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Deep Learning Advancements in Agriculture: A Survey

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Abstract. Deep neural technology has a significant contribution to the invention of various systems to enhance crop farming by preventing damage caused by various crop diseases. This study explores the implementation of deep learning in the agricultural domain within some aspects: 1. Importance of deep learning in agriculture, 2. Method- ology and Aspects, and 3. Evaluation Matrices. In order to train convolution neural networks (CNN), databases are required, whereas evaluation matrices evaluate the architecture performance to check the effectiveness of the databases. This paper effectively explains all the databases and methods utilized in deep learning for crop disease identification and crop classification. This research also mentions the future aspects of deep neural methods to implement in the crop health monitoring system.

Keywords: *Automated Identification, Convolution Neural Networks (CNN), Evaluation Matrices, Deep Learning, Crop Disease Identification, Crop Classification*

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I. INTRODUCTION

Every year farmers becomes mentally depressed as field crop gets damaged while farming through out whole year due to the misused pesticides, pests and crop diseases. This exact situation considerablly affects the annual financial growth of India and other countries.

According to an 2016 article [1], The annual crop prodution reduced approximately 15-25 percent due to pests and mites affiliction along with viral, bacterial and fungal infections. As per another corresponding report [2], because of the damaged crop the annual financial loss reaches upto Rs. 50,000 crore

According to an intensive survey [3] of Prof. Maria Lodovica and her team which consists of 10 scientists, annually the loss of global crop yield is around 40 percent. The UN Food and Agriculture Organization’s Director General elaborated this topic during 2021 convention, mentioning the 70 billon dollar loss globally due to the reduction of crop production. Various plant diseases resulted in an annual financial loss of upto 220 billion dollars globally.

This paper focuses primarily on the study of methodology and aspects which intensively contributed in agricul- tural technology. Several authors proposed databases and methodologies for artificial intelligence integrated agricul- tural prospects. The databases such as PlantVillage

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Dataset [4], PlantDoc Dataset [6], Leaf disease detection and moss species identification dataset [7], Cassava Leaf Disease Detection Dataset [5], Eggplant Leaf Disease Detection Dataset [8], Leaf Disease Detection Dataset (Cucurbitaceae family) [9], Grape Leaves Disease Dataset (GLDD) [10], and Nature's Diabetes Helpers: Insulin Leaves Repository [11] are utilized to train the deep neural architectures like AlexNet [12], VGG16 [13], ResNet152 [14], MobileNetv2 [15], Inceptionv3 [16], Xception [17], etc. Evaluation ma- trices such as Precision [18], Recall [18], F1 Score [18], Accuracy [18] check effectiveness of the databases validating though deep neural networks. For example some authors in [19] and [20] implemented CNN on image databases to benchmark CNN architectures.

II. METHODOLOGY AND ASPECTS

To train convolution deep neural architectures, high-quality datasets are utilized. These datasets have various labeled images of leaves, which are captured under various illumination conditions, to train architectures for adapting across different real-world scenarios.

Here are some important datasets: and foster the exchange of knowledge among researchers, the PlantVillage dataset has been a widely used tool. It functions as an open-source platform, where contributors get scores depending on the contributions. These scores can also change the contributions of other researchers. This plat- form has a library file covering 18,000 diseases which affected 150 different types of crops. 54,309 images of 14 different crop species were present in the PlantVillage dataset.

- *Cassava Leaf Disease Detection Dataset [5]*

Traditionally, the disease detection in cassava relied on the manual inspection by experts. But this method needed manual labour, high expenditure and was prone to human error. To overcome this challenge, the National Crops Resources Research Institute (NaCRRI) and Makerere University's AI lab made a collaboration to create the Cassava Leaf Disease Detection Database. This dataset comprises of 21,637 images from the farmlands of Uganda, captured by the farmers using their mobile cameras, which were labelled by pathologists.

- *PlantDoc Dataset [6]*

To tackle the shortcomings of PlantVillage dataset featuring single leaf images in grey back- ground leading to poor performance of models in real-life field conditions, the PlantDoc dataset was developed. 20,900 images were downloaded from Ecosia and Google Images and filtered by four users using website metadata and ASP- Net guidelines, which resulted in the development of PlantDoc dataset consisting of 2,598 images which are labelled and annotated, spanning 27 classes across 13 different crop species.

- *Leaf Disease Detection and Moss Species Identification Dataset [7]*

In this study, a method based on deep neural network was proposed for detecting healthy and diseased leaves from various species. This dataset uses a Siamese network architecture. It has triplet loss function and three network branches. It is based on MobileNetV2 network. For supporting the research, two distinct databases were developed. In the first one, 935 images of 256x256 pixels covering about 25 distinct classes from five species of crops (cotton, cucumber, corn, grape and wheat) was developed for detection of plant diseases.

- *Eggplant Leaf Disease Detection Dataset [8]*

In this study, classification of the diseased leaves of eggplants by the utilization of pre-trained VGG16 as a feature extractor combined with a Multi-Class Support Vector Machine (MSVM) as a classifier was conducted. For supporting the research, a dataset with 1,088 labelled images of diseases eggplant leaves, mainly representing five different types of diseases: Cercospora Leaf Spot, Epilachna Beetle, Tobacco Mosaic Virus, Little Leaf Disease and Two-spotted spider mite.

- *Leaf Disease Detection Dataset (Cucurbitaceae family) [9]*

Here, a deep neural architecture-based method to detect healthy and diseased leaves from various species within the cucurbitaceous family (including cucumber, watermelon, squash and pumpkin) was proposed. The Cucurbitaceae family comprises of 965 species, which was the primary reason for choosing this family. A seven- layered CNN was designed to classify diseased leaves using convolutional, max-pooling layers followed with dense, and softmax layers.

- *Grape Leaves Disease Dataset (GLDD) [10]*

A Faster DR-IACNN model based on deep learning to detect diseases of grape leaves: Black Measles, Leaf Blight, Black Rot, and Mites of Grape was proposed in this study. Inspired from the design of Faster RCNN, their model featured three distinct modules. The first module, INSE-ResNet incor- porated residual structures, SE blocks and inception modules; the second module, Region Proposal Network (RPN) supplied with multi-scale features; and the third module consisted of fully connected layers. The dataset was compiled with 4,449 labelled and annotated images of diseased grape leaves across four disease classes. Captured from actual grape vineyards in Ningxia hui Autonomous region, Wei Jiani Chateau and Yinchuan, China under various climatic conditions.

- *Nature's Diabetes Helpers: Insulin Leaves Repository [11]*

This dataset features total 429 photos of Chamaecostus cuspidatus (commonly known as insulin plant), including 265 healthy and 164 diseased leaves. Captured in Redmi Note 9 Pro Max in real-world environments in Ranaghat district of West Bengal, India. The author mainly captured the images with complex natural backgrounds including elements like soil, weeds and parts of neighbouring plants were featured in the dataset to represent the real life significance of the database which aims to support research in plant disease detection and facilitate the development of AI-driven health-monitoring tools for crops.

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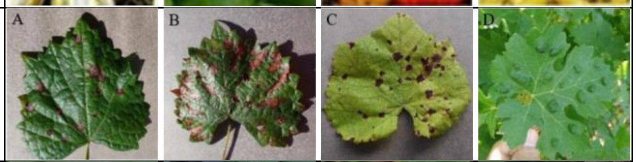
Table 1 Various Leaf Disease Detection Datasets with Sample Images

S. No.	Name	Images of Dataset
1	PlantVillage Dataset [4]	
2	Cassava Leaf Disease Detection Dataset [5]	
3	PlantDoc Dataset [6]	
4	Leaf Disease Detection and Moss Species Identification [7]	
5	Eggplant Leaf Disease Detection Dataset [8]	
6	Leaf Disease Detection Dataset (Cucurbitaceae Family [9]	
7	Grape Leaves Disease Detection [10]	
8	Nature's Diabetes Helpers: Leaves Repository [11]	

III. ARCHITECTURES

Many deep learning based models were used for the classification and detection of leaf diseases which vary in the complexity, efficiency, and sustainability in real-world applications. Some models focus on accuracy while some are for lightweight devices.

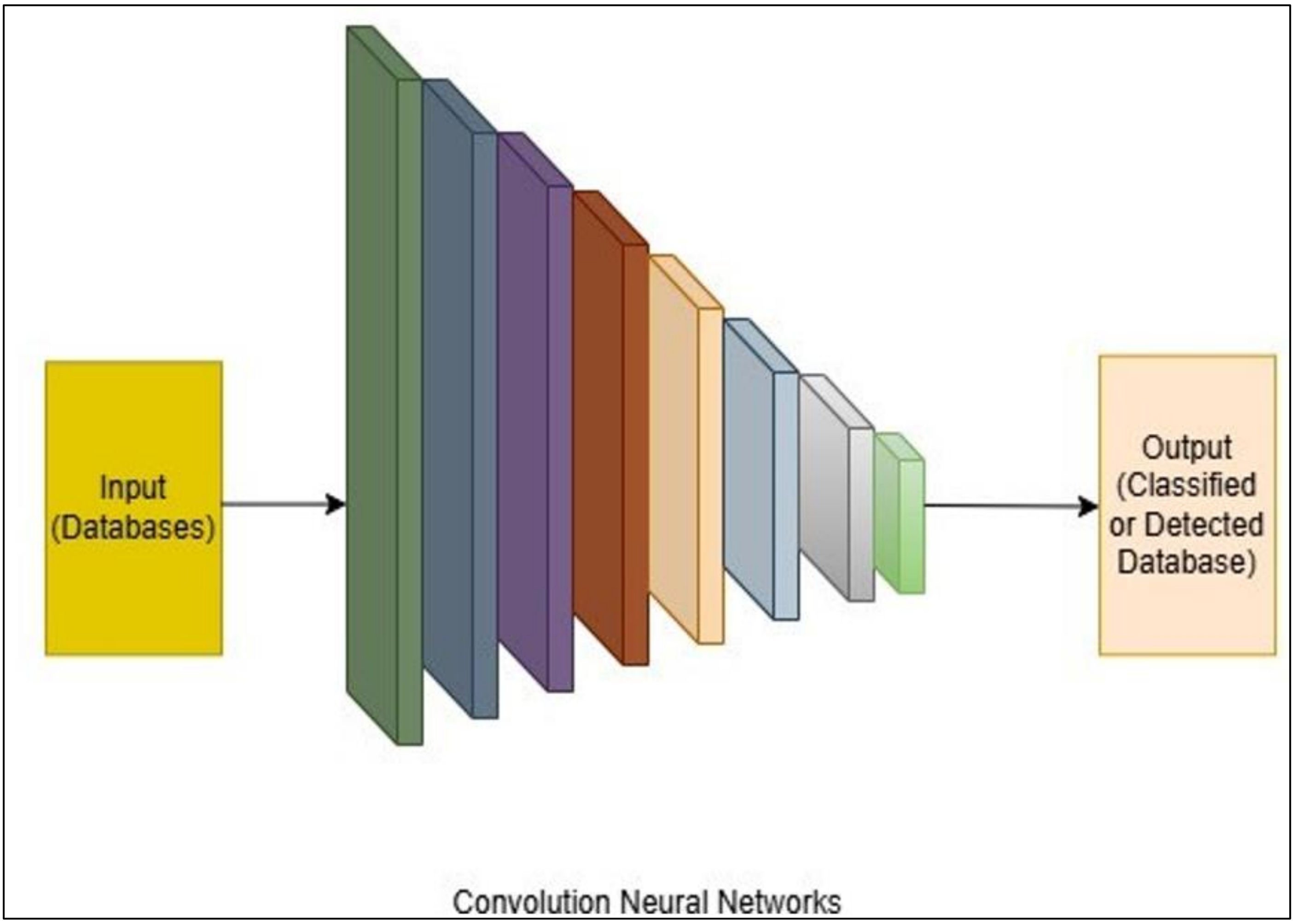


Fig 1 Representation of CNN

A. Some Models are Discussed Below:

➢ *AlexNet [12]*

As a groundbreaking deep neural network, AlexNet considerably influences computer vision. With a total of eight layers, this model, which is renowned for being one of the first to contribute significantly to multidisci- plinary image analysis, consists of five convolutional layers and three fully connected layers. It utilizes various filters within the convolutional layers to derive informative features from input images. Max-pooling of layers allow feature maps' down-sampling, successfully maintaining key aspects while minimizing computational burden. Although it has achieved tremendous performance, AlexNet requires large memory capacity owing to its relatively large parameter size, around 60 million.

➢ *VGG16 [13]*

Like AlexNet, exemplary efficiency in image classification problems in computer vision is demonstrated by Vgg16. The model consists of sixteen layers, comprising three fully connected layers followed by thirteen convo-lutional layers. A unique feature of Vgg16 is its uniform structure, in which all convolutional layers use 3x3 kernel size filters extracting features from the input data.

Although it has great efficiency, the Vgg16 model has a high computational cost, with about 138 million pa-rameters. This large number of parameters leads to higher memory and computational costs, possibly affecting the efficiency of the model. Nevertheless, the trade-off is worth it due to the outstanding efficiency Vgg16 achieves in several tasks related to image classification.

➢ *ResNet152 [14]*

ResNet152 is a deep convolutional neural network from the ResNet (Residual Network) family. It pos- sesses residual blocks, such as convolutional and batch-normalization layers, utilizing Rectified Linear Unit (ReLU) for activation function. Unlike AlexNet and Vgg16, ResNet introduced skip-connections that enable the network to learn residual functions and maintain multi-scale features effectively. Comprising 152 layers and more than 11 billion parameters, a high computational expense is incurred by ResNet152. The huge number of parameter increases the model's computational and memory requirements, which is supported by the improved performance and the ability of ResNet152 to record detailed information at multiple scales.

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➢ *MobileNetv2 [15]*

It is a light CNN model known for its efficiency acquired using depth-wise separable convolution layers rather than traditional convolutional layers. The computational burden of the network is considerably lowered by the choice of the design. Also, MobileNetv2 uses linear bottlenecks with fewer channels, which reduces the computational needs.

For improving performance and reducing the vanishing gradient problem, MobileNetv2 uses skip-connections. These associations allow the network to learn residual functions which improves the overall stability. The blend of depth-wise separable convolution layers, linear bottlenecks, and skip-connections guarantees low computational com- plexity at an impressive performance.

This architecture is advantageous for mobile devices, including object detection and classification. Its effective design makes it appropriate for deployment on resource-limited devices, to enable efficient image analysis on mobile platforms.

➢ *Inceptionv3 [16]*

Inceptionv3 is among the most excellent CNN models following the idea of parallel computation with filters of different dimensions. This design has some inception modules, blending 1x1, 3x3, and 5x5 convolu- tions. The special fusion enables the multi-scale feature map extraction to enhance the model's capacity for collecting diversified information.

One of the main advantages of this architecture is application of 1x1 convolution blocks that lead to decrease in the computational cost of the network but has around 23 million parameters which incurs an enormous computational cost with respect to AlexNet and Vgg16.

It is greatly acclaimed for the capability of successfully processing and extracting features at multiple scales. Using the following parallel computing principle and applying a mix of convolutional filters, this architecture demonstrates its capability to several tasks related to computer vision.

➢ *Xception [17]*

In line with the theory of inception modules of Inceptionv3, "Extreme Inception" (Xception) varies mainly in its design, which displaces conventional depth-wise convolutional layers with convolutional layers in its initial modules, focusing on minimizing computational burden and enhancing feature extraction by separating between spatial and channel-wise details.

This architecture employs residual links, separable convolutions, and skip connections in depth. The combination enhances memory function, and high performance in recording minute differences and achieving great accuracy. Depth-wise separable convolutions improve feature processing, in which skip and residual connections assist in stabi- lizing the model and retaining information. Briefly, this architecture provides a robust and memory-conscious design that effectively captures intricate details and delivers remarkable accuracy in various applications.

IV. EVALUATION MATRICES

Evaluation metrices are important measures for evaluating the effectiveness of machine learning models, particularly in the classification, object detection and segmentation. Within the domain of leaves, detecting diseases using deep learning, it is important to select proper evaluation metrices to properly assess the performances of the models. Due to the complexity and potential class imbalance in the datasets, relying on a single evaluation metric may not provide reliable information about the model's diagnostic capabilities. Therefore, it is important to use multiple metrices for the evaluation purpose.
Some evaluation metrices are discussed below:

➢ *Accuracy [18]*

It is one of the most important metrices. It measures the ratio of correctly predicted instances(both diseased and healthy) to the aggregate number of predictions. Although it offers the model's overall performance, it can misleading at some instances where the disease class is overrepresented. For instance, a model predicting the most prevalent disease at most of the times can yield high accuracy even without capturing any rare but critical infections.

➢ *Precision [18]*

It computes the ratio of true positive predictions to the total positive predictions made by the model. For leaf disease detection, high precision indicates that if the model identifies a disease, it is most probably correct. It is essential to prevent false predictions, such as diagnosing a diseased leaf as a healthy leaf.

➢ *Recall [18]*

It is also known as sensitivity or True Positive Rate(TPR), which calculates the ability of the model to recognize all the instances of disease. High recall is particularly important in agricultural settings, where missing diseased leaves can result in huge agricultural losses.

Table 2 Review on Methods and Aspects, Model Performance, Limitations, and Future Work

Dataset	Model	Accuracy of Test Set (%)	Limitations	Future Works
PlantVillage Dataset (2015) [4]	– VGG16 [13] – AlexNet [12] – MobileNet [25] – MobileNetv2 [15] – MobileNetv3 [22] – VGG19 [23] – GoogleNet [24]	99.34 (AlexNet [12])	– Images are captured in con- trolled lab settings, which lack real-world complexities. Images include isolated single leaves and not the entire plants. – Very limited variations in angles, lighting and back- grounds. – No bounding box information.	Collect images in real field conditions with natural light- ings and backgrounds. – Add bounding boxes for better model training.
Cassava Leaf Disease Detection Dataset (2015) [5]	– VGG16 [13] – Inceptionv3 [16] – Xception [17] – ResNet50 [14]	86.50 (VGG16 [13])	– Limited to a single crop species. Images limit geographical di- versity. – Most images have similar backgrounds, which risk model overfitting.	– Increase dataset and diversity. – Include images with various environmental conditions.
PlantDoc Dataset Dataset (2019) [6]	– VGG16 [13] – Inceptionv3 [16]	70.53 (VGG16 [13])	Manual filtering and labelling may lead to inconsistency. Only 2598 images may limit training scalability.	– Expansion to cover more plant species and disease types.
Leaf Disease Detection and Moss Species Identification (2021) [7]	– MobileNetv2 based Siamese Network with 3 twins [7] – ResNet50 [14]	97.80 (MobileNetv2 based Siamese Network with 3 twins [7])	– Datasets are relatively very small. Images are of low resolu- tion(256x256) which may lack minute detail extraction.	– Increase the dataset to improve model training. Capture images with better res- olutions.
Eggplant Leaf Disease Detection Dataset (2020) [8]	– VGG16 [13] – AlexNet [12] – GoogleNet [24] – ResNet101 [14]	99.9 (GoogleNet [24])	Dataset size is limited for five different disease types. – Dataset is crop-specific.	– Expansion of dataset with new classes and mixed infections.
Leaf Disease Detection Dataset (Cucurbitaceae Family) (2021) [9]	– Convolution Neural Network [26]	72 (Training)	– Images are collected from on- line databases which may lead to labelling inconsistency. – Primarily used for classifica- tion but not for detection or segmentation.	– Creation of balanced classes with similar sample sizes. – Inclusion of bounding boxes for object detection.
Grape Leaves Disease Detection (2020) [10]	– VGG16 [13] – GoogleNet [24] – ResNet18 [14] – ResNet34 [14] – ResNet50 [14] – ResNet101 [14] – INSE-ResNet [27]	99.28 (INSE-ResNet [27])	– Healthy class is not included in the dataset, which may bias model learning. Dataset is limited to four dis- ease types.	Increase the dataset to cover more healthy leaves and mixed infections.
Nature's Diabetes Helpers: Insulin Leaves Repository (2024) [11]	– AlexNet [12] – VGG16 [13] – ResNet152 [14] – MobileNetv2 [15] – Xception [17] – Inceptionv3 [16] – GreenMedNet [24]	99.47 (GreenMedNet [20])	– Confined to single geographic region. – The dataset is limited.	– Expansion of dataset. – To reduce device-specific bias.

➢ *F1 Score [18]*

It signifies the harmonic mean of precision and recall, offering a balanced evaluation of both false negatives and false positives. It is important when there is an uneven distribution between classes or when both recall and precision is necessary to evaluate the model's effectiveness.

V. CONCLUSION

Crop health directly affects the productivity and sustainability of global agriculture. Therefore, it is important to de- tect crop diseases to ensure food security and minimize financial losses. To reduce such losses automated recognition system is required i.e. why novel databases are curated just like in [21]. Deep learning models with diverse and well-classified datasets offers effective solutions for implementing such well-oriented automated recognition systems. Despite considerable advancement, challenges remain to improve model generalization, diversity of dataset, and de- ployment of models on lightweight devices for leaf disease classification. Plant pathologists, computer scientists and agricultural stakeholders need to collaborate for further advancements in this field.

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