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SURVEY

Role of Artificial Intelligence in Agriculture: An Analysis and Advancements With Focus on Plant Diseases

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ABSTRACT The increased demand for food is accelerating plant diseases globally. Hence, a manual process of detection of plant diseases is almost impossible. Artificial intelligence (AI) can offer several solutions to farmers' problems. AI is facile to mitigate farmer's agriculture challenges. With the unpredictable changing climate, plants are often affected by several diseases where AI can play an important role. AI techniques such as Machine learning and deep Learning have been employed in literature to detect, predict, and design recommendation systems for plant diseases. Significant work has been done in this area in the last two decades, which can change farmer's lives in the coming years. This paper presents a systematic multi-fold survey and analysis of such work focusing on recent AI techniques developed to combat plant diseases. This article discusses various challenges faced by farmers and their AI solutions. It analyzes several applications of AI in agriculture and current trends. Recent advancements in AI for plant disease detection, like Identification Model Improvement (IMI), Few Shot Learning (FSL), Generative Adversarial Networks (GANs), and Self Supervised Learning (SSL), are also discussed in this article. Several challenges while employing AI in plant disease detection are also discussed in this article. It will serve researchers as a valuable document for further research to solve farmer's issues.

INDEX TERMS Artificial intelligence, plant, disease, smart farming, IoT, machine learning, deep learning, self supervised learning.

I. INTRODUCTION

The agriculture sector is vital in enhancing the world economy [1] by providing employment and food security to the large population of developing countries. With the global rise in population, conventional farming methods are insufficient to meet the demands of the growing populace worldwide. Thus, it is subduing the benefits of this sector in turn. According to Worldometer of Population, the world's population is 8 billion. It is expected to reach 8.5 billion in 2030 and 9.7 billion in 2050, with a yearly change of 0.51% [2]. With the increasing food demand worldwide, there is pressure to produce quantitative and qualitative crop yields. Several countries' governments are providing farmers with affordable credit and financial services to invest in improved seeds, equipment, and technologies and implementing strategies to reduce post-harvest losses, improve supply chain efficiency, and minimize food waste at various stages of production and distribution. Additionally, they are raising consumer awareness about the importance of reducing food waste, making sustainable food choices, and supporting local farmers.The restrictions on exports due to pandemics and wars are also major concerns of the food crisis.Plant diseases, weeds, and pests are other

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factors responsible for low productivity [3]. The world economy is bearing a loss of $ 220 billion [4] every year due to plant diseases. Farmers have used pesticides and herbicides extensively to eliminate pests and weeds for the past few decades. It can be a solution for improving crop yield if used in a limited manner. Otherwise, it affects the overall health of the agricultural land and humans. Over-dosage of pesticides and herbicides contaminates the agricultural land and groundwater. Several studies provide evidence of the inflation of human diseases such as cancer, asthma, diabetes, and reproductive and neurodegenerative disorders. Climate change is the foremost factor affecting crops qualitatively and quantitatively. Drought, hailstorms, thunderstorms, and heat waves damage the crop partially or fully and may provide a suitable environment for the pest to develop. Thus, early detection of crop diseases is the ultimate solution to all the above problems. Farmers and agriculture experts with bare eyes identify diseases depending on their experience with conventional disease detection methods, which are time-consuming, inefficient, and impractical for large farms. Therefore, smart farming is used to automate and fasten this task. It includes IoT sensors, cloud computing, and AI techniques to collect and analyze the data for better monitoring and further decision-making. In vision-based techniques, Images are taken with the help of drones, satellites, and cameras to detect disease symptoms. It comprises Image Processing(IP), Machine Learning(ML), and Deep Learning(DL) techniques. In the last few decades, IP has been used to analyze images using computer algorithms because extracting the features from a complex background is very hard. However, it provides many techniques, such as image enhancement, restoration, compression, and segmentation, to improve the quality of images. With time, it is crucial to classify and identify plant diseases. Several machine learning methods, such as SVM, K-means, random forest, KNN, ensemble models, and artificial neural networks (ANN), are used for classification. After the image acquisition, images are preprocessed, followed by feature extraction, and plant disease classification is done using ML techniques. In recent years, researchers have widely used deep learning techniques. Since the introduction of deep learning, plant disease detection surveying and results in recent years have been confounding due to their powerful extraction and pattern recognition capabilities. Convolutional neural networks (CNNs) can match the high requirements of trait representation of complex diseases. CNNs have a wide variety of applications in the agricultural area [5], [6], [7], [8], [9]. In agriculture, CNN(convolution neural network) is used prominently for plant disease detection, classification, and weed detection. CNN is the advanced version of ANN. It constitutes convolution layers consisting of kernels for automatic feature extraction from the input image, pooling layers to downsample the image to minimize the overhead of computations, and fully connected layers to further classification of the images. CNN requires a large amount of data to give more accurate results. But in agriculture, data is very scanty, and variety is also limited. Therefore, to overcome this problem, transfer learning is widely used to detect plant diseases. In transfer learning, a model is trained on a different large dataset, and then, a pre-trained model is used for the smaller dataset. Therefore, in current advancements, researchers primarily focus on an Identification Improvement Model(IMI)for better performance using CNNs or transformers. To address the problem of unavailability of labeled data in the agriculture sector, few-shot learning and Self-supervised learning(SSL) techniques are also eye-catchers. By using few-shot learning, the problem of the unavailability of large datasets can be resolved. Self-supervised learning(SSL) is also catching researchers' attention nowadays. In SSL, the model can be pretrained on unlabeled data.

With the development of AI throughout the world, agriculture is a sector where AI is still to be fully utilized. Moreover, pests and crop diseases are a big challenge for farmers, a hurdle for meeting food demand. Due to plant disease, the yield of crops reduces up to 20% to 40%. As a result, farmers are concerned about the quality and quantity of the cultivated crops and illnesses impacting crop life expectancy, which directly leads to financial loss. The traditional plant disease detection methods could be more efficient, rapid, precise, and accessible for more enormous farmlands. So, automatic plant disease detection methods must be designed to help farmers enhance crop yield and early detection of plant diseases. AI methods deployed in the last two decades are also inefficient, slow, and poorly diagnosed because of data scarcity problems, complex backgrounds, and various pests and plant diseases. However, there is a lot of scope where AI can be fully employed in multiple areas of agriculture, especially in plant disease detection [24]. In the current scenario, plenty of work is going on in this area where researchers are designing automatic methods of detection of plant diseases. Several deep-learning algorithms have been developed, and much work is ongoing. Therefore, this hour needs to address this problem as there is vast potential in this area, and it demands analyzing current work, which is the motivation of this paper. This survey discusses the challenges faced by the farmers in identifying infections or damage in the plant. This survey also explains the use of AI in plant disease detection, a non-invasive method for providing farmers with a dependable, powerful, cost-effective, and errorless solution.

Several surveys and review papers that cover plant disease detection have been published. For example, Kamilaris et al. [15] published a review paper that surveys Deep learning techniques in agriculture in which a total of 40 articles are studied with the comparison of them, and it depicts the supremacy of deep learning in the agriculture domain. Few other survey papers were published to address plant disease detection using deep learning [14], [16], [18]. Dominagues et al. [10] and Thakur et al. [19] published review papers that address plant disease detection and classification using Machine learning algorithms. Lu et al. [17] survey CNN techniques employed for plant leaf disease detection and classification. Lu et al. [21] surveyed generative adversarial networks (GANs) for different augmentation applications in agriculture with several challenges and opportunities. An example of all such recent studies based on plant disease detection encompassing a range of objectives and goals is provided in Table 1. This table highlights the methodologies employed, current citations, and the scope of each study in plant disease classification and detection. The review spans from early methods to state-of-the-art techniques, covering disease detection and classification. It encompasses an array of strategies, i.e., Image Processing (IP), Machine Learning (ML), and Deep Learning (DL) for plant disease detection and classification.

The focus and content of this article are somewhat different from the surveys shown in Table 1. Whereas other surveys focused on machine learning, deep learning, and image processing algorithms implemented for either plant disease detection or classification or their applications in agriculture, this article extensively surveys existing AI techniques for plant disease detection and classification. A detailed analysis of each method is presented with applications, limitations, and advantages. An advancement in plant disease detection is analyzed in this paper. Unlike prior studies, this paper discusses challenges, their AI-based solutions, and applications in agriculture, respectively. This article covers areas unexplored by recent surveys, such as the focus on the advancement in plant disease detection, so this study systematically and thoroughly reviews artificial intelligence approaches in agriculture and detecting plant disease, including attention approaches, multi-modal data fusion, Internet of Things (IoT), Generative adversarial Network (GAN), Self-supervised Learning(SSL), and Few-shot learning techniques(FSL), all contributing to the advancement of plant disease detection.

The main contributions of this paper are:

1) This is the first systematic survey covering farmers' challenges with AI-based solutions and mainly focuses on plant disease detection using AI.
2) The review provides applications of AI in Agriculture.
3) The review covers AI techniques employed on different plants, diseases, datasets, and performance parameters.
4) The review covers an analysis of AI and allied techniques on plant disease detection like Machine learning, Deep Learning, and IoT.
5) A discussion on the advancement in plant disease detection and the potential of new approaches in solving farmer's and researcher's challenges.

The rest of the paper is organized as follows. The research paradigm with search strategy using PRISMA is explained in section II. Section III discusses AI in agriculture, including challenges faced by farmers, and their AI-based solutions are outlined. Several applications of Agriculture are also listed in this section. Sector IV explains the basics of plant diseases. In Section V, plant disease detection using AI techniques is surveyed with allied techniques like machine learning, deep learning, image processing, IoT, and fusion approaches, which are explained and deeply analyzed on

TABLE 1. Recent survey papers in plant disease diagnosis and classification.

Ref	Technique	Survey Area	Citations as on 24.11.2023
[10]	Machine Learning	Classification, Detection, Crop diseases and pests	26
[11]	Biblometric, AI	Plant leaf disease detection	72
[12]	AI Techniques	Plant diseases Detection	12
[13]	Image Processing	Pest and Disease Recognition	272
[14]	Deep Learning	Plant diseases and pests detection	360
[15]	Deep Learning	Agriculture	2820
[16]	Deep Learning	Identification, diagnosis Leaf diseases	44
[17]	CNN	Plant Leaf disease Classification	170
[18]	Deep Learning	Classification, Detection	242
[19]	Machine Learning	Plant diseases identification	45
[20]	AI Techniques	Plant disease detection classification	0
[21]	Augmentation GAN	Agriculture	62
[22]	Machine Learning	Precision Agriculture	350
[23]	Few Shot Learning	Smart Agriculture	72

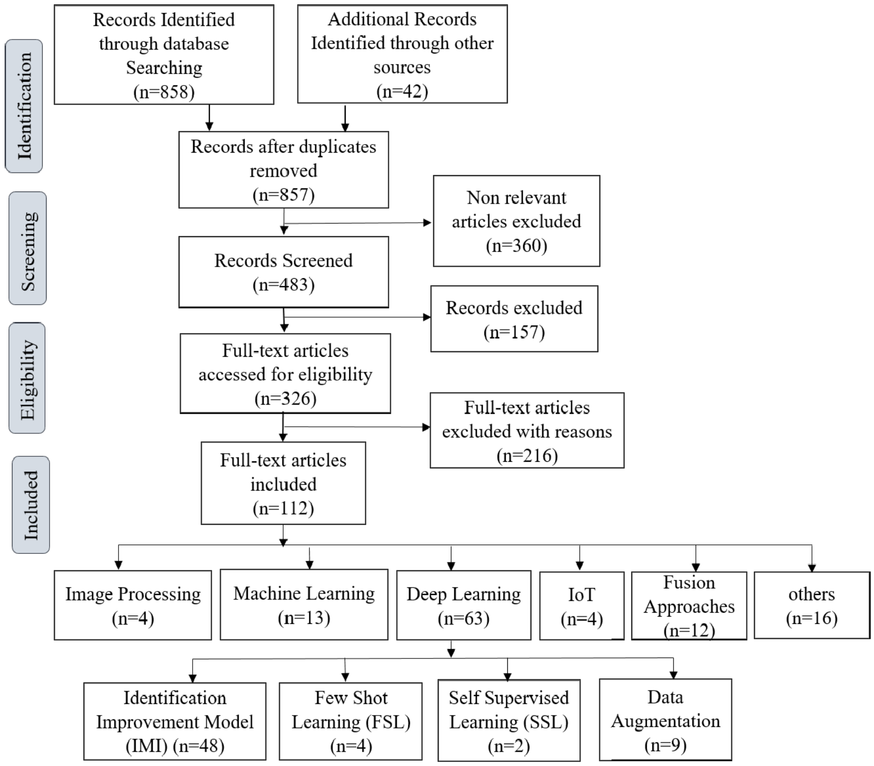

FIGURE 1. PRISMA model.

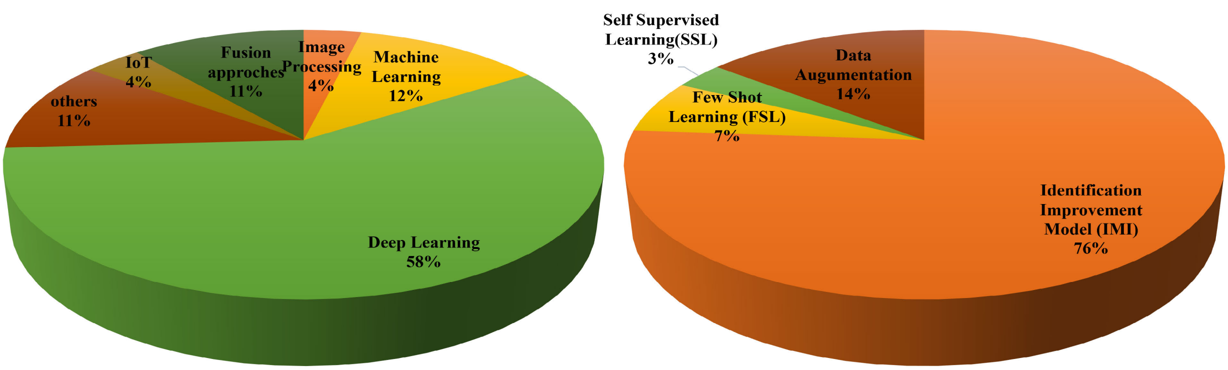

FIGURE 2. Break up of articles in terms of techniques employed.

several parameters. In section VI, advancements in plant disease detection are discussed with future scope in plant disease detection. Section VII discusses the AI challenges in plant disease detection. Section VIII concludes the survey with further research direction for AI in plant disease detection, where there is still scope for improvement.

II. METHODOLOGY

A detailed search was performed using the PRISMA model as illustrated in Figure 1. The PRISMA Model depicts the plant disease detection references that have been utilized in this study [25]. Initially, 900 papers were searched using databases like Google Scholar, IEEE Xplore, Science Direct, Scopus, and ACM with keywords agriculture, artificial intelligence, plant disease detection, plant disease detection, image processing, deep learning, machine learning, IoT, fusion, self-supervised learning, few-shot learning, attention mechanism, generative adversarial network, and argumentation. To ensure data accuracy, we employed the "Find Duplicates" feature within the EndNote software by Clarivate Analytics to eliminate duplicate entries. We applied three exclusion criteria, namely (i) studies not pertinent to AI, (ii) articles lacking relevance, and (iii) articles with insufficient data. By implementing these criteria, we successfully filtered the 360, 157, and 216 studies, respectively. Finally, 112 research papers are surveyed in this paper after filtering

FIGURE 3. Challenges in agriculture.

based on the above three criteria. Figure 2 depicts the pie chart of 112 research papers of all techniques and 63 deep learning research articles, respectively.

III. CHALLENGES, AI-BASED SOLUTIONS, AND ADVANTAGES OF AI IN AGRICULTURE

This section discusses farmers' challenges, such as Climate change, Water shortage, etc., and their AI-based solutions. AI is employed not only in plant disease detection but also in various domains of agriculture, such as crop yield production, irrigation management, fertilizer, and predictive analysis. All these applications are also discussed in this section.

A. CHALLENGES IN AGRICULTURE

The agriculture sector faces specific challenges. Increased food demand as the population is rising exponentially, low productivity, limited water resources, irrigation, Soil erosion, global economic factors, and climatic changes are a few of the challenges in the agriculture domain [24], [26], [27], [28]. Figure 3 represents these challenges and are explained below:

- **Increased food Demand**: The demand for a particular crop or food is the critical factor that decides the price and production of that crop in the market. Due to increasing population, industrialization, modernization, urbanization, and deforestation, there appears to be a lack of food production in the local market, which in turn causes an increase in the demand for crops/food. Small farmers with a small area of agricultural land often cannot satisfy the sudden increase in food demand. This causes a hike in the crop price, resulting in fewer sales and financial loss in production.
- **Low Productivity**: The term low agriculture productivity means that crops' production was less than expected. The most common reasons for low productivity are low soil fertility, which degrades the quality and quantity of the crop, the high price of fertilizers, which poor farmers cannot afford, and the lack of proper nutrients in the crops. Less land for cultivation is also a reason, and spreading crop diseases that damage the crop caused by pests, rodents, and unwanted herbs decreases its production scale.
- **Irrigation**: Proper irrigation is a main factor that gives the crop nutrients and decides its health. The issue that arises regarding irrigation is inadequate execution of water supply that causes less intake of water by crops. The use of old irrigation methods and lack of modern irrigation methods like drip irrigation, sprinkler irrigation, surface irrigation, etc., are other problems faced in agriculture.
- **Soil Erosion**: It is the process that happens when the top soil layer is swept away by mostly either water or high wind, causing the soil to lose its nutrients, and often

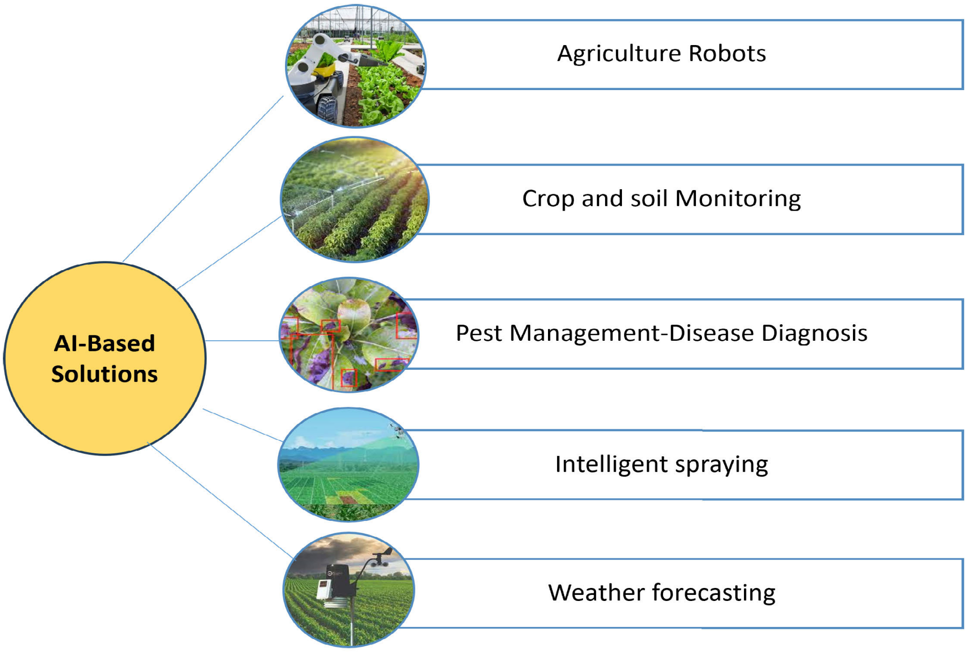

FIGURE 4. AI based solutions.

the roots of the plants are also exposed to making them vulnerable to exterior damage and diseases. Soil erosion occurs mainly by high-speed running water or floods, which remove the loose sand. High-speed wind sweeps the dry dust or sand. Soil erosion affects agriculture in many ways. The most common problem is making the land incapable of holding water, losing the nutrients of the land, and increasing the chances of flooding.

- **Water Shortage**: Water shortage is the most critical and common challenge faced by farmers worldwide. There are various reasons for water shortage, such as overuse in fields, industries, and even homes. Water pollution that happens on a large scale by factories and industries as they dump their wastes into water bodies causes a shortage of water supply in the fields. Farmers without access to surface water or groundwater suffer significant financial loss. Large-scale planting of crops with high water requirements and inefficiency of land to hold water also causes water shortage.
- **Rising Income and changing diet**: As with the development of a country, the per capita income of citizens also increases, which, on the other hand, changes the lifestyle of many people and, therefore, changes the type of food they eat. Most people used to eat healthy food at home, but now they have adjusted to unhealthy junk foods with fewer nutrients, more oil, and more fats. Also, many have shifted from vegetarian to non-vegetarian flesh food items. This caused a drastic change in agricultural production as the need for certain foods has fallen, due to which we can observe that many things that we used to get in the old days are not available now. People also shift their professions from agriculture to other employment sectors for higher income.
- **Climate Change**: It is a known fact that each year, the climate changes drastically compared to the previous year, especially the heat, as each year it is hotter, which has a significant effect on the agricultural field. The challenges faced due to climatic changes are Increased. Due to heavy rainfall, floods destroy the crops and the land on a large scale. Increasing heat and lack of rainfall cause droughts, which make the land infertile and dry up the crop water content, even in the winter. Due to very low temperatures, some crops become dry and lose nutrients. High, windy weather often destroys plants, crops, and trees.
- **Global Economics factor**: Since agriculture is a globally practiced field and the primary source of food supply worldwide, some global and economic factors affect the agricultural field. The main factor that affects agriculture is rising food demand as the global population is also growing, which pressurizes the global market for more agricultural production. Global development is also a factor that directly affects the production of agriculture. Transportation is another factor that allows various food items and recipes worldwide to reach other places.

B. AI-BASED SOLUTIONS

AI-based modern implementation and sustainable farming techniques include agroforestry, precision agriculture, and organic farming. The use of efficient AI-based irrigation systems,drought-resistance crops, and soil conservation practices should be promoted to optimize the usage of water and soil health maintenance. High-yielding, disease-resistant, and adapted to changes in climate conditions, crops can be developed using AI-based technologies [29]. Figure 4 depicts these AI Based solutions and are explained below:

- **Agriculture Robots**: Agricultural robots, also known as agrobots or agri-bots, play a significant role in modernizing and improving various aspects of agriculture. These robots have advanced technologies that can perform tasks autonomously or with minimal human intervention. Agricultural robots can accurately plant seeds in specified locations, ensuring optimal seed spacing and depth for improved crop growth. Robots with sensors can analyze soil conditions and apply fertilizers precisely where needed, reducing excess fertilizer use and environmental impact. Robots collect data on soil moisture, nutrient levels, and other parameters, enabling farmers to make informed irrigation and nutrient management decisions. The data collected by agricultural robots can be used to analyze trends, predict outcomes, and optimize farming practices for better results. Robots can be designed and programmed to suit the specific needs of different crops, ensuring that tasks are carried out effectively and efficiently.
- **Crop and soil Monitoring**: Crop and soil monitoring are crucial in modern agriculture and involve continuously observing crops and soil conditions. This monitoring helps farmers make precise decisions, look at resource usage, and maximize crop yield while minimizing environmental impact. Modern technology allows monitoring, such as satellites, capturing high-resolution images of agricultural fields and providing data on crop health and growth patterns. Drones with cameras and sensors can capture detailed images and data from different perspectives to monitor crops and soil closely. Internet of things (IoT) is vital as soil moisture sensors measure soil moisture levels at different depths, helping farmers optimize irrigation and prevent overwatering. Crop health sensors detect signs of stress, disease, or nutrient deficiencies in crops by measuring chlorophyll content and leaf temperature. Nutrient sensors that measure nutrient levels in the soil allow farmers to adjust fertilization strategies for optimal plant nutrition. Data analysis and modeling are also crucial for monitoring crops and soil occasionally [30].
- **Pest Management-Disease Diagnosis**: Pest management and disease diagnosis are crucial in maintaining healthy crops and ensuring agricultural productivity. It involves strategies and techniques to control and mitigate the impact of pests, including insects, weeds, and other organisms that negatively affect crops. Regular inspection of crops for signs of pest presence and damage is necessary. Identification of specific pests causing problems and understanding their life cycle is essential. Practices like crop rotation, companion planting, adjusting planting times to disrupt pest life cycles, and maintaining proper plant spacing and hygiene to reduce pest habitats are helpful.
- **Intelligent spraying**: Intelligent spraying is known as precision or variable-rate spraying. It is a modern agricultural practice that utilizes advanced technologies to optimize the application of pesticides [31] and other crop protection products. Intelligent spraying aims to minimize the use of chemicals while maximizing their effectiveness in controlling pests and diseases. Intelligent sprayers are equipped with sensors that can detect and map variations in the field, such as pest infestations, disease outbreaks, and differences in plant health. Global Positioning System (GPS) technology accurately determines the sprayer's position in the field. Data collected from sensors and GPS is combined to create precise field maps highlighting areas requiring treatment.
- **Weather forecasting**:Many weather apps and websites provide up-to-date weather forecasts for specific locations. Farmers can use these tools to monitor daily and weekly weather conditions, including temperature, precipitation, humidity, wind speed, and more. Some popular weather sources include Weather.com, AccuWeather, and the Weather Channel. Installing weather stations on the farm can provide real-time weather data tailored to the specific location. These stations measure temperature, humidity, wind direction, and precipitation, allowing farmers to monitor their farms' conditions accurately. Satellite and radar data offer a broader view of weather patterns and can help predict severe weather events such as storms or heavy rainfall. Farmers can access this information through government agencies or commercial services that provide radar imagery. Advanced machine learning and AI models can analyze historical weather data alongside other relevant factors like soil moisture, crop type, and geographic location to generate more accurate and localized weather predictions. These models can be tailored to specific farms or regions..

C. APPLICATIONS OF AI IN AGRICULTURE

Figure 5 depicts various applications of AI in the agricultural domain. The applications are listed below:

- **Yield prediction**: AI can be used in yield prediction in agriculture by leveraging various data sources, machine learning techniques, and advanced analytics.AI is used to predict crop yield, which depends on various factors such as weather conditions, water content, and the level of micro and macronutrients in the soil. These elements are also necessary to track crop health.
- **Feeding crop- Fertilizer and Irrigation**: Highly inefficient irrigation systems are common, resulting in water wastage. Proper and precise irrigation can be done using sensors that measure several parameters of fields. AI can also help explore soil health to monitor conditions and

FIGURE 5. Applications of artificial intelligence (AI) in agriculture.

recommend fertilizer applications [32]. With the help of sensors, we can precisely use fertilizers and pesticides.

- **Harvesting**: It is the final process of agriculture and requires huge labor, so AI can be used to reduce this labor, and AI machines can be implemented to perform multi-purpose tasks such as detecting if the crop is ready to be harvested, quality and quantity of the crop. Manually operated machines can be automated using AI to do tasks such as harvesting.
- **Managing Risk**: Agriculture has several risks. One major risk is complete crop damage due to diseases and pests. Plant diseases can be analyzed and detected beforehand using AI, and steps can be taken to prevent them from spreading to other crops. Also, AI can identify risks like soil deficiencies affecting production.
- **Breeding Seeds**: AI is increasingly being utilized in seed breeding to accelerate and enhance the development of new and improved crop varieties. Genomic Selection, Phenotyping, and Crossbreeding Recommendations are beneficial nowadays.
- **Plant Health Monitoring**: AI in agriculture can also monitor plant health and sustainability. For example, AI can detect the farms' diseases, pests, and soil nutrition. AI algorithm can tell where the fertilizer is needed. This can reduce the amount of fertilizer considerably.
- **Food Processing**: AI and ML have revolutionized food sorting by reducing manual labor and ensuring high-quality products are sorted accurately. AI-based solutions can sort based on size, weight, and color, reducing waste and meeting quality requirements. Automation, using advanced technology like x-ray scanners, lasers, cameras, and robots, can save companies money by reducing manual labor.
- **Warehousing**: Crop monitoring, inventory control, quality assurance, logistics improvement, predictive maintenance, energy management, automation, supply chain visibility, data analytics, crop protection, sustainability, market analysis, and pricing are some of many the uses of AI in agriculture warehousing. These processes in agricultural warehousing increase effectiveness and quality control, cut down on waste and boost overall operations.

IV. PLANT DISEASES

A plant disease prevents and hampers a plant from performing to its paramount potential. Biotic(living components of the environment) factors include infectious agents (Pathogens) like bacteria, fungi, nematodes, viruses, and phytoplasmas, and abiotic (nonliving components of the environment) factors are the root cause of plant diseases. Generally, a plant becomes sick when persistently disturbed by some causative factor, resulting in an aberrant physiological process that affects its shape, development, and function. Figure 6 shows major causes, symptoms, occurrence, and spread reasons for plant diseases and are explained below.

A. MAJOR CAUSES OF PLANT DISEASES

- **Fungal**: Diseases caused by fungi that result in fungal infections in plants are called fungal diseases. Fungi or FLOs cause most plant diseases. It is a fungi-like organism that lacks chlorophyll and depends on the host for its nutrition and survival. Thus, it is incapable of making its food. Some examples are - Leaf spot,

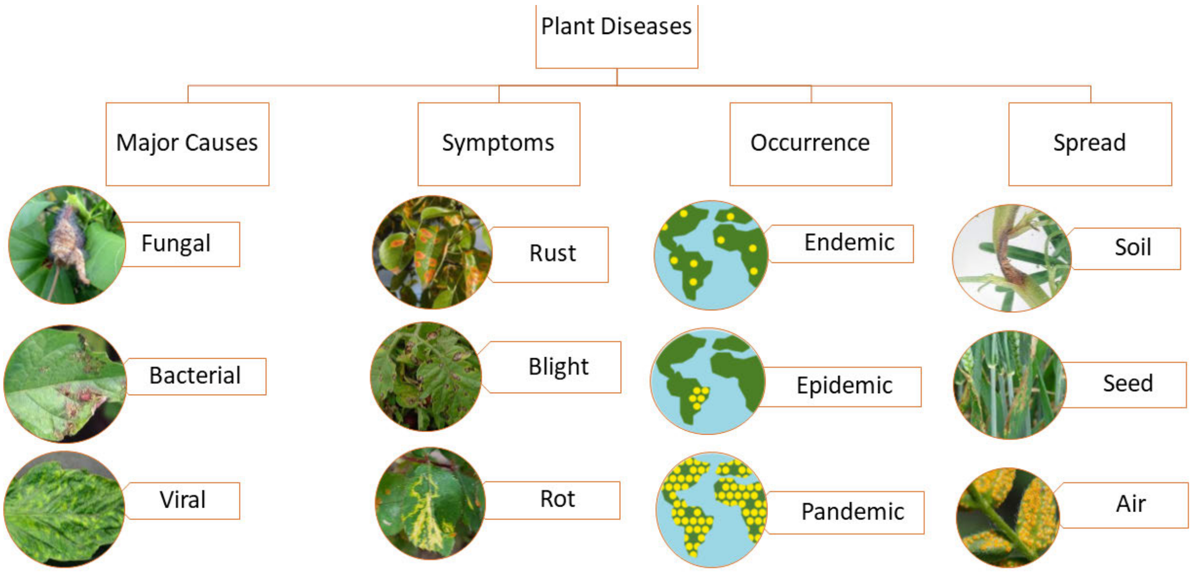

FIGURE 6. Plant diseases causes, symptoms, occurrence, and spread.

rust, wilt, rot, blight, and Clubroot (Plasmodiophora brassicae) affecting brassicas.

- **Bacterial**: A bacterial plant disease is the spread of plant diseases caused by bacterial germs over vast areas, substantially impacting plants, agriculture, and forest production or natural habitat. Bacterial diseases of plants are caused by six genera of bacteria: Agrobacterium, Corynebacterium, Erwinia, Pseudomonas, Streptomyces, and Xanthomonas. Some examples are Black Rot, Bacterial Blight, Leaf Spot, and Wilt.
- **Viral**: Viral diseases are diseases caused by viruses that are small, simple, and highly infectious microorganisms. They reproduce only within the living cells of plants. Some examples are - barley yellow dwarf, tobacco ring spot, watermelon mosaic, and potato mop top.

B. SYMPTOMS

- **Rust**: Rusts are a kind of fungal disease that affects the aerial sections of plants. Rust is usually seen on leaves but may also be found on stems, blossoms, and fruit. The color of spore pustules generated by rusts varies depending on the rust species and the kind of spore produced. Some rusts have complicated life cycles involving two separate plant hosts and up to five different spore types. Pale leaf spots develop into structures called pustules. In some cases, a leaf may contain numerous pustules, which in severity results in premature falling of leaves.
- **Blight**: Any of several plant diseases characterized by abrupt spotting and severe yellowing, withering, browning, or death of leaves, flowers, fruit, stems, or the entire plant commonly caused by fungi is known as blight. Leaf symptoms appear as irregular brown spots at the beginning of the leaf margin. Dark brown streaks develop in leaf petioles due to leaf blight. Lesions have a yellow halo and come into sight as waters-soaked. Floral parts may also be affected and become blighted.
- **Rot**: The rotting of a plant is caused by one of hundreds of soil-borne bacteria, fungi, and funguslike organisms (Oomycota). Plant breakdown and putrefaction are symptoms of rot diseases. Hard, dry, spongy, watery, mushy, or slimy rot can afflict any plant portion. Plants become yellow and show stunted growth as well as loose vigor. They may wilt or drop some leaves with no response to fertilizer and water.

C. OCCURRENCES

- **Endemic**: When a disease is constantly present but only limited to a particular region, it is called an endemic disease
- **Epidemic**: When there is an unexpected increase in disease cases in a specific geographical area, the respective disease is called an epidemic disease.
- **Pandemic**: When a disease spreads over continents or subcontinents, affecting large masses and involving extreme mortality, it is called a pandemic disease.

D. SPREAD

- **Soil**: Soil-borne illnesses are plant diseases caused by pathogens that enter the host through the soil. Vascular wilt, Damping-off, and root rot are common soil-borne diseases that can cause tissue discoloration, leaf drooping, root degradation, and abrupt mortality. Soil-borne illnesses may severely diminish plant production and destroy agricultural industries if not handled adequately.

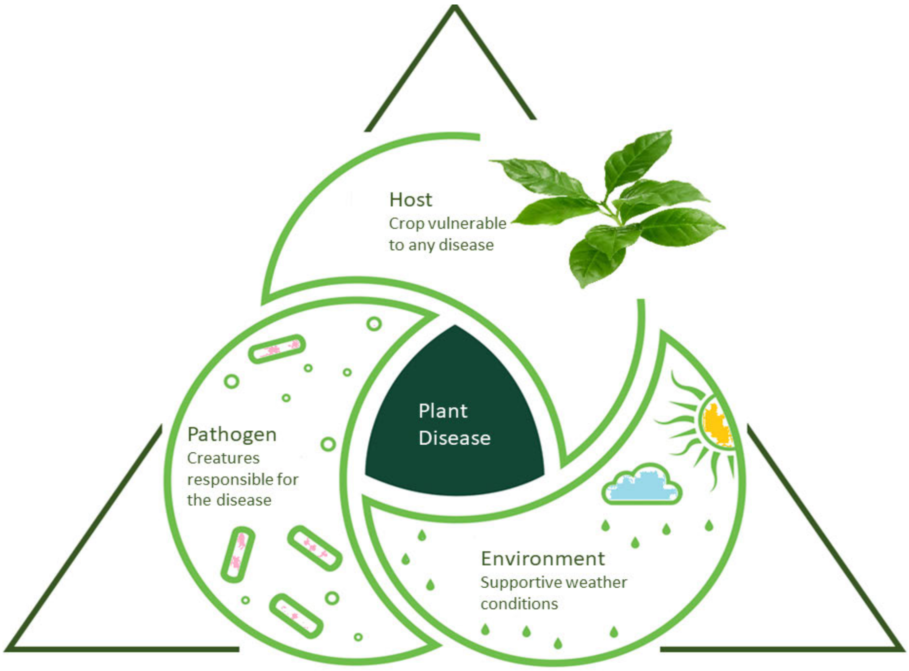

FIGURE 7. Plant disease triangle.

- **Seed**: When plant diseases spread by transmitting disease-prone seeds, they are known as seed-borne diseases. Pathogens such as bacteria, fungi, and viruses can dwell on the surface or inside the seed, propagating the illness to the following season's plant. Infection from seed-borne diseases varies greatly depending on plant, illness, and region. Examples are Red rot in sugarcane, loose smut, leaf stripe, and Fusarium.
- **Air**: Due to wind, airborne infectious agents or pathogens that are mainly fungi can travel long distances and cause a huge loss to plants over a large region, affecting the nearby vegetation and environment. Plants face extreme weather conditions during different growth phases like humidity, drought or rainfall, soils and nutrients, insects, nematodes, and microorganisms, and they may be favorable or not for plant health.

E. PLANT DISEASE TRIANGLE

Figure 7 represents the plant disease triangle. The Plant Disease Triangle tells us that for any disease to affect a plant, three conditions must exist: the presence of a pathogen, a susceptible host (plant), and proper environmental conditions. Any missing condition means the triangle is incomplete, and no disease will occur. Some other factors include - the time of the infection period, the widespread presence of the pathogen, how harmful the pathogen is, and the lifetime of the host plant.

- **Pathogen**: Several organisms that cause plant diseases include fungi, bacteria, viruses, nematodes, mycoplasmas, and spiroplasmas. These pathogens must be present in the greenhouse to create a disease problem.
- **Host**: Hosts are plants that a pathogen can infect. Not every plant is in danger of being attacked by the same pathogen, as pathogens prefer only certain plants. For example, Thielaviopsis usually attacks pansies, petunias, snapdragon, verbena, etc., and does not infect marigolds.
- **Environment**: The most complex of the three conditions is the Environment, which is not in our direct control. However, it can be manipulated to reduce disease issues. Any environment that causes plant stress can make a plant more vulnerable to a plant disease. The main factors to consider are water, Air Movement, and humidity.

V. ARTIFICIAL INTELLIGENCE IN PLANT DISEASE DETECTION

AI is helping us to live more healthy and comfortable lives. AI is the basis of this paper, and this section mainly explains how AI has been employed in plant disease detection in the last two decades. In AI for plant disease detection, machine learning, deep learning, image processing, attention approaches, multimodal data fusion, and IoT with AI techniques are explored. This section describes the fundamentals of these techniques utilized in the literature. Deep learning is mainly used in plant disease detection nowadays, and further advancement in deep learning in plant disease detection is explained in the next section. Figure 8 represents the AI in plant disease detection and is explained below.

- **Machine Learning in Classifying Plant Diseases**: In the last two decades, many Machine learning algorithms have been employed for plant disease detection,

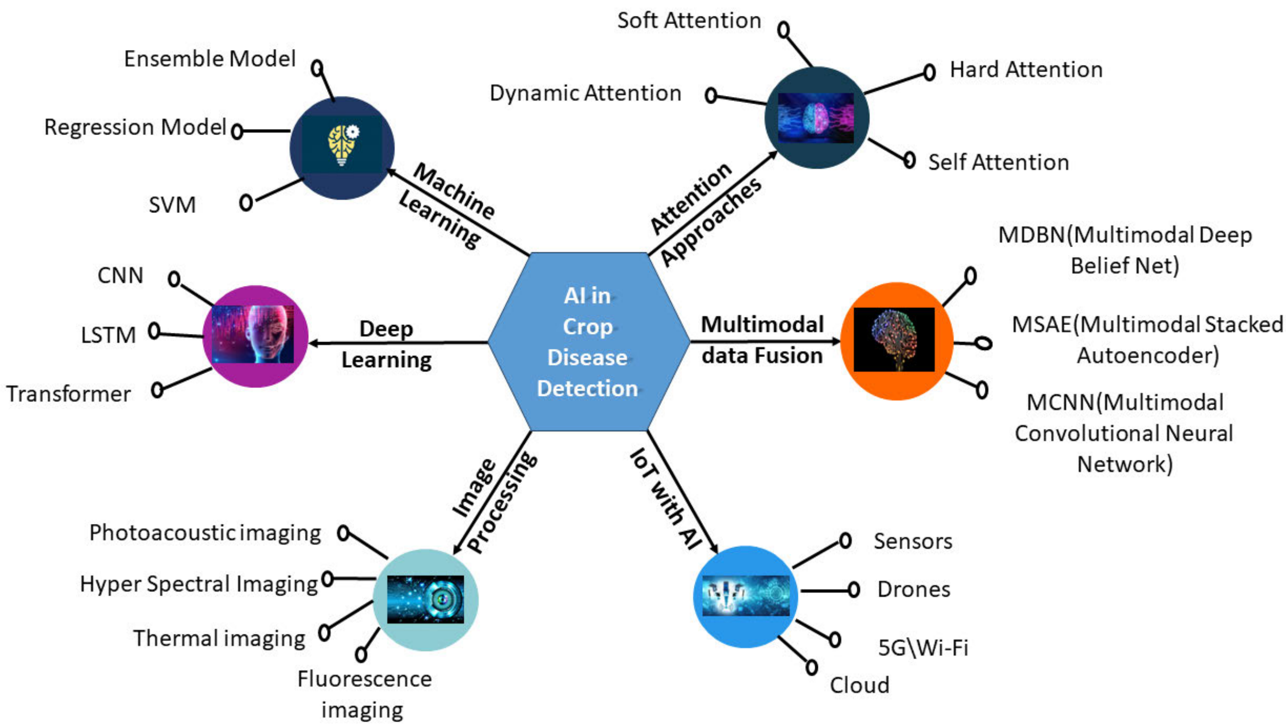

FIGURE 8. AI in plant disease detection.

like SVM, KNN, MLR, Naive Bayes, and K-means. Table 2 represents the analysis of the Machine Learning approaches in plant disease diagnosis and classification. Fungal disease in banana leaves is studied and detected using image enhancement and color segmentation [35]. Three main foliar diseases are classified: Sigatoka, Deightoneilla, and Cordana. ELBP features extracted from DTCWT showed the best results out of all LBP variants (ELBP, MeanLBP, and MedianLBP) and image transform methods(DWT, DTCWT, and Ranklet transform) with an accuracy of 95.4% when it was classified with ANN classifier. The diseases are identified at an early stage on the upper side of the leaf blade. These diseases tend to affect the photosynthesis ability of the plant, which affects the plant's production capability. Wahab et al. [37] proposed an image-processing algorithm to detect diseases in chili plants. They employed K means for image segmentation and the Support Vector Machine(SVM) for image classification. The extracted features are then classified into healthy and unhealthy. They detected a disease named cucumber mosaic in the chili plant. The accuracy of detecting healthy leaves and classification of background images is very high. However, the accuracy for cucumber mosaic is very low(57.1%), which can be improved by training more datasets of plants affected by cucumber mosaic virus. Deep learning techniques outperform Machine learning approaches because of the excellent image recognition capability of deep learning [56].

- **Deep Learning in Identifying plant Diseases**: Over recent years, researchers have been paying more attention to deep learning [5], [6], [7], [8], [9], [57], [58], [59], [60], [61], [62], [63] because of its ability to automatically extract features from images and videos and discriminate the objects. With the advancement of deep learning, transfer learning is also used in agriculture due to data scarcity. A pre-trained model on a large dataset can be used on a small dataset by using [64] fine-tuning method. So, by using this method, training of the model is not required from scratch. Therefore, artificial neural networks are famous in agriculture as they produce more accurate results in plant disease detection [65].
Table 3 represents the analysis of the Deep Learning approaches in plant disease diagnosis and classification. In [66], Bari et al. employed Faster RCNN to detect rice diseases in rice crops. To detect the exact location of the disease, the YoloV3 model is used, which is faster than RCNN [67]. In [68], Chen et al. used Bidirectional-LSTM to predict cotton disease based on weather conditions with an accuracy of 87.84% and an AUC score of 0.95. Hassam et al. [47] proposed a single-stream convolutions neural network architecture for detecting citrus fruit diseases. First, data augmentation using four contrast enhancement operations: Shadow removal, pixel intensity adjustment, brightness enhancement, and local contrast is performed. After data augmentation, the data is trained using transfer learning.

TABLE 2. Machine learning approaches in plant disease diagnosis and classification.

Ref No.	Crop	Disease	Dataset	Size of Data Set	Machine learning Technique	Performance metrics
[33]	Wine grapes	Grapevine leafroll disease(GLD)	Self acquired	500	SVM with Hyperspectral Image processing technique	Accuracy= 66.67-89.93%
[34]	Potato	Early Blight,Late Blight	Plant Village	1400	SVM K-NN Naive Bayes	Accuracy=99.67% Accuracy=97.67% Accuracy=89.33%
[35]	Banana Leaf	Sigatoka Leaf Spot Cordana Leaf Spot LeafSpot Deightoneilla Leaf spot	Self acquired	300	KNN,SVM,NB	Accuracy=95.4% Fscore=93.0 Specificity=96.4 Sensitivity=93.0 Specificity=96.4 Precision 93.2
[36]	Tea	Blister Blight	Self acquired	-	Multiple Linear Regression(MLR) with IOT sensors	Accuracy=91%
[37]	Chilli	Mosaic virus	Self acquired	-	SVM with K means for segmentation	Accuracy=57.1%
[38]	Soybean	Bactreial Blight, Phytoxicity, Mosaic, Target Spot Rust,Copper Downy Mildew, Powdery Mildew	Self acquired	354	SVM	Accuracy=75.8%
[39]	Pomegranate	Bacterial blight	Self acquired	610	k-means, SVM	Accuracy=66.67-89.93%
[40]	Tomato	Leaf Curl, Upward Curling	Public dataset	200	SVM	avg. Accuracy=90%
[41]	Potato	Potato Virus Y(PVY)	Self acquired	-	SVM with Spectral Signatures	Accuracy=89.8%
[42]	Okra Bitter Gourd	Yellow Mosaic Virus	Self acquired	79 75	Naive Bayes using entropy based discretization	Accuracy= 95% Accuracy=82.67%
[43]	Cucumber	Downy Mildew, Blight and Anthracnose	Self acquired	-	SVD with SVM	-

Finally, a pre-trained mobilenetv2 CNN model is used to extract deep features. However, the analysis shows little redundant information in the extracted deep features. In the experimental process, the augmented citrus dataset (Citrus Fruits, Leaves, and Hybrid Datasets) is used and achieved 99.4%, 99.5%, and 99.7% accuracy.

Object detection [55] is the fascinating area of computer vision, which interprets visual data such as images and videos in the same way humans do to an extent. Image classification is efficiently done by using CNN. However, object localization and detection of multiple objects in visual data can be done using object detection techniques using bounded boxes. Various object detection models, such as R-CNN, Fast R-CNN, Single Slot Detector(SSD), YOLO(You Only Look Once), and Transformer-based detectors, are trending [69], [70].

TABLE 3. Deep learning approaches in plant disease diagnosis and classification.

Ref No.	Crop	Disease	Dataset	Size of Data Set	Deep learning Technique	Performance metrics
[44]	Apple	Alternaria leaf spot, Brown spot Mosaic,Grey spot,Rust	Self acquired	26377	INAR-SSD model based on VG G-INCEP	mAP=78.80
[45]	Beans	Angular leaf spot, Bean Rust	Public Dataset	1296	MobileNetV2	Avg. Accuracy>97%
[46]	Cardamom	Colletotrichum blight, Phyllosticta leaf spot	Self acquired	1724	EfficientNetV2	Accuracy=98.26% Recall=98 F1 score=98 Precision=98
[47]	Citrus fruit	Black spot,Canker scab, Greening,Melanosis	Public Dataset	154	Pretrained MobileNetV2	Accuracy=99.4%
[48]	Corn	Northern leaf blight, Common rust, Gray leaf spot	Plant Village	15408	Pretrained EfficientNetB0, DenseNet121	Accuracy=98.56%
[49]	Cotton	Leaf curl,Sooty mold	Self acquired	1112	Spatial Pyramid Pooling based YOLOX-s	mAP=72.31
[50]	Rice	Brown spot	Self acquired	1296	CNN	Accuracy=97.71%
[51]	Tomato	Bacterial spot, Early blight tomato mosaic virus, Septorial Late blight,Leaf mold, Target spot Two spotted spider,Yellow leaf curl virus,	Plant Village	18160	Pretrained MobileNetV2	Accuracy=99.30%
[46]	Grape	Black rot,ESCA, Isariopsis leaf spot	Plant Village	4062	EfficientNetV2	Accuracy=96.45% Precision=96 F1 score=96 Recall=96
[52]	Cucumber	Downy mildew	Self acquired	-	DeepLabV3 and U-Net	Avg. Accuracy=92.85%
[53]	Tomato	Nine types	Plant Village	-	ResNet+ Modified U- Net using VGG 16	Mean severity error
[54]	9 different plant species	Healthy, General, Serious	Plant Village	-	PD^{2}SE-Net + CNN	Accuracy=91%, 99% and98%
[55]	Rice	Brown spot, Blast, Bacterial blight	Self collected images	-	EfficientNet-B0 + FRCNN	Accuracy= 96.3%

The Convolutional Neural Network is a type of deep learning algorithm used widely nowadays for object detection. In CNN, features are detected automatically to Overcome the problem with machine learning in which feature engineering is done manually. Thus, CNN is outperforming in the agriculture domain for detecting plant pests. Features are extracted automatically from the image using filters in the convolution layer, which is the fundamental part of CNN architecture. Feature maps are obtained as an output of the convolution layer, which is further sent to the pooling layer for downsampling of the feature maps while preserving the essential information. The output of the pooling layer is transferred to the fully connected layer for making predictions or classifications. Recent research are concentrating on the disease classification of crops by using CNN models. But to detect the disease at the starting phase is more crucial than disease classification. In computer vision tasks, convolution neural networks are used extensively because they work excellently in object detection by capturing patterns of the input images. Fuentes et al. in [9] merged R-CNN, Faster R-CNN, and SSD deep learning meta-learning with the Visual Geometry Group network (VGG net) and residual network to recognize nine different types of tomato diseases. Patil et al. [55] proposed a Severity Estimation System to tackle three rice diseases, Brownspot, Blast, and Bacterial blight, which can identify the type and severity of the infection using image processing. A dataset of 1,200 mixed images of infected and healthy plants was taken. Then, it was labeled and grouped as 75% of these images were infected by only one disease, more than 15% were healthy, and multiple diseases infected 5%. FRCNN(Faster region-based convolutional neural network was used to find the area of leaf instances and infected region. The best results were given when EfficientNet-B0 was used, giving an accuracy of 96.43%. S. K. Noon et al. [49] proposed a modified Spatial Pyramid Pooling (SPP)layer to efficiently find the pertinent features from training data at different scales. The proposed YOLOX-based model with improved SPPs had better identification results in cases of the same and overlapping disease symptoms. The proposed framework proposes to identify multiple diseases on one leaf and identify developing severity symptoms of one disease on cotton plants. The proposed improved YOLOX model had a better test accuracy of 73.13% on the self-collected dataset and 3.27% more test accuracy than the initial YOLOX model.

- **Image Processing in plant Diseases**: Image processing is used for plant disease detection, including collecting and pre-processing images, followed by segmentation, feature extraction, and classification. Numerous image processing methods have been proposed in the last two decades, [71], [72], [73] with different types of color space transformation, filtering, segmentation, and feature extraction followed by classification of plant diseases. Gao et al. [33] used an image processing method called Proximinal Hyperspectral Sensing to detect the infection in Pinot Noir(Red berried Wine-grape) and Chardonnay(Whiteberried) grapevine. Data were collected six times per cultivar. Partial least square discriminant analysis (PLS-DA) was used to detect GLD. This method was most accurate during harvest time, with a prediction accuracy of around 96% for Pinot Noir and 76% for Chardonnay. This method can be implanted on tools and machines to conduct testing over a wide range in the graveyard, thus detecting the disease early.
- **Internet of Things in plant Disease Detection**: The agriculture sector is becoming more advanced with the Internet of Things (IoT). Many sensors in IoT take actual time input from the fields and provide real-time prediction accordingly. Using IoT, Farmers can supervise their fields distantly [74], [75]. Data collected from the sensors can be further analyzed using machine learning algorithms to provide predictions that farmers can deal with severe weather conditions like flood and drought [76], [77]. It can play a vital role in detecting diseases in crops at the very initial stage. Thus, it can increase the yield by lowering the diseased crop loss. It addresses the problem of the unavailability of manpower by making the process automated. An IoT-based approach for predicting diseases is proposed by Liu et al. [36] with Multiple linear regression employed as an ML model for linear correlation between disease attacks and environmental conditions. The proposed solution is trained, tested, and validated based on 2015 to 2019 crop field environmental data with an accuracy of prediction of 91% in 2019.
- **Fusion Approaches in Plant Disease Diagnosis**: The fusion approach combines different data types in text, audio, and video to get more efficient and reliable output. MDBN(Multimodal Deep Belief Net), MSAE(Multimodal Stacked Autoencoder), and MCNN(Multimodal Convolutional Neural Network) are different types of network models which use multimodal data fusion technique [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89].
  Amin et al. [48] use a feature fusion end-to-end deep learning method to classify healthy and unhealthy corn plants. It uses two pre-trained CNN methods-EfficientNetB0 and DenseNet121. The features are then fused with other techniques so that the model can learn more about the dataset. The result is then compared with other trained CNN models, namely ResNet152 and InceptionV3. They achieve an accuracy rate of 98.56%, while ResNet and InceptionV3 have an accuracy of

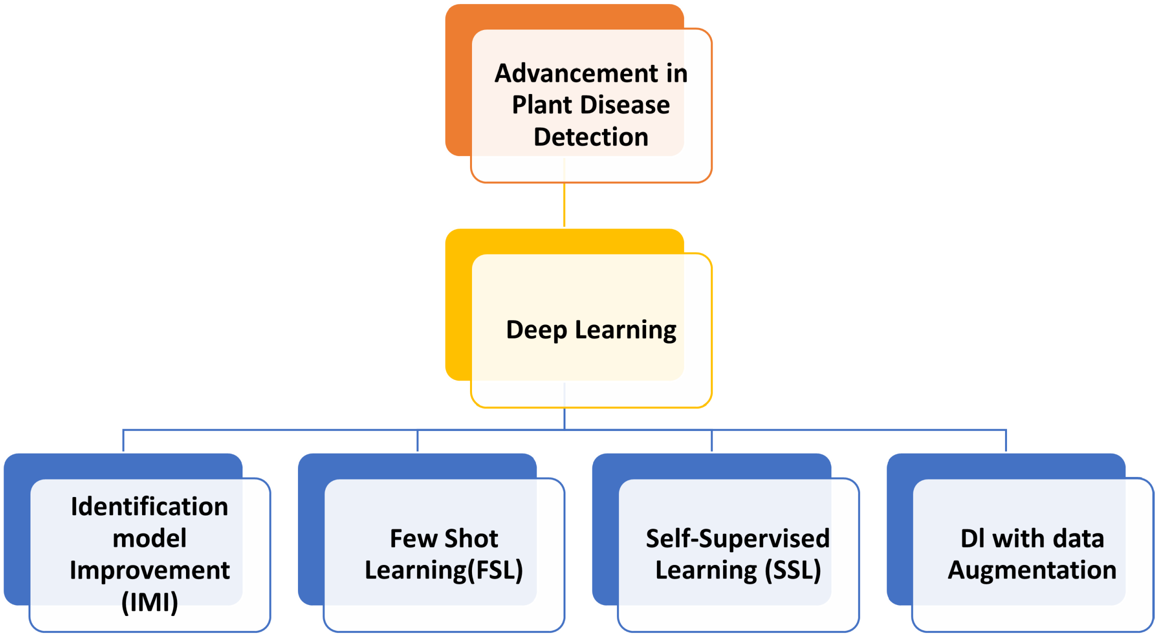

FIGURE 9. Advancement in plant disease detection.

98.37% and 96.26%, respectively. Features extracted from different CNNs and fusing them to produce a more complex set result in more accuracy.

VI. ADVANCEMENT IN PLANT DISEASE DETECTION

Currently, plant disease detection research is carried out mainly in deep learning with advancements in the areas of identification model improvement (IMI), few-shot learning, self-supervised learning, and data augmentation using GAN. Figure 9 depicts advancement in plant disease detection and is discussed below.

A. IDENTIFICATION MODEL IMPROVEMENT (IMI)

One of the primary research advancements in plant disease detection is in the area of identification model improvement (IMI), a model for identifying plant diseases that work with supervised learning and aims to increase accuracy. The models employing CNN transformers and attention mechanisms come under this category. Attention-based models focus more on a specific data part to provide more accurate predictions. Attention approaches consist of various techniques such as Soft Attention, Hard Attention, Dynamic attention, and Self Attention, etc. [90], [91], [92], [93], [94], [95], [96], [97], [98]. Regardless of higher accuracy, these techniques are based on supervised learning which relies on a large labeled data sets, and it doesn't provide a solution with limited labeled dataset. In this case, few-shot learning is used where a knowledge transfer happens between source samples to the target with a small labeled data set known as a support set.

B. FEW SHOT LEARNING (FSL)

Few-shot learning(FSL) is a machine learning and artificial intelligence technique focusing on training models to make accurate predictions or classifications with a very limited amount of labeled data known as a support set, and researchers are employing FSL in plant disease detection [99], [100], [101]. In traditional machine learning, models often require large data sets to perform well because they learn patterns and relationships from many examples. However, collecting and annotating large data sets in real-world scenarios can be expensive, time-consuming, or impractical. Few-shot learning is better than CNN in limited data scenarios, as CNNs require large amounts of labeled data for effective training. When obtaining extensive labeled data sets, such as plant disease data sets, is challenging, few-shot learning can be invaluable. Few-shot learning algorithms can adapt to new classes or categories with only a few examples, allowing models to make accurate predictions with minimal data. Few-shot learning accelerates the prototyping and development of AI systems. It allows developers to quickly build models for novel tasks without extensive data collection and annotation. In object detection tasks, CNN-based detectors like Faster R-CNN or YOLO require extensive annotated data for each object class. Few-shot learning can reduce the annotation burden by enabling the model to learn about new object classes with just a few examples, making it more practical for real-world applications. Few-shot learning also has one disadvantage: it performs well if the support set is similar to the source data set; otherwise, the performance degrades substantially.

C. SELF SUPERVISED LEARNING

Self Supervised Learning(SSL) [102], [103] is a method that uses the underlying information that humans use to understand certain data types for example, we can easily identify a picture of a dog and a cat and can differentiate between them without having any large data set. SSL makes predictions on unlabeled data to classify them into a particular category. It trains unlabeled data by fine-tuning and applying changes by keeping the original data at hand [103] This way, SSL manages to label certain data types using the structures available within the data. This feature of SSL can be very handy in classifying plant diseases as we can modify the available data sets and use them to group the diseases. There is a lack of labeled data in agriculture and farming. In contrast, plenty of unlabeled data is available, so SSL can be used to pre-train these unlabelled data by using the labeled data for fine-tuning and then classifying all these data. SSL is better than other supervised learning methods as SSL data is unlabeled, and labeling data is very expensive and tedious. The models in SSL are pre-trained and modified on small data sets for specific disease detection. SSL can easily grasp the pattern, structure, and features of an infected plant picture, and it can then use that to detect and identify more infected plant images by training the picture. Contrastive learning [102] method for Leaf disease identification with domain Adaptation (CLA) can be used for leaf disease identification. It works in two stages. The first stage includes pre-training unlabeled data; in the second stage, the labeled data is finely tuned.

D. DATA AUGMENTATION

The analysis of Agricultural images for plant disease detection is a very complicated task because of the variety of species and complex backgrounds of plants. To address this issue, there is a requirement for a huge image dataset of plants for different types of environments and conditions in the field. Again, this task is cumbersome as collecting large datasets of images and annotation is not easy. This becomes a bottleneck for plant disease detection while using Deep learning algorithms. In such a scenario, data augmentation [104], [105], [106], [107], [108], [109], [110], [111], [112] can be crucial in algorithmically generating images and increasing data sets, drastically boosting the DL model performance. Since 2014, Generative Adversarial Network (GAN) has been employed as a data augmentation technique, especially for an agricultural domain, which generates almost realistic images. GAN is a deep learning architecture that consists of two neural networks (Generator and Discriminator) working against each other in a zero-sum game framework. The main objective of GANs is to generate new, synthetic data that resembles input data or some known data distribution. A big challenge that most neural networks face is that these networks can easily be misled by adding a bit of noise to the input data. Still, on the contrary, we observe that even after adding noise, the GANs model has more conviction in wrong predictions than when it correctly predicted them. The reason is that most of the ML models are trained/learned from a very small set of data. Hence, it is a major disadvantage as it is easy to overfit these models. Also, the mapping from the input to the output is very linear. SSL can be better than data augmentation with GAN when we have limited access to data (as specific disease data are hard to obtain). Generative Adversarial Networks (GANs) consist of Generator and Discriminator models. The generator is being trained, but the discriminator remains idle. In this process, the generator generates counterfeit data. The discriminator then trains itself on the counterfeit data produced by the generator. As a result, we can get its predictions and use the results for training the Generator and getting better from the current state to try to mislead the Discriminator. The discriminator is being trained, the generator remains idle, the network proceeds forward, and no back-propagation is done. In this process, the discriminator is trained on counterfeit data generated from the generator and then tested to see if it can correctly predict them as fake.

VII. CHALLENGES IN AI FOR PLANT DISEASE DETECTION

- **Limited Availability of Real-time Datasets**: The development of AI models for real-time plant disease detection is hindered by the scarcity of datasets that provide up-to-date and relevant information [19].
- **Lack of Standardized Datasets**: The absence of standardized datasets makes it challenging to compare and benchmark the performance of different AI systems accurately [20].
- **Complex and Diverse Backgrounds**: Plant disease detection often involves distinguishing symptoms on plants from complex and diverse natural backgrounds [15], which poses a significant challenge for AI algorithms.
- **Close-distance Data Capture**: Acquiring high-quality data from close distances to identify small-sized disease symptoms [19] requires specialized equipment and techniques, adding complexity to the process.
- **Identifying Small-sized Symptoms**: Accurately detecting small-sized disease symptoms can be particularly challenging for AI systems, as these may be easily overlooked.
- **Variations in Lighting and Image Quality**: Fluctuations in lighting conditions and image quality can affect the performance of AI models, making robustness a critical concern [19].
- **Disease Progression and Inter-class Similarity**: Distinguishing between disease progression stages and addressing inter-class similarity issues require more sophisticated AI algorithms.
- **Computational Challenges with Large Datasets**: Processing large-scale datasets for training AI models presents computational challenges that must be overcome for efficient disease detection [20].

- **Real-time Field Detection**: Conducting real-time disease detection in the field demands high-speed processing and robustness against environmental variations [14].
- **Impact of Environmental Factors**: Environmental factors such as weather conditions and soil quality can influence the accuracy of disease detection, necessitating AI models to account for these variables.
- **Integration of Multi-modal Data**: Integrating data from various sources, such as images, sensors, and climate data, requires advanced techniques to create a holistic approach to disease detection [14].

In summary, AI in plant disease detection faces various challenges, from data availability and quality to the complexities of real-world conditions. Addressing these challenges is crucial for developing robust and effective AI-based solutions for agriculture.

VIII. CONCLUSION

This paper discusses the farmers' challenges and their AI-based solutions. AI has many applications in the agriculture sector, which this article reviews. Plant diseases and pests negatively impact the agriculture sector worldwide. In this article, an extensive analysis of recent research on detecting plant disease using various AI techniques is done. It highlights the challenges that must be discussed to provide real-time solutions for early disease detection. Plant diseases pose a significant threat to the global agricultural sector. Although AI-based solutions have seen rapid growth, several challenges must be addressed before developing high-performance, real-time Plant Disease Detection solutions. This assessment is based on a comprehensive review of research in Plant Disease Detection utilizing imaging applications. The review lists the advancement in plant disease detection using machine learning (ML) and deep learning (DL) techniques. Along with these techniques, researchers have also used transfer learning, attention approaches, and multimodal data fusion to enhance the performance of the models. In this study, a total of 112 articles published between 2015 and 2023 were taken into account. These articles were carefully chosen based on strict inclusion criteria and were drawn from various reputable databases, including Google Scholar, IEEE Xplore, Science Direct, Scopus, and ACM. Notably, most of these studies strongly emphasized disease detection systems for various crops, primarily leveraging Convolutional Neural Networks (CNNs). Data scarcity is the biggest problem in the agriculture sector, and the availability of public image datasets needs to be increased. DL models perform highly only if the network provides a large image dataset. Also, data augmentation with GAN can be employed to increase image data. Moreover, data collection is done in labs in a restricted environment. However, transitioning from a lab environment to a real-time environment is crucial, and models trained on this data must perform better. With this, it is concluded that this survey emphasizes the challenges in plant disease detection with AI solutions. The researchers have done much work, but farmers cannot fully utilize the technology. Most of the farmers still rely on conventional methods of disease detection. The current advancement in plant disease detection is mostly in the four areas of Deep learning, i.e., Identification model Improvement (IMI), which includes all CNN-based work and transfer learning, Few-shot learning, Self-supervised learning, and Data Augmentation.

REFERENCES

[1] F. Mi Alnaser, S. Rahi, M. Alghizzawi, and A. H. Ngah, "Does artificial intelligence (AI) boost digital banking user satisfaction? Integration of expectation confirmation model and antecedents of artificial intelligence enabled digital banking," *Heliyon*, vol. 9, no. 8, Aug. 2023, Art. no. e18930. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405844023061388

[2] Worldometer. (2023). *World Population Forecasting*. Accessed: Aug. 2023. [Online]. Available: www.Worldometers.info

[3] Y. Jararweh, S. Fatima, M. Jarrah, and S. AlZu'bi, "Smart and sustainable agriculture: Fundamentals, enabling technologies, and future directions," *Comput. Electr. Eng.*, vol. 110, Sep. 2023, Art. no. 108799. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0045790623002239

[4] USDA, *Researchers Helping Protect Crops From Pests*, Researchers Helping Protect Crops From Pests | National Institute of Food and Agriculture, USA, Aug. 2023. [Online]. Available: https://www.nifa.usda.gov/about-nifa/blogs/researchers-helping-protect-crops-pests

[5] X. Lu, R. Yang, J. Zhou, J. Jiao, F. Liu, Y. Liu, B. Su, and P. Gu, "A hybrid model of ghost-convolution enlightened transformer for effective diagnosis of grape leaf disease and pest," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 34, no. 5, pp. 1755–1767, May 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S131915782200088X

[6] S. Janarthan, S. Thuseethan, S. Rajasegarar, and J. Yearwood, "P2OP—Plant pathology on palms: A deep learning-based mobile solution for in-field plant disease detection," *Comput. Electron. Agricult.*, vol. 202, Nov. 2022, Art. no. 107371. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922006792

[7] A. S. Keceli, A. Kaya, C. Catal, and B. Tekinerdogan, "Deep learning-based multi-task prediction system for plant disease and species detection," *Ecological Informat.*, vol. 69, Jul. 2022, Art. no. 101679. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1574954122001297

[8] S. Pudumalar and S. Muthuramalingam, "Hydra: An ensemble deep learning recognition model for plant diseases," *J. Eng. Res.*, Sep. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2307187723002584, doi: 10.1016/j.jer.2023.09.033.

[9] A. Fuentes, S. Yoon, S. Kim, and D. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," *Sensors*, vol. 17, no. 9, p. 2022, Sep. 2017. [Online]. Available: https://www.mdpi.com/1424-8220/17/9/2022

[10] T. Domingues, T. Brandão, and J. C. Ferreira, "Machine learning for detection and prediction of crop diseases and pests: A comprehensive survey," *Agriculture*, vol. 12, no. 9, p. 1350, Sep. 2022.

[11] R. R. Patil and S. Kumar, "A bibliometric survey on the diagnosis of plant leaf diseases using artificial intelligence," *Library Philosophy Pract.*, pp. 1–26, Feb. 2020. [Online]. Available: https://digitalcommons.unl.edu/libphilprac/3987/

[12] R. R. Patil, S. Kumar, and R. Rani, "Comparison of artificial intelligence algorithms in plant disease prediction," *Revue d'Intell. Artificielle*, vol. 36, no. 2, pp. 185–193, Apr. 2022.

[13] L. C. Ngugi, M. Abelwahab, and M. Abo-Zahhad, "Recent advances in image processing techniques for automated leaf pest and disease recognition—A review," *Inf. Process. Agricult.*, vol. 8, no. 1, pp. 27–51, Mar. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214317320300196

[14] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: A review," *Plant Methods*, vol. 17, no. 1, pp. 1–18, Dec. 2021.

[15] A. Kamilaris and F. X. Prenafeta-Boldu, "Deep learning in agriculture: A survey," *Comput. Electron. Agricult.*, vol. 147, pp. 70–90, Apr. 2018.

[16] R. N. Jogekar and N. Tiwari, "A review of deep learning techniques for identification and diagnosis of plant leaf disease," in *Smart Trends in Computing and Communications: Proceedings of SmartCom 2020* (Smart Innovation, Systems and Technologies), vol. 182, Y. D. Zhang, T. Senjyu, C. So-in, and A. Joshi, Eds. Singapore: Springer, 2021, doi: 10.1007/978-981-15-5224-3_43.

[17] J. Lu, L. Tan, and H. Jiang, "Review on convolutional neural network (CNN) applied to plant leaf disease classification," *Agriculture*, vol. 11, no. 8, p. 707, Jul. 2021. [Online]. Available: https://www.mdpi.com/2077-0472/11/8/707

[18] L. Li, S. Zhang, and B. Wang, "Plant disease detection and classification by deep learning—A review," *IEEE Access*, vol. 9, pp. 56683–56698, 2021.

[19] P. S. Thakur, P. Khanna, T. Sheorey, and A. Ojha, "Trends in vision-based machine learning techniques for plant disease identification: A systematic review," *Exp. Syst. Appl.*, vol. 208, Dec. 2022, Art. no. 118117.

[20] W. Shafik, A. Tufail, A. Namoun, L. C. De Silva, and R. A. H. M. Apong, "A systematic literature review on plant disease detection: Motivations, classification techniques, datasets, challenges, and future trends," *IEEE Access*, vol. 11, pp. 59174–59203, 2023.

[21] Y. Lu, D. Chen, E. Olaniyi, and Y. Huang, "Generative adversarial networks (GANs) for image augmentation in agriculture: A systematic review," *Comput. Electron. Agricult.*, vol. 200, Sep. 2022, Art. no. 107208. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922005233

[22] A. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine learning applications for precision agriculture: A comprehensive review," *IEEE Access*, vol. 9, pp. 4843–4873, 2021.

[23] J. Yang, X. Guo, Y. Li, F. Marinello, S. Ercisli, and Z. Zhang, "A survey of few-shot learning in smart agriculture: Developments, applications, and challenges," *Plant Methods*, vol. 18, no. 1, pp. 1–12, Dec. 2022.

[24] D. Lo Presti, J. Di Tocco, C. Massaroni, S. Cimini, L. De Gara, S. Singh, A. Raucci, G. Manganiello, S. L. Woo, E. Schena, and S. Cinti, "Current understanding, challenges and perspective on portable systems applied to plant monitoring and precision agriculture," *Biosensors Bioelectron.*, vol. 222, Feb. 2023, Art. no. 115005. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0956566322010454

[25] S. Rahi, "Research design and methods: A systematic review of research paradigms, sampling issues and instruments development," *Int. J. Econ. Manag. Sci.*, vol. 6, no. 2, pp. 1–5, 2017.

[26] R. B. Wakweya, "Challenges and prospects of adopting climate-smart agricultural practices and technologies: Implications for food security," *J. Agricult. Food Res.*, vol. 14, Dec. 2023, Art. no. 100698. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666154323002053

[27] H. Guo, Y. Xia, J. Jin, and C. Pan, "The impact of climate change on the efficiency of agricultural production in the world's main agricultural regions," *Environ. Impact Assessment Rev.*, vol. 97, Nov. 2022, Art. no. 106891. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0195925522001573

[28] M. Javaid, A. Haleem, I. H. Khan, and R. Suman, "Understanding the potential applications of artificial intelligence in agriculture sector," *Adv. Agrochem*, vol. 2, no. 1, pp. 15–30, Mar. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S277323712200020X

[29] R. R. Patil and S. Kumar, "Priority selection of agro-meteorological parameters for integrated plant diseases management through analytical hierarchy process," *Int. J. Electr. Comput. Eng. (IJECE)*, vol. 12, no. 1, p. 649, Feb. 2022.

[30] Y. Wang, T. Huang, J. Liu, Z. Lin, S. Li, R. Wang, and Y. Ge, "Soil pH value, organic matter and macronutrients contents prediction using optical diffuse reflectance spectroscopy," *Comput. Electron. Agricult.*, vol. 111, pp. 69–77, Feb. 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169914003020

[31] S. Kumar, R. R. Patil, and R. Rani, "Smart IoT-based pesticides recommendation system for rice diseases," in *Intelligent Systems and Applications* (Lecture Notes in Electrical Engineering), vol. 959, A. J. Kulkarni, S. Mirjalili, and S. K. Udgata, Eds. Singapore: Springer, 2023, doi: 10.1007/978-981-19-6581-4_2.

[32] C. A. Zaragoza, R. G. Perea, I. F. García, E. C. Poyato, and J. A. R. Díaz, "Open source application for optimum irrigation and fertilization using reclaimed water in olive orchards," *Comput. Electron. Agricult.*, vol. 173, Jun. 2020, Art. no. 105407. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169920301022

[33] Z. Gao, L. R. Khot, R. A. Naidu, and Q. Zhang, "Early detection of grapevine leafroll disease in a red-berried wine grape cultivar using hyperspectral imaging," *Comput. Electron. Agricult.*, vol. 179, Dec. 2020, Art. no. 105807.

[34] A. M. Abdu, M. M. Mokji, and U. U. Sheikh, "Automatic vegetable disease identification approach using individual lesion features," *Comput. Electron. Agricult.*, vol. 176, Sep. 2020, Art. no. 105660.

[35] D. Mathew, C. Sathish Kumar, and K. Anita Cherian, "Foliar fungal disease classification in banana plants using elliptical local binary pattern on multiresolution dual tree complex wavelet transform domain," *Inf. Process. Agricult.*, vol. 8, no. 4, pp. 581–592, Dec. 2021.

[36] Z. Liu, R. N. Bashir, S. Iqbal, M. M. A. Shahid, M. Tausif, and Q. Umer, "Internet of Things (IoT) and machine learning model of plant disease prediction—Blister blight for tea plant," *IEEE Access*, vol. 10, pp. 44934–44944, 2022.

[37] A. H. Bin Abdul Wahab, R. Zahari, and T. H. Lim, "Detecting diseases in chilli plants using K-means segmented support vector machine," in *Proc. 3rd Int. Conf. Imag., Signal Process. Commun. (ICISPC)*, Jul. 2019, pp. 57–61.

[38] J. M. M. Araujo and Z. M. A. Peixoto, "A new proposal for automatic identification of multiple soybean diseases," *Comput. Electron. Agricult.*, vol. 167, Dec. 2019, Art. no. 105060.

[39] M. Bhange and H. A. Hingoliwala, "Smart farming: Pomegranate disease detection using image processing," *Proc. Comput. Sci.*, vol. 58, pp. 280–288, Jan. 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S187705091502133X

[40] U. Mokhtar, M. A. Ali, A. E. Hassanien, and H. Hefny, "Identifying two of tomatoes leaf viruses using support vector machine," in *Information Systems Design and Intelligent Applications*, vol. 1. Berlin, Germany: Springer, 2015, pp. 771–782.

[41] L. M. Griffel, D. Delparte, J. Whitworth, P. Bodily, and D. Hartley, "Evaluation of artificial neural network performance for classification of potato plants infected with potato virus Y using spectral data on multiple varieties and genotypes," *Smart Agricult. Technol.*, vol. 3, Feb. 2023, Art. no. 100101. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2772375522000661

[42] D. Mondal, D. K. Kole, and K. Roy, "Gradation of yellow mosaic virus disease of okra and bitter gourd based on entropy based binning and naive Bayes classifier after identification of leaves," *Comput. Electron. Agricult.*, vol. 142, pp. 485–493, Nov. 2017.

[43] S. Zhang and Z. Wang, "Cucumber disease recognition based on global–local singular value decomposition," *Neurocomputing*, vol. 205, pp. 341–348, Sep. 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S092523121630296X

[44] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks," *IEEE Access*, vol. 7, pp. 59069–59080, 2019.

[45] E. Elfatimi, R. Eryigit, and L. Elfatimi, "Beans leaf diseases classification using MobileNet models," *IEEE Access*, vol. 10, pp. 9471–9482, 2022.

[46] C. K. Sunil, C. D. Jaidhar, and N. Patil, "Cardamom plant disease detection approach using EfficientNetV2," *IEEE Access*, vol. 10, pp. 789–804, 2022.

[47] M. Hassam, M. A. Khan, A. Armghan, S. A. Althubiti, M. Alhaisoni, A. Alqahtani, S. Kadry, and Y. Kim, "A single stream modified MobileNet v2 and whale controlled entropy based optimization framework for citrus fruit diseases recognition," *IEEE Access*, vol. 10, pp. 91828–91839, 2022.

[48] H. Amin, A. Darwish, A. E. Hassanien, and M. Soliman, "End-to-end deep learning model for corn leaf disease classification," *IEEE Access*, vol. 10, pp. 31103–31115, 2022.

[49] S. K. Noon, M. Amjad, M. A. Qureshi, and A. Mannan, "Handling severity levels of multiple co-occurring cotton plant diseases using improved YOLOX model," *IEEE Access*, vol. 10, pp. 134811–134825, 2022.

[50] O. Debnath and H. N. Saha, "An IoT-based intelligent farming using CNN for early disease detection in rice paddy," *Microprocess. Microsyst.*, vol. 94, Oct. 2022, Art. no. 104631.

[51] S. Ahmed, M. B. Hasan, T. Ahmed, M. R. K. Sony, and M. H. Kabir, "Less is more: Lighter and faster deep neural architecture for tomato leaf disease classification," *IEEE Access*, vol. 10, pp. 68868–68884, 2022.

[52] C. Wang, P. Du, H. Wu, J. Li, C. Zhao, and H. Zhu, "A cucumber leaf disease severity classification method based on the fusion of DeepLabV3+ and U-Net," *Comput. Electron. Agricult.*, vol. 189, Oct. 2021, Art. no. 106373.
[53] P. Wspanialy and M. Moussa, "A detection and severity estimation system for generic diseases of tomato greenhouse plants," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105701.
[54] Q. Liang, S. Xiang, Y. Hu, G. Coppola, D. Zhang, and W. Sun, "PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network," *Comput. Electron. Agricult.*, vol. 157, pp. 518–529, Feb. 2019.
[55] R. R. Patil, S. Kumar, S. Chiwhane, R. Rani, and S. K. Pippal, "An artificial-intelligence-based novel rice grade model for severity estimation of rice diseases," *Agriculture*, vol. 13, no. 1, p. 47, Dec. 2022. [Online]. Available: https://www.mdpi.com/2077-0472/13/1/47
[56] R. Sujatha, J. M. Chatterjee, N. Jhanjhi, and S. N. Brohi, "Performance of deep learning vs machine learning in plant leaf disease detection," *Microprocess. Microsyst.*, vol. 80, Feb. 2021, Art. no. 103615. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0141933120307626
[57] O. W. Kent, T. W. Chun, T. L. Choo, and L. W. Kin, "Early symptom detection of basal stem rot disease in oil palm trees using a deep learning approach on UAV images," *Comput. Electron. Agricult.*, vol. 213, Oct. 2023, Art. no. 108192. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992300580X
[58] S. Ashwinkumar, S. Rajagopal, V. Manimaran, and B. Jegajothi, "Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks," *Mater. Today, Proc.*, vol. 51, pp. 480–487, Jan. 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214785321042115
[59] P. Bansal, R. Kumar, and S. Kumar, "Disease detection in apple leaves using deep convolutional neural network," *Agriculture*, vol. 11, no. 7, p. 617, Jun. 2021. [Online]. Available: https://www.mdpi.com/2077-0472/11/7/617
[60] H.-J. Yu and C.-H. Son, "Leaf spot attention network for apple leaf disease identification," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2020, pp. 229–237.
[61] M. Nawaz, T. Nazir, A. Javed, S. Tawfik Amin, F. Jeribi, and A. Tahir, "CoffeeNet: A deep learning approach for coffee plant leaves diseases recognition," *Exp. Syst. Appl.*, vol. 237, Mar. 2024, Art. no. 121481. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417423019838
[62] F. Arshad, M. Mateen, S. Hayat, M. Wardah, Z. Al-Huda, Y. H. Gu, and M. A. Al-antari, "PLDPNet: End-to-end hybrid deep learning framework for potato leaf disease prediction," *Alexandria Eng. J.*, vol. 78, pp. 406–418, Sep. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S111001682300666X
[63] S. Verma, P. Kumar, and J. P. Singh, "A meta-learning framework for recommending CNN models for plant disease identification tasks," *Comput. Electron. Agricult.*, vol. 207, Apr. 2023, Art. no. 107708. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923000960
[64] N. Krishnamoorthy, L. N. Prasad, C. P. Kumar, B. Subedi, H. B. Abraha, and V. E. Sathishkumar, "Rice leaf diseases prediction using deep neural networks with transfer learning," *Environ. Res.*, vol. 198, Jul. 2021, Art. no. 111275, doi: 10.1016/j.envres.2021.111275.
[65] R. R. Patil and S. Kumar, "Predicting rice diseases across diverse agro-meteorological conditions using an artificial intelligence approach," *PeerJ Comput. Sci.*, vol. 7, p. e687, Sep. 2021.
[66] B. S. Bari, M. N. Islam, M. Rashid, M. J. Hasan, M. A. M. Razman, R. M. Musa, A. F. Ab Nasir, and A. P. A. Majeed, "A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework," *PeerJ Comput. Sci.*, vol. 7, p. e432, Apr. 2021.
[67] D. Li, R. Wang, C. Xie, L. Liu, J. Zhang, R. Li, F. Wang, M. Zhou, and W. Liu, "A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network," *Sensors*, vol. 20, no. 3, p. 578, Jan. 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/3/578
[68] P. Chen, Q. Xiao, J. Zhang, C. Xie, and B. Wang, "Occurrence prediction of cotton pests and diseases by bidirectional long short-term memory networks with climate and atmosphere circulation," *Comput. Electron. Agricult.*, vol. 176, Sep. 2020, Art. no. 105612. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169918317794
[69] C. Liu, H. Zhu, W. Guo, X. Han, C. Chen, and H. Wu, "EFDet: An efficient detection method for cucumber disease under natural complex environments," *Comput. Electron. Agricult.*, vol. 189, Oct. 2021, Art. no. 106378. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921003951
[70] J. Li, Y. Qiao, S. Liu, J. Zhang, Z. Yang, and M. Wang, "An improved YOLOv5-based vegetable disease detection method," *Comput. Electron. Agricult.*, vol. 202, Nov. 2022, Art. no. 107345. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922006536
[71] M. Shantkumari and S. V. Uma, "Grape leaf segmentation for disease identification through adaptive snake algorithm model," *Multimedia Tools Appl.*, vol. 80, no. 6, pp. 8861–8879, Mar. 2021.
[72] B. VijayaLakshmi and V. Mohan, "Kernel-based PSO and FRVM: An automatic plant leaf type detection using texture, shape, and color features," *Comput. Electron. Agricult.*, vol. 125, pp. 99–112, Jul. 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169916301193
[73] Y. Li, Z. Cao, H. Lu, Y. Xiao, Y. Zhu, and A. B. Cremers, "In-field cotton detection via region-based semantic image segmentation," *Comput. Electron. Agricult.*, vol. 127, pp. 475–486, Sep. 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816991630480X
[74] G. Garg, S. Gupta, P. Mishra, A. Vidyarthi, A. Singh, and A. Ali, "CROPCARE: An intelligent real-time sustainable IoT system for crop disease detection using mobile vision," *IEEE Internet Things J.*, vol. 10, no. 4, pp. 2840–2851, Feb. 2023.
[75] G. Delnevo, R. Girau, C. Ceccarini, and C. Prandi, "A deep learning and social IoT approach for plants disease prediction toward a sustainable agriculture," *IEEE Internet Things J.*, vol. 9, no. 10, pp. 7243–7250, May 2022.
[76] W.-L. Chen, Y.-B. Lin, F.-L. Ng, C.-Y. Liu, and Y.-W. Lin, "RiceTalk: Rice blast detection using Internet of Things and artificial intelligence technologies," *IEEE Internet Things J.*, vol. 7, no. 2, pp. 1001–1010, Feb. 2020.
[77] M. G. Nayagam, B. Vijayalakshmi, K. Somasundaram, M. A. Mukunthan, C. A. Yogaraja, and P. Partheeban, "Control of pests and diseases in plants using IoT technology," *Meas., Sensors*, vol. 26, Apr. 2023, Art. no. 100713. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2665917423000491
[78] R. R. Patil and S. Kumar, "Rice-fusion: A multimodality data fusion framework for rice disease diagnosis," *IEEE Access*, vol. 10, pp. 5207–5222, 2022.
[79] R. Yang, X. Lu, J. Huang, J. Zhou, J. Jiao, Y. Liu, F. Liu, B. Su, and P. Gu, "A multi-source data fusion decision-making method for disease and pest detection of grape foliage based on ShuffleNet v2," *Remote Sens.*, vol. 13, no. 24, p. 5102, Dec. 2021. [Online]. Available: https://www.mdpi.com/2072-4292/13/24/5102
[80] K. M. Hosny, W. M. El-Hady, F. M. Samy, E. Vrochidou, and G. A. Papakostas, "Multi-class classification of plant leaf diseases using feature fusion of deep convolutional neural network and local binary pattern," *IEEE Access*, vol. 11, pp. 62307–62317, 2023.
[81] S.-E. Lee and J.-O. Kim, "Multi-scale attention based plant disease segmentation network," in *Proc. Int. Tech. Conf. Circuits/Syst., Comput., Commun. (ITC-CSCC)*, Jun. 2023, pp. 1–4.
[82] S. D. Thepade, J. H. Dewan, and K. H. Chauhan, "Fusion of thepade SBTC and GLCM features for improved rice leaf disease detection," in *Proc. IEEE North Karnataka Subsection Flagship Int. Conf. (NKCon)*, Nov. 2022, pp. 1–5.
[83] S. D. Thepade, D. Abin, and K. H. Chauhan, "Improved rice leaf disease detection using fusion of Otsu thresholding and thepade SBTC features," in *Proc. Int. Conf. Recent Trends Microelectron., Autom., Comput. Commun. Syst. (ICMACC)*, Dec. 2022, pp. 1–6.
[84] S. A. Kumar and S. Sasikala, "Disease detection in tomato leaves using machine learning and statistical feature fusion," in *Proc. Int. Conf. Advancements Electr., Electron., Commun., Comput. Autom. (ICAECA)*, Oct. 2021, pp. 1–6.
[85] P. Shankar, A. Johnen, and M. Liwicki, "Data fusion and artificial neural networks for modelling crop disease severity," in *Proc. IEEE 23rd Int. Conf. Inf. Fusion (FUSION)*, Jul. 2020, pp. 1–8.

[86] C. K. Sunil, C. D. Jaidhar, and N. Patil, "Tomato plant disease classification using multilevel feature fusion with adaptive channel spatial and pixel attention mechanism," *Exp. Syst. Appl.*, vol. 228, Oct. 2023, Art. no. 120381. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417423008837

[87] Y. Kaya and E. Gürsoy, "A novel multi-head CNN design to identify plant diseases using the fusion of RGB images," *Ecological Informat.*, vol. 75, Jul. 2023, Art. no. 101998. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1574954123000274

[88] X. Fan, P. Luo, Y. Mu, R. Zhou, T. Tjahjadi, and Y. Ren, "Leaf image based plant disease identification using transfer learning and feature fusion," *Comput. Electron. Agricult.*, vol. 196, May 2022, Art. no. 106892. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922002095

[89] R. Dwivedi, S. Dey, C. Chakraborty, and S. Tiwari, "Grape disease detection network based on multi-task learning and attention features," *IEEE Sensors J.*, vol. 21, no. 16, pp. 17573–17580, Aug. 2021.

[90] R. Saini, K. S. Patle, A. Kumar, S. G. Surya, and V. S. Palaparthy, "Attention-based multi-input multi-output neural network for plant disease prediction using multisensor system," *IEEE Sensors J.*, vol. 22, no. 24, pp. 24242–24252, Dec. 2022.

[91] Y. Liu, G. Gao, and Z. Zhang, "Crop disease recognition based on modified light-weight CNN with attention mechanism," *IEEE Access*, vol. 10, pp. 112066–112075, 2022.

[92] X. Wang and W. Cao, "Bit-plane and correlation spatial attention modules for plant disease classification," *IEEE Access*, vol. 11, pp. 93852–93863, 2023.

[93] Q. Dai, X. Cheng, Y. Qiao, and Y. Zhang, "Crop leaf disease image super-resolution and identification with dual attention and topology fusion generative adversarial network," *IEEE Access*, vol. 8, pp. 55724–55735, 2020.

[94] G. Dai, J. Fan, Z. Tian, and C. Wang, "PPLC-net: Neural network-based plant disease identification model supported by weather data augmentation and multi-level attention mechanism," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 35, no. 5, May 2023, Art. no. 101555. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1319157823001015

[95] Y. Zhao, C. Sun, X. Xu, and J. Chen, "RIC-net: A plant disease classification model based on the fusion of inception and residual structure and embedded attention mechanism," *Comput. Electron. Agricult.*, vol. 193, Feb. 2022, Art. no. 106644. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992100661X

[96] L. Chen, J. Zou, Y. Yuan, and H. He, "Improved domain adaptive rice disease image recognition based on a novel attention mechanism," *Comput. Electron. Agricult.*, vol. 208, May 2023, Art. no. 107806. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923001941

[97] R. Karthik, J. J. Alfred, and J. J. Kennedy, "Inception-based global context attention network for the classification of coffee leaf diseases," *Ecological Informat.*, vol. 77, Nov. 2023, Art. no. 102213. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S157495412300242X

[98] J. Chen, D. Zhang, A. Zeb, and Y. A. Nanehkaran, "Identification of rice plant diseases using lightweight attention networks," *Exp. Syst. Appl.*, vol. 169, May 2021, Art. no. 114514. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417420311581

[99] F. Zhong, Z. Chen, Y. Zhang, and F. Xia, "Zero- and few-shot learning for diseases recognition of Citrus aurantium L. using conditional adversarial autoencoders," *Comput. Electron. Agricult.*, vol. 179, Dec. 2020, Art. no. 105828. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169920315052

[100] J. Pan, L. Xia, Q. Wu, Y. Guo, Y. Chen, and X. Tian, "Automatic strawberry leaf scorch severity estimation via faster R-CNN and few-shot learning," *Ecological Informat.*, vol. 70, Sep. 2022, Art. no. 101706. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S157495412200156X

[101] C. Wang, J. Zhou, C. Zhao, J. Li, G. Teng, and H. Wu, "Few-shot vegetable disease recognition model based on image text collaborative representation learning," *Comput. Electron. Agricult.*, vol. 184, May 2021, Art. no. 106098. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921001162

[102] R. Zhao, Y. Zhu, and Y. Li, "CLA: A self-supervised contrastive learning method for leaf disease identification with domain adaptation," *Comput. Electron. Agricult.*, vol. 211, Aug. 2023, Art. no. 107967. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923003551

[103] R. Güldenring and L. Nalpantidis, "Self-supervised contrastive learning on agricultural images," *Comput. Electron. Agricult.*, vol. 191, Dec. 2021, Art. no. 106510. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921005275

[104] Q. H. Cap, H. Uga, S. Kagiwada, and H. Iyatomi, "LeafGAN: An effective data augmentation method for practical plant disease diagnosis," *IEEE Trans. Autom. Sci. Eng.*, vol. 19, no. 2, pp. 1258–1267, Apr. 2022.

[105] L. Bi and G. Hu, "Improving image-based plant disease classification with generative adversarial network under limited training set," *Frontiers Plant Sci.*, vol. 11, Dec. 2020, Art. no. 583438. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fpls.2020.583438

[106] F. Wang, Y. Rao, Q. Luo, X. Jin, Z. Jiang, W. Zhang, and S. Li, "Practical cucumber leaf disease recognition using improved Swin transformer and small sample size," *Comput. Electron. Agricult.*, vol. 199, Aug. 2022, Art. no. 107163. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992200480X

[107] A. Guerrero-Ibañez and A. Reyes-Muñoz, "Monitoring tomato leaf disease through convolutional neural networks," *Electronics*, vol. 12, no. 1, p. 229, Jan. 2023. [Online]. Available: https://www.mdpi.com/2079-9292/12/1/229

[108] Q. Zeng, X. Ma, B. Cheng, E. Zhou, and W. Pang, "GANs-based data augmentation for citrus disease severity detection using deep learning," *IEEE Access*, vol. 8, pp. 172882–172891, 2020.

[109] Y. Zhao, Z. Chen, X. Gao, W. Song, Q. Xiong, J. Hu, and Z. Zhang, "Plant disease detection using generated leaves based on DoubleGAN," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 19, no. 3, pp. 1817–1826, May 2022.

[110] W. Chen, J. Chen, R. Duan, Y. Fang, Q. Ruan, and D. Zhang, "MS-DNet: A mobile neural network for plant disease identification," *Comput. Electron. Agricult.*, vol. 199, Aug. 2022, Art. no. 107175. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922004926

[111] M. Xu, S. Yoon, A. Fuentes, J. Yang, and D. S. Park, "Style-consistent image translation: A novel data augmentation paradigm to improve plant disease recognition," *Frontiers Plant Sci.*, vol. 12, p. 3361, Feb. 2022. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fpls.2021.773142

[112] H. Jin, Y. Li, J. Qi, J. Feng, D. Tian, and W. Mu, "GrapeGAN: Unsupervised image enhancement for improved grape leaf disease recognition," *Comput. Electron. Agricult.*, vol. 198, Jul. 2022, Art. no. 107055. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922003726

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