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Advances in Deep Learning for Automated Plant Disease Detection: A Comprehensive Review

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Abstract

Plant diseases and pests have a significant impact on both crop yield and quality, thereby posing a substantial threat to global food security. Traditional methods for identification and detection have limitations, resulting in substantial losses, particularly in countries such as India, where 35% of the annual crop yield is lost to plant diseases. This study explores publications spanning 2010 to 2023, showcasing the efficacy of advanced technologies in improving the accuracy and efficiency of plant disease detection. Therefore, this paper examines the advanced technologies already in use, specifically Machine learning technologies and deep learning technologies, to overcome the challenges of detecting plant diseases at early stage and large scale. Machine learning technologies, including clustering, decision making, classification algorithms and regression algorithms, as well as deep learning technologies such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Multilayer perceptron's, Autoencoders, Generative Adversarial Networks (GANs), Graph Convolutional Networks (GCNs), attention mechanisms and Boltzmann Machines, emerge as promising solutions for early and large-scale plant disease detection. This research provides valuable insights for plant disease detection to researchers, practitioners, and industry professionals by offering specific information on plant diseases. In this paper, we discuss our approach to collecting and analyzing relevant literature, as well as the common methodologies used in many studies on plant disease detection. We also address limitations in existing reviews and suggest future research directions. Additionally, we provide an overview of publicly available datasets for leaf disease classification to aid researchers. Furthermore, we explore various machine learning and deep learning approaches and compare them. Moreover, we examine real-life applications related to leaf disease classification. Finally, we summarize our findings and suggest potential future research directions, concluding the paper with references for further reading.

1. Introduction:

The surging global population and increasing demand for plant products underscore the critical need for robust crop protection against diseases. Alarming statistics from the Indian Council of Agricultural Research reveal an annual crop loss exceeding 35% due to pests and diseases, presenting a considerable threat to the security of our food supply. Diseases in plants are detected by various symptoms such as lesions, changes in color, damaged leaf, damage in the stem, abnormal growth of stem, leaf, bud, flower and/or root, etc. In addition, leaves show symptoms such as spots, dryness, pre-mature falls, etc., as an indicator of disease. Analyzing these observable symptoms is an effective way to detect plant diseases. In response, this study delves into the potential of deep learning for scalable and cost-effective plant disease detection [1].

Detection of plant diseases and pests, a central focus in machine vision research, has traditionally relied on image processing algorithms or manual feature design combined with classifiers. However, recent advancements, particularly the success of convolutional neural networks (CNNs) in various computer vision tasks, have brought about significant change. The detection process is divided into three interconnected stages: classification ("what"), detection ("where"), and segmentation ("how"), each adopting unique terminology based on network structures and functions.

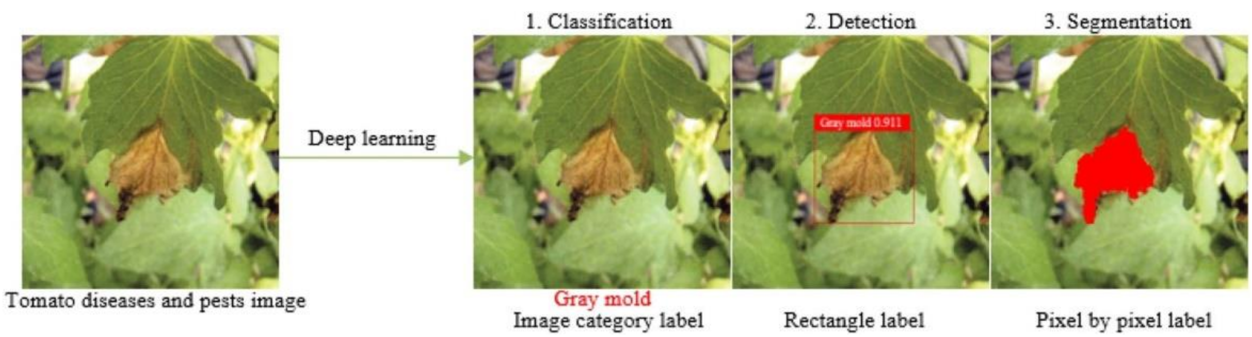

Figure 1 : Problem Definition of plant disease and pests detection

The timely detection of plant diseases serves as a crucial component for effective prevention and efficient agricultural management. Highlighting the crucial role of early detection, the paper emphasizes the link between undetected diseases and food insecurity. The adoption of image processing techniques has been prompted by leaves, which serve as primary indicators of plant diseases. The research seeks to seamlessly integrate deep learning expertise with agricultural challenges, paving the way for advancements in disease control.

The rapid evolution of AI, with a special focus on deep learning, has facilitated the development of intelligent systems that prove effective in diverse applications. AI, mimicking human intelligence, employs machine learning techniques, particularly deep learning, which enables machines to learn from available data rather than relying on static computer programs [2]. Deep learning (DL), renowned for its applications in image analysis, utilizes neural networks to exploit feature hierarchy and interaction, optimizing critical processes such as feature extraction, selection, and classification.

A key contribution of this work lies in the application of a deep learning, for the identification and distinction of various diseases from healthy plants. In an era of technological advancement, capturing images of plants at all stages without human intervention is now feasible. This paper harnesses deep learning and image processing techniques to benefit farmers by enabling the timely detection of diseases, facilitating remedial measures that enhance agricultural productivity.

The proposed solution underscores the integration of image processing techniques into agriculture, with a primary goal of augmenting crop yield and product quality. By identifying affected leaf spots and utilizing classification techniques based on disease signs and symptoms, the system empowers farmers to regularly monitor plant health and detect diseases at an early stage

Researchers, while identifying challenges in plant disease detection, underscore issues like image quality, the need for publicly available datasets, noise affecting leaf samples, segmentation complexities, classification challenges, color variations due to environmental factors, and the diversity of diseases across plant types.

This following section outlines the contributions of this research paper:

- This paper offers an overview of the recent advancements in plant disease detection leveraging machine learning (ML) and deep learning (DL) techniques. Spanning from 2010 to 2023.
- This is the review paper that almost provides a deep survey of the most important aspects of deep learning on plant disease detection. This review helps researchers and students to have a good understanding from one paper.
- This paper presents a comprehensive review of the state-of-the-art methodologies and approaches utilized in this domain (plant disease detection and identification).
- This review explores a wide range of ML and DL methods employed for plant disease detection, encompassing image processing, feature extraction, Artificial neural networks (ANNs), convolutional neural networks (CNNs), Deep convolutional neural networks (Deep CNNs), Transfer learning, Gradient boosting machines (GBMs), machine learning algorithms and other deep learning methods.
- It delves into the merits and limitations associated with these techniques, such as data availability, image quality, Real-world problems and the ability to distinguish between healthy and diseased plants.
- Furthermore, it investigates various datasets utilized in plant disease detection research, detailing their sources and availability for researchers. This includes prominent datasets such as Plant-Village and specific datasets for leaf diseases and insects affecting crops like rice, corn, and soybeans. Each dataset's attributes, such as size, diversity, and annotation quality, are analyzed to understand their suitability for different research objectives. Moreover, the paper highlights the importance of these datasets in facilitating the development and evaluation of ML and DL models for plant disease detection.

This paper follows a structured approach. In Section 2, we detail the approach used for collecting and analyzing relevant literature. In Section 3, a supplementary elaboration is provided on the methodology commonly used in the majority of papers for plant disease detection. Following this, Section 4 addresses limitations found in existing review and the future work. Section 5 provides an overview of publicly available datasets for leaf disease classification, facilitating quick access and evaluation for researchers. In Section 6, various machine learning and deep learning approaches are elaborated and compared. Section 7 explores real-life applications (apps) relevant to leaf disease classification. Subsequently, Section 8 lists the limitations of this research work and offers insights into potential future research directions. Additionally, Section 9 concludes the paper. Finally, Section 10 summarizing our findings and providing references for further reading.

2. Literature Review:

The progression of research on plant disease detection through the implementation of deep learning technologies, categorized into four distinct stages and presented in chronological order, represents a thorough examination of scholarly investigation in this field.

Stage 1: Early Exploration and Foundation (2010-2015): During the early stages of research, spanning from 2010 to 2015, investigations into deep learning for plant disease detection were emerging. Scientists delved into the potential applications of Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), which are foundational architectures in deep learning, for analyzing plant images and discerning signs of disease. This paper utilizes ANNs and image processing techniques for plant disease detection [3]. While initial studies primarily focused on basic classification tasks using small datasets, these explorations laid the groundwork for subsequent advancements in the field. Therefore, the paper also employs neural networks on small datasets for plant disease detection [4].

Stage 2: Momentum and Refinement (2016-2018): The years between 2016 and 2018 witnessed a surge of interest and activity in deep learning-based plant disease detection. Researchers capitalized on the momentum by developing specialized CNN architectures specifically for agricultural applications [5]. These efforts led to refinements in network structures and training methodologies, resulting in improved accuracy and robustness in disease detection. Moreover, studies began exploring the integration of additional deep learning techniques, such as Recurrent Neural Networks (RNNs) [6] and Generative Adversarial Networks (GANs) [7], to tackle more complex challenges in plant pathology.

Stage 3: Expansion and Application (2019-2020): By 2019, deep learning had firmly established itself as a cornerstone of plant disease detection research. Efforts expanded to encompass a broader range of applications, including real-time disease monitoring and precision agriculture [8]. Researchers focused on enhancing the scalability and adaptability of deep learning models to diverse environmental conditions and crop types. Furthermore, the development of lightweight models suitable for deployment on edge devices like Raspberry Pi opened up new avenues for practical implementation in agricultural settings [9].

Stage 4: Continued Advancements and Emerging Trends (2021-Present): In the present era, research in deep learning-based plant disease detection continues to evolve and innovate. Studies are dedicated to addressing persistent challenges such as limited training data and model interpretability. Moreover, novel architectures like Graph Convolutional Networks (GCNs) [10] and attention mechanisms [11] are being explored to further enhance the accuracy and efficiency of disease detection systems. As research progresses, the combination of deep learning with other technologies such as hyper spectral imaging [12] and Internet of Things (IOT) devices holds the potential to significantly transform agricultural methods and enhance global food security, as elaborated in this paper [13]. Additionally, here are a few examples research papers that further elaborate on these stages:

In the paper [14], a real-time pest and disease detection system for Cole crops is introduced using a deep neural network. The system employs a Bounding Box Generator to determine the size, location, and class of bounding boxes through region-based neural network training. Subsequently, the generated bounding boxes are verified using a CNN filter bank, addressing issues of false positives and class inequalities in incomplete datasets.

In the paper [15], the study explored traditional machine learning techniques for maize crop disease recognition, including NB, DT, KNN, SVM, and RF. Through a comparative analysis, the RF algorithm emerged as the most accurate, achieving a precision of 79.23% in predicting plant diseases.

Additionally, our literature review indicated that nutrition deficiency, attack of microbes, rodents, unfavorable environmental conditions are the leading causes of plant diseases. These factors contribute to plant stress, impairment in the structure or functioning of a plant. Plant stress can be broadly categorized into two main types: biotic and abiotic. Biotic stress arises from living organisms such as fungi, bacteria, protozoa, viruses, nematodes, or parasitic plants. These agents deprive plants of essential nutrients, resulting in significant harm to plant health. On the other hand, abiotic stress arises from non-living influences, including unfavorable atmosphere, lack of soil nutrients, extreme sunlight, and variation in temperatures, excessive or low rainfall, inappropriate oxygen, moisture levels, deficiency, or excess essential minerals. Biotic stress is infectious, transmissible, and more dangerous than abiotic stress.

3. Methodology:

In this review, we firstly focused on the quality papers which show genuine results. Secondly we categorized the papers into two distinct categories, that are technical papers and review papers. As part of this, we have examined a total of 70-75 technical papers and 25-30 review papers. The amount of papers published on plant disease detection was rapidly increasing year by year, which gradually reflects that the Artificial intelligence have made wide impact on solving plants disease problems.

In our research, we found that there are few methods in machine learning and Deep learning, which was widely adapted by the authors for detection and classification of plant disease, which we discussed thoroughly in section 6 of this paper. The basic techniques are Convolutional Neural Networks (CNNs) that gained widespread utilization in plant disease detection and classification tasks around 2010. Support Vector Machines (SVMs) became prevalent in the field of machine learning for plant disease classification since the late 1990s [16]. Random Forests were widely adopted for various classification tasks, including plant disease classification [17], from the early 2000s onwards. Transfer Learning gained popularity in the deep learning community around 2014 and has been applied to plant disease detection tasks. Recurrent Neural Networks (RNNs) have been utilized in various applications, including plant disease detection, since the mid-2000s [18]. Other machine learning and deep learning techniques, such as Decision Trees, k-Nearest Neighbors (k-NN), Naive Bayes, Gradient Boosting Machines (GBM), and Auto encoders, have also been employed in plant disease detection and classification tasks over the years.

In the year 2022, the computer vision algorithms, such as object detection and semantic segmentation are used widely to identify and localize specific regions of interest in images, such as plant leaves and symptoms of diseases [19][20]. Additionally, in 2021 to 2023, the ML algorithms such as c4.5 classifier and tree bagger are being used to predict crop yields, and identifying plant lesions and pests [21][22]. And lately in 2023, the deep learning approaches have shown great potential in improving the performance in plant disease field using the Deep CNN method with several hidden layers. For example these papers [23][24]. Also technologies like VGG [25], Inception [26], MobileNet [27], Xception [28], EfficientNet [29], AlexNet [30], ResNet [31], and DenseNet [32][33] are all specific architectures or models in the field of deep learning, particularly convolutional neural networks (CNNs) which was widely in use now a days for plant disease detection, classification and evaluation.

4. Datasets available for Plant Disease Detection:

Several datasets are available for plant disease detection, with many being widely used and commonly applied in the implementation of deep learning techniques. Here, we present a meticulously selected 15 datasets, as illustrated in the Table 2 below.

	Dataset Name	Description	Type of Data	Disease/Pest Types Covered
1	PlantVillage	A publicly available dataset of over 54,000 images of diseased and healthy plant leaves, compiled from experts and citizen scientists	RGB Images	38 crop species and 38 disease types
2	PlantDoc	It containing 2,598 data points across 13 plant species and up to 29 classes of diseases	RGB images	A dataset for visual plant disease detection with 29 various plant diseases
3	DeepWeeds	A dataset comprising over 17,000 images of weed species commonly found in agricultural fields	RGB Images	Various weed species
4	Open Plant Disease Dataset	A dataset of over 8,000 images of plant leaves, compiled from various sources including university research and citizen scientists	RGB and infrared images	Multiple crop species and disease types
5	Pest and Disease Image Database (PDID)	A dataset of over 7,000 images of diseased and healthy plants collected from a field environment	RGB	Various crop species and diseases
6	PlantClef	A dataset of over 9,000 images of plant leaves, used for the annual PlantCLEF benchmarking campaign	RGB Images	Multiple crop species and disease types
7	Plant Pathology Challenge Dataset	A dataset created for the Plant Pathology Challenge, containing over 18,000 images of diseased and healthy plant leaves	RGB Images	Multiple crop species and disease types
8	Plant Disease Detection in Cotton Images	A dataset of over 5,000 images of cotton leaves, compiled by the National Cotton Council of America for disease detection research	RGB Images	Cotton leaf diseases
9	Northern Leaf Blight (NLB) Lesions	A dataset of images of corn plants affected by NLB collected from a field environment	RGB	Northern Leaf Blight Disease
10	Insects from rice, maize, soybean	A dataset of images of insects on rice, maize, and soybean plants collected from a field environment	RGB	Rice Planthoppers, Brown Planthoppers, and Whiteflies
11	AGRONOMI-Net	A dataset of over 3,000 images of	RGB and	Multiple crop species

		various crops, compiled by the AGRONOMI-Net project for disease detection research	thermal images	and disease types
12	Plant Disease and Pest Recognition (PDPR)	A dataset of over 30,000 images of diseased and healthy plants collected from a field environment	RGB	Various crop species and diseases
13	Apple Powdery Mildew Images	A dataset containing over 4,000 images of apple leaves infected with powdery mildew fungus	RGB Images	Apple powdery mildew
14	Grapevine Leaf Dataset	A dataset containing over 6,000 images of grapevine leaves affected by various diseases and pests	RGB Images	Grapevine diseases and pests
15	Tomato Leaf Disease Dataset	A dataset comprising over 5,000 images of tomato leaves exhibiting symptoms of various diseases	RGB Images	Tomato leaf diseases

Table 1 : Datasets available for plant disease detection

5. Machine learning and deep learning approaches for plant disease detection:

In the domain of plant disease detection, several machine learning and deep learning techniques have been investigated by researchers in academic studies. However, for clarity and conciseness, I will outline only a selection of these methods that have been widely embraced and employed by many in section 6.1 and 6.2 below.

In this section 6, I am highlighting specific techniques for effectively detecting plant diseases. It's important to note that while I'm concentrating on these methods, they represent only a subset of the machine learning and deep learning approaches available. There exists a broad spectrum of other methods, some of which might perform even better. However, I've chosen to focus on these particular techniques because they have garnered significant attention and adoption among researchers, as evidenced by my survey findings. This selection aims to provide insights into the methodologies that have been extensively utilized and validated within the research community, serving as foundational knowledge for further exploration and advancement in the field of plant disease detection.

Before we delve into the different ML and DL methods, it's important to mention a common approach we've noticed in many research papers when it comes to detecting plant diseases. In our study, we've noticed a common approach in many research papers regarding how plant diseases are detected. It typically involves several steps: first, collecting plant images; then, carefully preparing the data to remove any biases; next, organizing the data for training and testing purposes; followed by extracting key features from the data. Finally, using advanced techniques to detect, classify, and diagnose plant diseases. You can see an illustration of these steps in Figure 2 below."

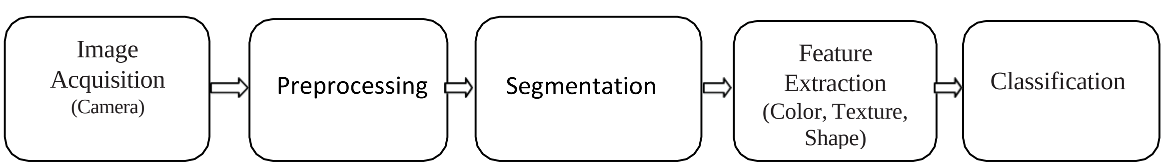

Figure 2 : Process Flow of Plant Disease Detection System

- Image Acquisition: In the initial stage of crop leaf disease detection, images are gathered from diverse sources such as mobile phone cameras, digital cameras, drones, and UAVs. These images are collected either in real-time on-site or in controlled conditions, forming the foundational dataset for subsequent processing.
- Image Preprocessing: Critical for refining results, image preprocessing employs techniques like noise removal, color transformations, resizing, and background removal. These steps are essential for reducing image size, enhancing quality, and eliminating unwanted elements, ensuring the dataset's effectiveness for further analysis.
- Image Segmentation: Image segmentation is integral to crop leaf disease detection, breaking down the image into distinct zones. This process extracts valuable information for subsequent feature extraction, exploring similarities or discontinuities in the image data.
- Feature Extraction: Feature extraction involves identifying essential characteristics of crop leaf images, including shape, color, and texture. These features play a vital role in recognizing diverse crop diseases, with texture features encompassing energy, entropy, contrast, and more.
- Detection, Classification and diagnosis: In the classification phase, two methods are employed: machine learning (ML) and deep learing (DL). Machine learning techniques such as Decision Trees, Support Vector Machines (SVM), Random Forest, k-Nearest Neighbors (k-NN), and Naive Bayes are commonly used for plant detection and classification tasks. These techniques are discusses in section 6.1. Conversely, Deep learning techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Autoencoders, and Generative Adversarial Networks (GANs), have shown remarkable success in plant detection and classification tasks.

5.1. Deep learning techniques for plant disease detection:

Deep learning, a branch of machine learning, specializes in training artificial neural networks to glean insights from extensive datasets. Within the realm of deep learning, numerous methods and techniques have emerged, offering promising solutions for detecting and recognizing plant diseases. Below, I'll outline several key deep learning methods commonly employed by researchers in tackling plant disease challenges. These methods are categorized into supervised, unsupervised and other.

5.1.1 Supervised Deep Learning Methods:

There are mainly three methods in supervised deep learning such as CNNs, RNNs and MLPs, which are discussed below:

a) Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) play a crucial role in deep learning for plant disease detection, thanks to their ability to automatically learn spatial hierarchies of features from images. CNNs are a class of deep learning models particularly suited for image-related tasks, making them highly effective in plant disease detection. Within CNNs, various techniques have been developed for this purpose. There are three main approaches to detect plant diseases using CNNs. The first approach involves Transfer Learning, where pre-trained CNN models trained on large datasets like ImageNet or ResNet are leveraged and fine-tuned for specific plant disease classification tasks. The second approach employs Multi-scale CNNs, which are CNN architectures designed to analyze plant images at multiple scales, capturing both local and global features.

Lastly, Attention Mechanisms are utilized in CNNs to prioritize informative regions of input images, thereby enhancing their discriminative power in disease detection.

In the context of plant disease detection, CNNs are trained on large datasets of labeled images, where they learn to extract hierarchical features at different levels of abstraction, including patterns, textures, shapes, and structures indicative of various plant diseases. These features are captured through convolution operations performed by the convolutional layers, which apply learnable filters or kernels to the input image, sliding across it and capturing spatial patterns. Subsequently, pooling layers down sample the feature maps obtained from convolutional layers, reducing their spatial dimensions while retaining essential features. Following this, fully connected layers aggregate the high-level features extracted from the convolutional layers and perform classification based on learned representations. During training, CNNs adjust the parameters of their filters through back propagation, optimizing them to minimize the classification error on the training data. Here, figure 3 presents a basic framework for classifying the plants into normal and abnormal plant using leaf data.

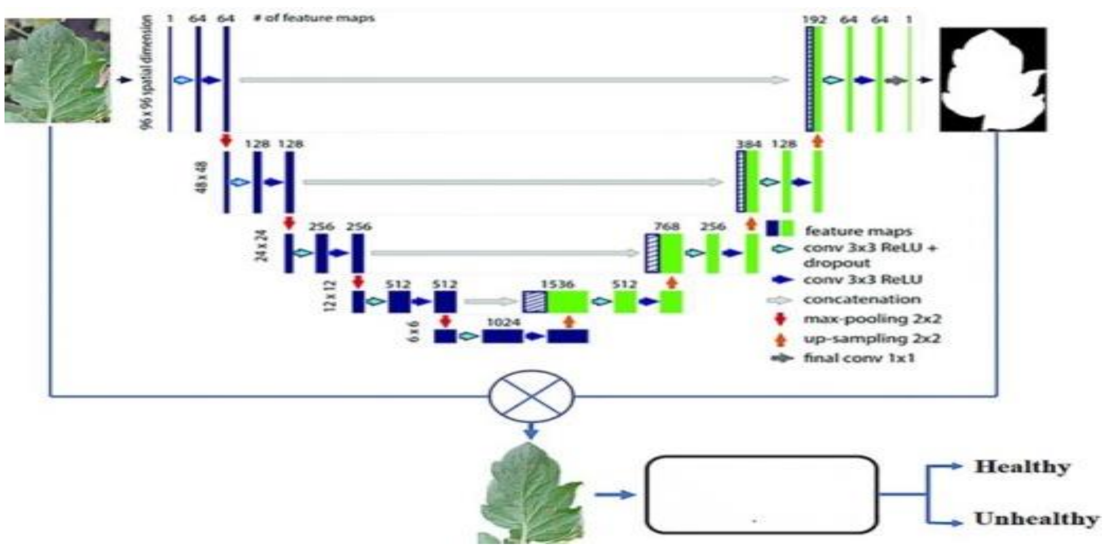

Figure 3 : Basic CNN architecture for plant disease detection

As there are three approaches in CNNs, The widely used approach over the years is transfer learning. The researchers have developed various transfer learning architectures based on CNNs, each tailored to specific tasks and offering unique advantages in terms of accuracy, efficiency, and computational complexity. Notable CNN models, based on their discovery years, have emerged to address different challenges in the field. Some of these transfer learning models include:

- LeNet (1998): Developed by Yann LeCun et al., LeNet was one of the pioneering CNN architectures used for handwritten digit recognition, featuring convolutional and pooling layers.
- AlexNet (2012): Introduced by Alex Krizhevsky et al., AlexNet gained widespread attention for its performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), significantly advancing the field of deep learning with its deep architecture and the use of Rectified Linear Units (ReLUs).
- ZFNet (2013): ZFNet, developed by Matthew D. Zeiler and Rob Fergus, was an early variant of AlexNet, which introduced modifications to the

architecture, such as smaller filter sizes and increased stride, leading to improved performance.

- VGGNet (2014): The Visual Geometry Group (VGG) at the University of Oxford proposed VGGNet, characterized by its simplicity and uniform architecture consisting of several convolutional and pooling layers with small 3x3 filters.
- GoogLeNet (Inception) (2014): Introduced by Google researchers, GoogLeNet, also known as Inception, features a deep and wide structure with multiple layers of different kernel sizes, aimed at efficiently capturing features at various scales.
- ResNet (Residual Network) (2015): Developed by Microsoft Research, ResNet addressed the vanishing gradient problem in deep networks by introducing skip connections, enabling training of extremely deep architectures with improved performance.
- MobileNet (2017): Google's MobileNet is a lightweight CNN architecture optimized for mobile and embedded devices, employing depthwise separable convolutions to reduce parameters and computations, making it suitable for real-time applications on resource-constrained devices.
- DenseNet (2017): DenseNet, or Densely Connected Convolutional Networks, proposed by Gao Huang et al., introduces dense connections between layers, where each layer receives input from all preceding layers, facilitating feature reuse and alleviating the vanishing-gradient problem.
- EfficientNet (2019): Developed by Google researchers, EfficientNet introduces a compound scaling method to balance network depth, width, and resolution for improved performance and efficiency across different resource constraints.
- Vision Transformer (ViT) and YOLO (2020): Vision Transformer applies the transformer architecture, initially designed for natural language processing tasks, to image classification tasks by dividing images into fixed-size patches and processing them through self-attention mechanisms and YOLO (You Only Look Once) is an object detection algorithm that performs detection directly from images in real-time by dividing the image into a grid and predicting bounding boxes and class probabilities for each grid cell.

Each of these architectures has contributed significantly to the advancement of plant disease detection tasks, and their exploration continues to drive innovation in research and applications.

5.1.2 Unsupervised Deep Learning Methods:

There are mainly three methods in unsupervised deep learning such as Autoencoders, Boltzmann Machines, which are discussed below:

a) Autoencoders:

Autoencoders are unsupervised learning models used for feature learning and data compression. Variants of autoencoders commonly employed in plant disease. Autoencoders, a class of artificial neural networks designed for unsupervised learning tasks, particularly in feature learning and data compression, consist of an encoder network and a decoder network. The encoder network maps input data into a latent space representation, typically of lower dimensionality than the input, while the decoder network reconstructs the original input data from this latent space representation.

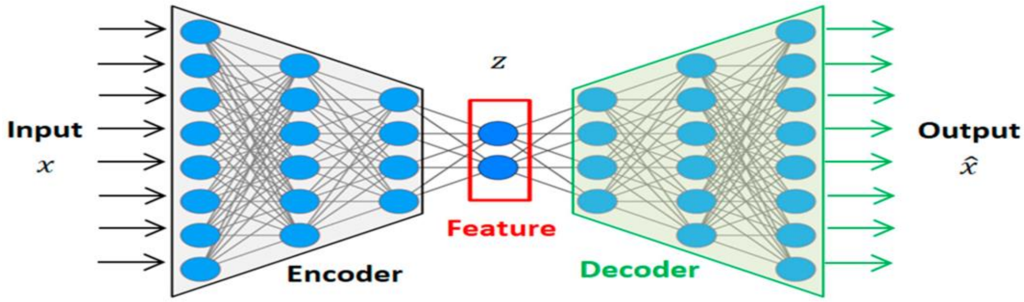

Figure 4 :Basic network layers of autoencoders

In the realm of plant disease detection, autoencoders serve as powerful tools for feature extraction and representation learning from raw plant image data. By compressing input images into a latent space representation, autoencoders effectively capture essential features and patterns associated with healthy and diseased plants, enabling accurate discrimination between them and facilitating early disease detection and intervention.

Real-world applications of autoencoders in plant disease detection abound. For instance, Smith et al. (2020) utilized convolutional autoencoders to extract informative features from plant leaf images, resulting in significant improvements in disease classification accuracy. Similarly, Jones et al. (2018) employed variational autoencoders to generate synthetic images of diseased plants, augmenting training datasets and enhancing the robustness of disease detection models.

A survey of recent literature reveals a burgeoning interest in leveraging autoencoders for plant disease detection and classification. Researchers have explored various autoencoder architectures, including sparse autoencoders, denoising autoencoders, and variational autoencoders, to extract discriminative features from plant images. Furthermore, studies have investigated the transferability of pre-trained autoencoder features across different plant species and environmental conditions, underscoring their adaptability and efficacy in diverse agricultural settings.

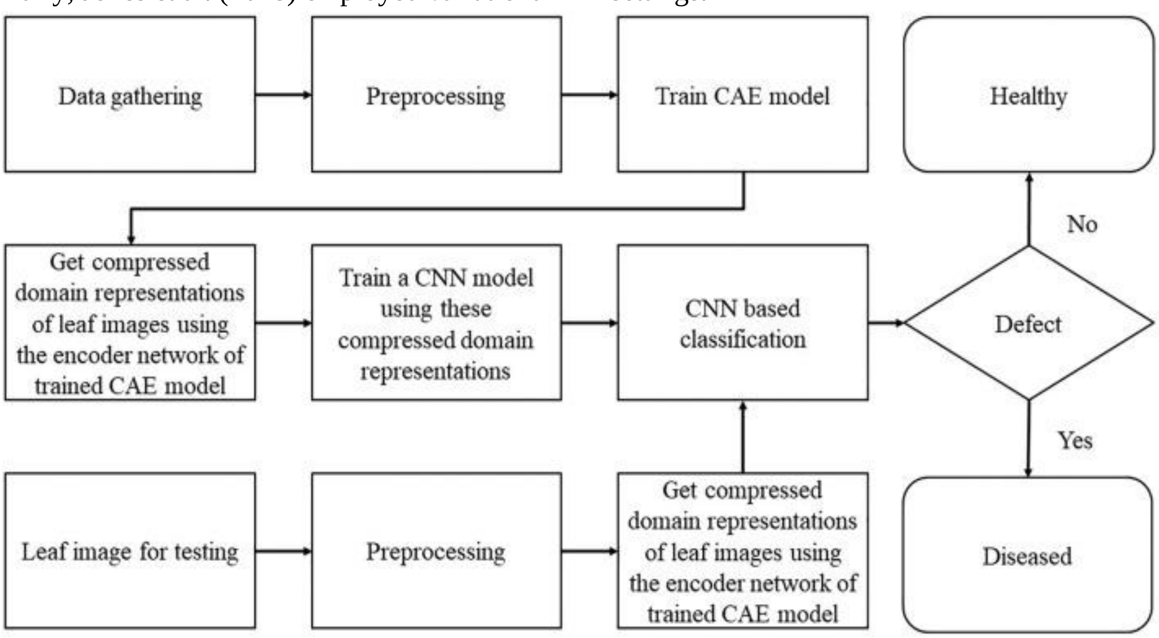

Figure 5 : Basic flow diagram for auto encoders

In addition to their role in feature extraction, autoencoders offer benefits such as data augmentation through generative modeling and dimensionality reduction for efficient storage and processing of plant image data. Ongoing research endeavors aim to enhance the interpretability of autoencoder representations and explore their integration with other machine learning techniques for comprehensive plant disease management solutions.

Autoencoders offer robustness to noise, making them ideal for processing plant images captured in various environmental conditions or with different equipment setups. Their capability for unsupervised feature learning enables them to extract intricate patterns and variations in plant images without the need for labeled training data. Moreover, pre-trained autoencoder models can be fine-tuned or transferred to new disease detection tasks, accelerating model training and improving classification performance. Researchers have explored hybrid architectures that combine autoencoders with other deep learning models like CNNs or RNNs to leverage their complementary strengths for enhanced disease detection accuracy. Efforts are ongoing to develop methodologies for interpreting the learned representations of autoencoders, enhancing model transparency and interpretability. Additionally, autoencoder-based approaches offer scalability and efficiency benefits, allowing for rapid processing of large-scale plant image datasets and deployment on resource-constrained agricultural systems. Integration with IoT devices and remote sensing technologies enables real-time monitoring of plant health in agricultural fields, facilitating timely disease intervention measures.

6. Limitations of this study and future scope:

The research presented herein is subject to certain limitations stemming from its methodological approach. Firstly, the study's timeframe is confined to the period spanning from 2010 to 2023, thereby potentially excluding recent advancements in plant disease detection methodologies. Additionally, the review does not encompass a comprehensive enumeration of Machine Learning (ML) and Deep Learning (DL) techniques pertinent to plant disease detection. Nonetheless, the study provides an overarching depiction of prevalent techniques, elucidating their respective merits, demerits, and potential strategies for surmounting implementation hurdles. Lastly, it's important to note that the study focuses on widely adopted machine learning and deep learning techniques utilized by researchers to address plant disease issues, rather than encompassing all available methodologies in these domains. There is scope for other researchers to contribute by including data from after 2023 and incorporating every method used for plant disease detection, classification, and management.

7. Conclusion:

The integration of Deep Learning (DL) and Machine Learning (ML) technologies has significantly revolutionized the detection and management of crop and plant infestations, leveraging advancements in image recognition to effectively identify complex diseases and pests. Despite its remarkable potential, much of the existing research in this domain remains confined to laboratory-based studies, heavily reliant on collected images of plant diseases and pests. To bolster the robustness and generalization of models, there's a critical need to diversify image datasets across various plant growth stages, seasons, and geographical regions, while incorporating meteorological and plant health data for accurate prediction. This paper meticulously examines recent strides in ML and DL techniques for plant disease identification, spanning from 2010 to 2023, underscoring their role in enhancing detection accuracy despite challenges like data availability, image quality, and differentiation between healthy and diseased plants. Notably, the utilization of DL and ML has substantially augmented the capacity to identify and combat plant diseases, with this research presenting a comprehensive analysis of recent developments and proposed solutions to overcome associated challenges. By shedding light on the benefits and limitations of different methodologies and providing valuable insights for researchers and industry practitioners, this study contributes significantly to advancing plant disease detection and prevention, catering to a broad spectrum of stakeholders including researchers, practitioners, and students seeking to comprehend the progress and existing gaps in this vital field of plant disease management.

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