithms are the most efficient, with greater accuracy and efficiency. Through the ability to identify diseases at an early stage and with great accuracy, these systems can aid in reducing the application of pesticides, ensuring optimal resource allocation, and generally improving crop care. This goes on to promote increased agricultural productivity, reduced environmental impact, and increased food security. Of the CNN architectures investigated, DenseNet, RegNet50, and EfficientNet are especially suitable for recognizing a broad spectrum of crop and plant diseases. The study also highlights the contributions of the proposed method and discusses future possibilities

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