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REVIEW PAPER

A Review on Automated Tomato Leaf Disease Detection Using Deep Learning in Smart Farming Systems

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***Abstract*—Tomato cultivation is an important agricultural practice across the world, but it confronts many obstacles because of many diseases that negatively affect crop quality and production. This article discusses deep learning-based automated tomato leaf disease sensors for smart farming systems. It discusses publicly accessible datasets such as PlantVillage and other large repositories, as well as preprocessing and data augmentation techniques to improve model performance. Different DL networks, such as Convolutional Neural Network (CNNs), MobileNet, VGG, ResNet, Inception and YOLO, are analyzed based on their soundness in classification and detection. Besides, the review has indicated the combination of artificial intelligence and internet of things, drones and cloud-based decision support systems to provide real-time monitoring of crops. Critical issues like imbalance in the data, complexity of computation, inadequate field data and unexplainability are also discussed. Lastly, the research directions in the future, including lightweight models, edge computing and explainable AI, are discussed in order to move towards more accurate solutions of precision agriculture and sustainable smart farming.**

Keywords—Tomato Leaf Disease Detection, Smart Agriculture, Precision Farming, Deep Learning, Convolutional Neural Network (CNN), Image Classification, Plant Village Data.

I. INTRODUCTION

Early detection, along with farmers, stakeholders, and precision agriculture researchers, is essential to prevent crop disease and lower production losses. Sustainable farming and the world's food supply are impacted by plant diseases (PD). Early and accurate detection of these diseases is essential for crop preservation and loss prevention. Tomatoes (Solanum lycopersicon) are one of the most extensively grown and important commodities in terms of global trade since they are a staple food and a source of essential nutrients. However, a variety of diseases are becoming a bigger threat to tomato output, such as leaf curl virus, bacterial wilt, and late blight. These diseases can result in substantial output losses and decreased fruit quality [1]. The agricultural economy of many developing countries depends heavily on tomato cultivation, which provides a considerable source of revenue for farmers. About 200 million metric tonnes of tomatoes are produced worldwide each year, mostly due to growing demand for the product's pharmacological and nutritional advantages. The frequency of plant diseases, especially those that affect tomato plant leaves and are brought on by bacterial, viral, fungal, phytoplasmic, and viroid pathogens, makes tomato production difficult. Tomato cultivation is made more difficult by unseasonable weather, intense heat, copious amounts of rainfall, and declining soil and water quality [2]. Therefore, disease prevention, productivity preservation, and quality improvement all depend on precise tomato leaf disease detection.

The disease detection system uses an automated method to identify leaf diseases, and smartphone users may obtain leaf disease information [3]. Accurate illness kinds may be identified using the disease detection method. Employing the disease detection system allows farmers to reduce the harm that diseases do in their early phases. It takes a team of experts and constant observation to manually identify leaf disease with the unaided eye. Large farms are expensive. In contrast to traditional methods, illnesses in leaves may be automatically detected using image processing techniques, which can save time, money, and effort. Early identification of leaf diseases improves crop yields. Early detection of disease-affected leaves by image processing techniques including as segmentation, identification, and classification can increase crop quality and yield. It's more expensive, time-consuming, and incorrect due to the fact that many farmers lack the resources or expertise to consult specialists [4]. In this instance, crop observation was more benefited by the recommended method. The method is less expensive and easier to use for identifying plant disease through leaf symptoms. Utilizing an automated detection method reduces the amount of time, effort, and accuracy required. Leaf illness cannot be manually detected with the naked eye without the assistance of a team of experts and constant observation.

Applications of artificial intelligence (AI), such as machine learning (ML), allow a system to learn from its past experiences and get better without the need for programming [5]. To properly detect the object or illness, image analysis techniques, such as ML, may be used to identify the diseased leaf and estimate the boundaries of the afflicted region [6]. The DL approaches are widely used to categorize plant diseases due to their high efficacy. Among all DL techniques, a deep CNN is the most commonly utilized for crop disease detection. Plant disease detection has been done using a DL system called YOLOv5, which has been enhanced. The principal objective of this review article is to examine and critically assess the different methods, such as models, used in PD detection using ML and DL techniques.

The following goals are intended to be accomplished by this review:

- To assess and investigate the most recent DL methods for detecting tomato leaf disease.
- To review various datasets, preprocessing and model architectures used in tomato disease classification.
- To assess how smart farming technologies (i.e., IoT, drones, and cloud computing) can help in disease monitoring.
- To detect major obstacles and weaknesses of existing automated disease detectors.

A. *Structure of the Paper*

This paper is organized as follows: Section II overview of Smart Farming's Automated Tomato Leaf Disease Detection Initiative. Section III discusses DL approaches for tomato leaf disease detection. Section IV presents application, future work and challenges. The literature is reviewed in Section V. Section VI, Conclusions.

II. Overview of Automated Tomato Leaf Disease Detection in Smart Farming

Tomato plants, also known as Solanum lycopersicum, have long been regarded in terms of its nutritional content, as one of the most significant crops. Bacterial spots, fungus, algae, and other organisms are the ones that cause the majority of diseases that occur when tomatoes are planted [7]. As seen in Fig. 1, there are 9 groups of disorders and healthy classifications in tomatoes: 1) The target spot 2) Mosaic Virus, 3) Bacterial Spot, 4) Late Blight, 5) Leaf Mould, 6) Yellow Leaf Curl Virus, 7) Spider Mites: Two-Spot Spider Mite, 8) Early Light, and 9) Septoria Leaf Spot and Healthy Class Diseases. Tomato plant leaf disease, or late blight, was very harmful.

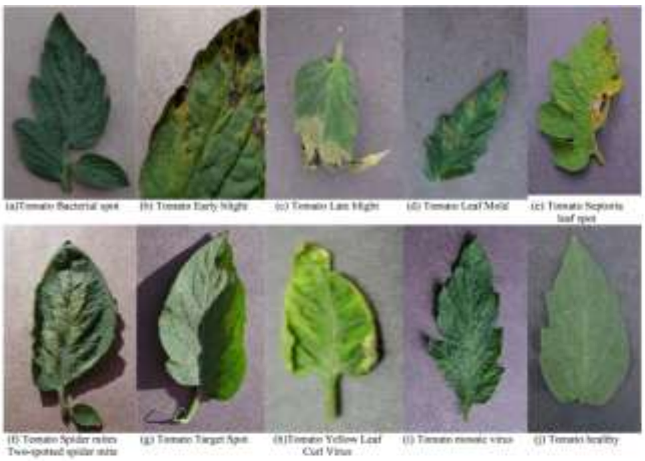

Fig. 1. Sample images of the tomato leaf.

- **Fungal Diseases**

It is possible to link fungus or organisms with comparable structures to around 85% of PD. Because fungus and bacteria are so little and light, they just need to settle on a nearby surface to infect neighboring plants and trees. In addition to being vulnerable to insect pests, tomatoes can develop various plant diseases caused by fungi that result in disease spots on the fruit, leaves, and stems. The three types of fungal diseases include leaf mould, early blight, and septoria-leaf spot.

- **Bacterial Diseases**

There are around 200 different kinds of bacteria that cause it. Other infected plants, insects, splashing water, or equipment can all transmit the disease. Similar to peppers, peppers are now susceptible to disease. During wet seasons, The sickness spreads more often. Spots on fruits and foliage can harm plants or result in their withering and eventual death due to solar damage, in addition to lowering agricultural productivity. Symptoms include angular to uneven, moist to dry, and fruit with purchase or scabby areas on the leaves.

- **Viral Diseases**

This type of plant disease is the rarest and is brought on by viruses. To stop the infection, all questionable plants should be killed because there are no chemical treatments for viruses after they have spread. The most frequent carriers are insects, which must physically enter the plant.

By examining different disease allows one to observe the different types of procedures and factors that need to be taken into account. A number of disease variants are covered in more detail.

- **Bacterial Spot:** Bacterial infections refer to the areas produced by the bacterium Xanthomonas. When heat, rain, and high temperatures are coupled, crops may suffer damage and lose their leaves [8].
- **Early blight:** Early blight is caused by bacteria or fungi. First, little black dots show up on elder leaves. Dead, dried leaves that adhere to the stem or brown and fall off are two possible outcomes of infection.
- **Late Blight:** Fungal infections induce late blight. Late blight on leaves is indicated by water-soaked lesions that are irregularly shaped and have a lighter halo.
- **Leaf Mold:** Leaf mould, which is classified as a fungus by scientists, grows best in moist environments with high relative humidities (over 85%). The disease's primary symptom is yellow patches on the top leaf surface.
- **Septoria Leaf spot:** The leaves are attacked by a fungal disease called Septoria Leaf Spot. After the first fruit forms, it usually appears on the lower leaves. Each leaf has several round patches with dark brown edges and numerous dots. When several leaf lesions are present, the leaves initially become yellow, then brown, and eventually wither.
- **Two-spotted spider mite:** Tomato leaves might develop white spots due to the two-spotted spider mite. Plant leaves with diseased patches become yellow or grey before going away after consuming a lot of insects for several days.
- **Target spot:** Tomatoes thrive at temperatures between 68 and 82 degrees. Fahrenheit with 16-hour intervals between leaf wetness. It results in the formation of circular necrotic tumors on leaves.
- **Target Mosaic virus:** The primary cause of crop loss resulting from tomato plant yellowing and shrinkage is the tomato mosaic virus. Leaves that are twisted, curled, or unusually tiny are symptoms.
- **Yellow leaf curl Virus:** This virus, to put it simply, causes enormous financial losses in tropical and subtropical areas. This illness is spread by the fungus gnats, a kind of insect. Because of this illness, leaves get significantly smaller and curl or cup upward.

A. Importance of early detection

There are several reasons why early detection of tomato leaf diseases is essential:

- **Preventing Disease Spread:** Early disease detection enables prompt treatment, perhaps stopping the spread of the illness to healthy plants. For example, farmers can uproot and kill ToMV-infected plants when they are identified early. This stops the virus from propagating by vectors or mechanical means or vectors.
- **Reducing Economic Losses:** Conserving agricultural productivity and quality, early action can cut down on financial losses considerably. In the absence of treatment, illnesses such as late blight can cause catastrophic losses. The use of suitable fungicides and cultural activities that reduce damage is made feasible by early detection.
- **Enhancing Treatment Effectiveness:** The stage of the disease at which a therapy is administered frequently affects how effective it is[9]. In general, early-stage therapies work better. Additionally, compared to therapies in advanced stages of the disease, they demand less extensive resource input. For instance, fungicides can be used as soon as Early Blight signs appear to successfully restrict the disease's development.
- **Promoting Sustainable Agriculture:** Disease detection in a timely manner supports sustainable farming methods. Overuse of chemicals can be decreased with effective management. This lessens farming's negative effects on the environment. It also encourages ecological harmony.

B. Image Acquisition Methods

In the area of agricultural applications for DL-based image processing, cell phones and drones are two popular ways to acquire images. Both approaches have special advantages as well as challenges:

- **Mobile Phones:** Mobile phones are affordable, accessible, and easy to use [10]. They make it possible to take close-up, high-resolution images that are perfect for catching the fine details of tomato leaves. Both farmers and scholars can benefit from this approach. It makes regular monitoring possible without necessitating a large expenditure on specialized machinery.
- **Drones:** Drones can efficiently cover big regions by taking images from a range of angles and elevations. They are especially useful for surveying areas and finding trends that might point to the spread of disease. However, little study has been done on utilizing drones to capture an image of tomato leaves.

C. Cultivating Insights: Precision Agriculture

Technology-driven agricultural concepts include smart farming and precision farming that concentrate on organizing and preparing the agricultural sector to employ cutting-edge technology like DL and ML for operations monitoring and tracking, analysis, automation, and execution [11]. In the field of smart farming, ML and DL algorithms have several uses. At the moment, technology-driven tools are used for everything from choosing a certain piece of land for farming to turning the produced crops into consumable foods.

1) Maintaining crop health

It takes time to continuously examine crops in order to optimize their health. The health of the crops is affected by a number of internal and external variables. Plant development requires a variety of factors, including adequate soil conditions, temperature, sunshine, and rainfall. A good crop output is not certain even if the plant obtains all of these prerequisites. They may become ill and barren due to internal factors including insect infestation, infections, or broken seeds.

2) Production of high-quality yield

A difficult aspect of both small- and large-scale farming is producing high-quality output. This is mostly due to the fact that several factors affect yield production, including soil, climate, water supplies, temperature, etc, [12]. Therefore, a good quality yield is the consequence of a healthy mix of all these components.

3) Crop Management and Harvesting

Crop management is a crucial component as it plays a big part in a country's economy. As a result, it is essential to ensure that they are being properly monitored at regular intervals. However, managing the crops on a huge countryside is never easy. Additionally, doing this by hand is significantly more tedious.

4) Seeds and sapling Quality Prediction

The quality of the seeds utilized is another difficult aspect of crop development. It is useless to plant a dormant or unhealthy seed, even if the farmers employ high-quality terrain [13]. Therefore, it is crucial to ensure that the seeds and saplings employed are robust and fruitful. In the past, it was an impossible feat. But these days, it can quickly determine a seed's health with the use of technologies like ML, DL, etc.

D. Plant Leaf disease Datasets

This study examines datasets for tomato leaf disease identification in its primary portion. The application of DL techniques is highlighted. A wide variety of images are available in these databases. For accurate disease detection, they make it possible to produce and assess reliable models. A brief description of the datasets used to identify tomato leaf diseases is shown in Table I:

- The PlantVillage database's **tomato plant disease dataset** includes folders for testing, validation, and training. Nine illness kinds and one sample of a health type are included. There are 14,000 images available for testing. Lastly, extraneous photographs are eliminated from the collection, and the 256 * 256 image size is decreased to 227 * 227.
- The dataset used in this work to assess the algorithms' performance is extensive and diverse, drawn from the Roboflow platform's publicly available **tomato leaf disease dataset**. Approximately 18,000 images were produced as a consequence, making this a useful dataset for testing and training ML models [14]. 9 of the 10 groups it was divided into reflected disease classifications that were specific to tomato plant diseases. The illnesses that are part of the dataset include Spider Mites, Mosaic Virus, Yellow Leaf Curl Virus, Bacterial Spot, Early Blight, Late Blight, Leaf Mould, Septoria Leaf Spot, and Target Spot. In order to provide a baseline for comparison versus sick

specimens, there was also a class devoted to healthy tomato leaves.

- The **PlantVillage dataset** used in this investigation included 14,536 pictures, each measuring 227 by 227 pixels. The images must be adjusted to the proper size in order to guarantee that they work with the chosen model. This was accomplished by utilizing Python code to scale the PlantVillage dataset's images to 224*224 pixels (TensorFlow Hub) [15].

TABLE I. SUMMARY OF TOMATO LEAF DISEASE DATASETS

S.No	Dataset Source	Total Images	Image Size	Number of Classes	Disease Types
1	Tomato plant disease dataset	~14,000 images	Resized from 256×256 to 227×227	10 classes (9 diseases + 1 healthy)	Bacterial Spot, Mosaic Virus, Yellow Leaf Curl Virus, Leaf Mould, Septoria Leaf Spot, Spider Mites, Target Spot, Early Blight, Late Blight, and Healthy
2	Tomato Leaf Dataset	18,000+ images	Varies (standardized during preprocessing)	10 classes (9 diseases + 1 healthy)	Early Blight, Late Blight, Bacterial Spot, Leaf Mould, Septoria Leaf Spot, Spider Mites, Target Spot, Mosaic Virus, Yellow Leaf Curl Virus, and Healthy
3	PlantVillage dataset	14,536 images	Resized to 224×224	10 classes	Same as above (9 diseases + healthy)

E. Preprocessing and Data Augmentation

The collected information known as images may have outlier and unclear images, so preprocess them or clean them to build up a model. Comparatively preprocessed or cleaned data give better accuracy than uncleaned data. Resizing should be done to constant size as the images come from various locations, must resize the images to maintain consistency. Normalizing the pixel value make the neural network to learn easily. A after preprocessed images as shown in Fig. 2. Data augmentation can also be done it does flip, shifting and changing the brightness on the images. Blurring of image is done to reduce the noise of the image.

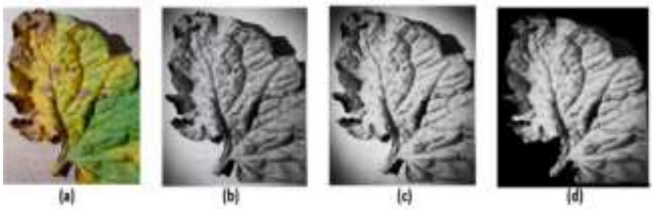

Fig. 2. A preprocessed images.

As explained in the next section, the images may now be used as input for the DL following preprocessing.

III. DEEP LEARNING APPROACHES FOR TOMATO LEAF DISEASE DETECTION

In DL, the main goal of picture classification is to train a computer system. CNNs are mostly used for object or pattern recognition and classification in images. By acting as effective feature extractors, they conserve computer power. Through the application of information from one classification problem to another, transfer learning improves model performance. Choosing the input layers, output classes, and hyperparameters is part of the model setup process. Appropriate training and the right classification technique are necessary for a successful categorization. The ultimate goal of the procedure is to produce accurate and effective models for diagnosing tomato diseases from images. The steps involved in creating a model for tomato plant disease detection are explained below:

A. Basic CNN Architectures

CNN have become widely adopted for detecting leaf diseases, representing a significant application of ML and DL in agriculture [16]. CNNs' layered convolutional filters have the innate ability to automatically extract pertinent elements from image. Firstly, gathered high-resolution images of tomato leaves, capturing both healthy specimens and those exhibiting signs of disease. The collected images effectively depict various diseases that impact tomato plants. The images underwent resizing and preprocessing to optimize them for CNN analysis [17]. This provided dataset was used to train the CNN model, which had convolutional, pooling, and fully connected layers. For accurate diseases detection and categorization, CNN's architecture is designed. The normalized input images of size 256 × 256 pixels for efficient training [18]. Fig. 3 illustrates how the convolutional layer creates an output feature map by convolving the input picture, which is represented in n-dimensional metrics, using convolutional filters.

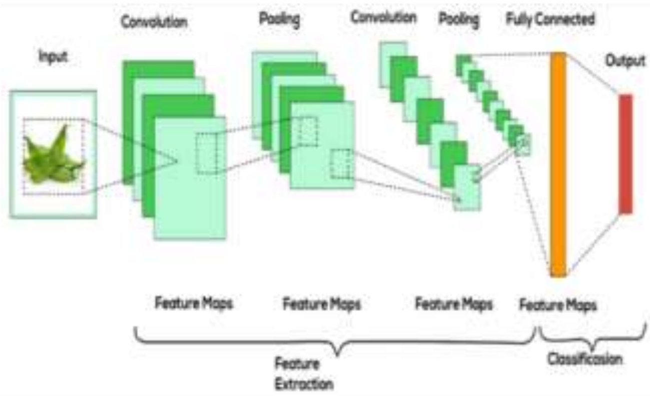

Fig. 3. CNN Architecture.

B. MobileNetV2

The productivity and numerous diseases cause tomato plants' quality to steadily decline. Early detection of tomato plant diseases might reduce crop loss and increase yield [19]. This study extracts information from each tomato image to aid in categorization using a pretrained model called MobileNetV2. It may be applied to a variety of situations and is also known as a lightweight CNN model. Additionally, it offers increased efficiency and accuracy, and real-time applications are where it is most frequently utilized. The objective of employing the MobileNetV2 model for tomato plant disease detection.

C. Inception–V4

An extension of the Image Net idea is the Inception V4 deep CNN network, which has 48 layers. Maximum pooling layer, average pooling (8 × 8), Some of the symmetric and asymmetric blocks of the model include maximum pixel, which reduces the computing cost parameters for learning, and convolution, resulting in a feature map when a filter is applied to an image.

D. VGG–16

A deep CNN model called the "visual geometry group," or VGG, was created by Oxford University for the 2014 "Image Net Large scale recognition of visual challenge" (ILSVRC). As far as DNNs go, this topology provides the greatest function to date [20]. This structure only focuses on the results of the softmax layer with the padding convolution layer, fully connected layer, and max pool, despite the fact that there are several additional kinds of parameters 5.3.

E. VGG –19

In terms of image identification, this resembles VGG-16 and other VGG variants with three convolution layers as an additional feature. The basic idea is to build DNN that are moderately sized and have continuous convolution.

F. YOLOv5

The improved object detection model YOLOv5, which was made available in 2020, is ideal for identifying tomato leaf disease [21]. To improve the detection of tiny objects, it uses spatial pyramid pooling and dynamic anchor boxes. Its architecture consists of a YOLO head for bounding box, score, and classification prediction, a CSPDarknet backbone for feature extraction and an improved PANet neck for feature aggregation with BottleNeckCSP and Spatial Pyramid Pooling.

G. ResNet18

A deep residual network called ResNet-18 was created to enhance gradient flow and use residual learning to lessen the vanishing gradient issue. Its 18 layers, which improve feature extraction and training effectiveness through shortcut connections, are built utilizing convolutional layers, batch normalizations, and ReLU activations on residual blocks. ResNet-18, despite its small size, performs well on tasks such as object identification and image categorization.

IV. Applications, Challenges, and Future Scope in Smart Agriculture

This section highlights the primary applications, challenges, and possible uses of DL-based automated tomato leaf disease detection in smart agriculture.

A. Applications in Smart Agriculture for Automated Tomato Leaf Disease Detection

Tomato leaf disease detection-based DL implementation in smart agriculture has contributed greatly to the current farming practices. AI, the IoT, drones, and cloud computing may all be utilized to monitor plants in real time and identify diseases early. These automated systems aid farmers in making timely decisions, minimize losses on crops and enhancing productivity.

- **Real-Time Crop Monitoring:** Deep learning applications that can be used along with phones and cameras allow real-time tracking of tomato plants. The farmers are able to immediately take pictures of leaves and identify diseases early enough to avoid major losses of crops.
- **Surveillance of disease using drones:** Surveying vast tomato plantations is one of the many uses for UAVs in smart agriculture. Aerial shots are captured by drones and processed with AI models to detect disease locations with high precision and speed.
- **Smart Farming Systems based on IoT:** IoT sensors are used to measure the environmental parameters like the temperature, humidity, and soil moisture [22]. These sensors, together with DL systems, are useful in predicting the occurrence of diseases and delivering automatic warnings to preventive measures.
- **Decision Support Systems on Cloud:** The agricultural data that is obtained in the farms are stored and processed by cloud platforms. The role of DL models on the cloud is to perform disease analysis, offer suggestions on how to manage the disease, and offer data visualization dashboards to achieve improved farm management.

B. Challenges and Limitations

The following factors make it difficult to identify plant viruses using only visual characteristics:

- **Data Scarcity and Imbalance:** The majority of existing models rely significantly on sizable, well annotated datasets, like PlantVillage [23]. Regretfully, these datasets frequently fall short of capturing the entire spectrum of uncommon diseases or crop changes that are peculiar to a given location and found in real agricultural environments. This can lead to biased or faulty model projections, especially for scenarios that are under-represented.
- **Limited Availability of Region-Specific Datasets:** The absence of locally specific datasets limits the capacity of many models to adjust to local farming circumstances. Additionally, these systems' actual usefulness across varied communities is further limited by their lack of support for local languages and pesticide usage information.
- **Model Complexity and Resource Demand:** Deep CNNs are known for their great accuracy, although they frequently need significant amounts of computing power for both training and inference. Implementation on low-resource devices, such as cellphones or embedded systems commonly utilized by farmers, is hindered by the need for high-end hardware, such as GPUs.
- **Integration with Pesticide Recommenders:** Real-time, context-aware, and regulatory-compliant pesticide advice is still lacking, despite the fact that plant disease classification models have advanced significantly. There is still a lack of effective integration of these components.
- **Explainability and Trust:** The "black box" aspect of DL models is a common criticism, which can erode user confidence, particularly among non-technical stakeholders like farmers. This problem is made worse by the absence of concise, understandable explanations or demonstrations for model decisions.
- **Regulatory and Safety Concerns:** It is necessary for automated pesticide recommendation systems to adhere to changing agricultural safety regulations. Despite the need of keeping pesticide databases current, this part is frequently overlooked, which might pose safety and regulatory concerns.

C. Future Research Directions

Further studies in automated tomato leaf disease detection through DL ought to consider enhancing the accuracy of models, real-time applications, and combined applications with smart farming technologies. Despite the fact that tremendous steps have been undertaken, there are still challenges that comprise limited field datasets, high cost of computation, and deployment in rural areas.

- **Creation of Lightweight Deep Learning Models:** The researchers in the future consider developing light and powerful models that can be operated on smartphones and other low-energy powered devices, in order to make it possible to allow real-time illness detection outside of the field.
- **Support of IoT and Edge Computing:** Embarking on deep learning and IoT sensors along with edge computing would allow processing data faster and predicting diseases in real-time without having to rely on cloud computing.
- **Multi-Crop and Multi-Disease Detection Systems:** Future studies can examine integrated systems with the potential to monitor various diseases in various crops, which would result in the system being more feasible in terms of smart farming.
- **Interpretable and explainable AI Models:** Explainable AI methods assist the farmers and agricultural professionals to see how the deep learning models arrive at their predictions and enhance trust and acceptance of the system in the real world of farming.

V. Literature of Review

In this section, the presentation of earlier studies on tomato leaf disease detection. Table II offers an organized comparison of earlier studies with an emphasis on Dataset, Model, Accuracy, Key Contributions and Limitations/Future Work.

Mohebbanaaz et al. (2025) focus on increasing forecast accuracy, guaranteeing scalability, and preserving resilience under a variety of environmental conditions. The Plant Village Dataset is considered in this research. By developing affordable and user-friendly tools, this research seeks to help farmers better manage plant diseases and promote sustainable agricultural practices. The proposed model, Deep Neural Network (DNN), achieved an accuracy of 98.17%. The findings demonstrate how AI-driven methods have the potential to completely change disease detection and improve agricultural output [24].

Chebrolu et al. (2025) explore AI-driven approaches, integrating DL and ML methods for automated disease detection. This study employs CNNs, specifically leveraging the VGG16 architecture for feature extraction. Additionally, compare its effectiveness with classical classifiers such as KNN and SVM. Using a publicly available dataset of tomato leaves with and without diseases, the results demonstrate that CNN-based models perform more accurately and efficiently than conventional ML classifiers [25].

Verma and Kaur (2025) performed using four DNN architecture models viz. AlexNet, DenseNet, Inception and Xception on the tomato Leaf Disease dataset. In this process, firstly, the raw images are preprocessed and segmented, which are subsequently fed to the respective four models. Each model extracts the features based on their architecture and produces the classification results with train-test-validation mechanism. Among all models, Exception and the accuracy of AlexNet models is superior than that of other models metric having values as 95% and 90% respectively [26].

Srivastav et al. (2024) using the MobileNet architecture, suggest a novel deep-CNN-based model for tomato leaf disease detection. Finally, the proposed MobileNet model are trained for identifying these five prevalent Tomato leaf diseases utilizing a dataset of 962 images of diseases tomato leaves for the leave-out test. The detection performance of the proposed framework is demonstrated experimentally to be 95.79% mAP [27].

Kumar, Taluja and Kumar (2024) expect a synthesized picture of the current literature concerning the procedure that seeks to employ DL techniques to diagnose diseases affecting tomato leaves. The approaches used in the survey make it possible to achieve high accuracy rates of the DL models; some of the models are characterized by an accuracy of more than 95%; thus, can be applied to practical use in the agricultural industry. It also explains some of the issues like lack of supply of data, much complexity of the model and computational resources that are needed [28].

Bahrami, Pourhatami and Maboodi (2024) the PlantVillage and CCMT datasets were used to test several transfer learning algorithms, such as VGG19, ResNet-101, and MobileNet-v2. On the test set of the PlantVillage and CCMT datasets, VGG19 performed the best, with the greatest acc, pre, rec, and F1 being 99.48%, 99.27%, 99.28%, and 99.27%, and 92.76%, 92.74%, 95.09%, and 90.86%, respectively. The results demonstrate that VGG19 can detect tomato leaf disease precisely and robustly [29].

Deepika and Arthi (2023) tomato plant diseases are examined using DenseNet121, AlexNet, ResNet50, EfficientNetB5, Inception_Resnet_V2, InceptionV3, MobileNet, VGG16, and VGG19 are the DL architectures. Images of tomato leaves taken from the actual environment are used for implementation. When the nine architectures are compared, DenseNet121 and MobileNet outperform the other DL architectures in terms of accuracy [30].

Srivastava, Sisaudia and Meena (2023) to identify tomato leaf diseases, first propose a hybrid approach using transfer learning and ELM. TLMV2-ELM model includes MobileNetV2 for feature extraction that generates efficient feature vectors, which are then categorized using ELM. The TLMV2-ELM method is validated using a tomato leaf dataset, and the results of the experiment show that it outperforms current approaches with 0.99% accuracy and 0.06 loss in terms of disease detection [31].

Tej et al. (2022) is employing DL techniques to identify and categorize different tomato and pepper diseases. With and without data augmentation, two models of CNNs, Resnet 152 and Resnet 50, are employed. This technique adds more training images without developing any new ones, making it appropriate for limited datasets. An agricultural engineer employed by the plant protection section of the Minister of 488 images of tomato and pepper disease leaves from the Monastir, Tunisia, region were collected by agriculture and comprise the self-dataset [32].

TABLE II. COMPARATIVE ANALYSIS OF DEEP LEARNING-BASED TOMATO LEAF DETECTION METHODS

Author & Year	Techniques/Models Used	Dataset Used	Key Results	Limitations / Future Work
Mohebbanaaz et al. (2025)	Deep Neural Network (DNN)	PlantVillage dataset	Accuracy: 98.17%	Needs improved scalability across diverse crops and real-time deployment under varying climatic conditions.
Chebrolu et al. (2025)	CNN (VGG16), KNN, SVM comparison	Tomato leaf dataset	CNN outperformed ML models in accuracy and efficiency	Limited to tomato leaves; future work should focus on multi-crop disease detection and lightweight models.
Verma & Kaur (2025)	AlexNet, DenseNet, Inception, Xception	Tomato leaf dataset	Xception: 95%, AlexNet: 90% accuracy	Requires dataset expansion and real-time mobile deployment for field-level disease monitoring.
Srivastav et al. (2024)	MobileNet-based deep CNN	962 tomato leaf images	mAP: 95.79%	Small dataset size; future work should include large-scale datasets and cross-environment testing.
Kumar, Taluja & Kumar (2024)	Survey of deep learning models	Multiple datasets	>95% accuracy reported in many models	Highlights the need for large annotated datasets, reduced computational complexity, and efficient resource usage.
Bahrami et al. (2024)	Transfer learning (VGG19, ResNet101, MobileNetV2)	PlantVillage & CCMT datasets	VGG19: 99.48% accuracy (PlantVillage)	Performance drops in real-field datasets; future work should focus on robustness in natural environments.
Deepika & Arthi (2023)	Multiple DL models (DenseNet121, MobileNet etc.)	Real-time tomato images	DenseNet121 & MobileNet performed best	Requires optimization for low-power devices and real-time smart farming applications.
Srivastava et al. (2023)	Hybrid TL + ELM (MobileNetV2-ELM)	Tomato leaf dataset	Accuracy: ~99%, Loss: 0.06	Needs validation on multi-disease and multi-crop datasets with real-time deployment.
Tej et al. (2022)	ResNet50, ResNet152 with augmentation	Self-collected dataset (488 images)	Effective classification with augmentation	Limited dataset size; future research should use large-scale datasets and cloud-based detection systems.

VI. CONCLUSION AND FUTURE WORK

A significant development in smart farming, tomato leaf disease identification with DL offers a dependable and effective way to enhance crop health management. The tomato crop is highly susceptible to bacterial, viral, and fungal diseases, which significantly reduce yield and quality. This review has discussed the different DL architectures developed such as CNN, MobileNet, VGG, ResNet, Inception, and YOLO that have been able to perform well in identifying and categorizing tomato leaf diseases using image collections such as PlantVillage and other open-source repositories. Combining preprocessing, data augmentation, and transfer learning enhances the model's accuracy and durability. Nevertheless, issues such as the scarcity of real-field data, class imbalance, computational complexity, lack of interpretability, and deployment in rural environments are all important issues. By tackling such constraints by incorporating lightweight models, edge computing, IoT integration, and explainable AI frameworks, it will enhance practical application. Generally, the disease-detecting systems using deep learning are crucial to facilitating precision agriculture, supporting sustainable agriculture, minimizing economic losses, and enhancing food security in the world by developing intelligent crop surveillance systems.

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