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A Detailed Survey of Deep Learning Frameworks for Early Prediction and Classification of Tomato Leaf Diseases

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***Abstract*—Tomato leaf diseases caused by bacterial, viral, and fungal pathogens constitute a significant global barrier to agricultural production and tomato crop quality. Early and correct diagnosis/detection are crucial to limit economic losses and sustainable farming. Using leaf images for identifying diseases of the plant has proved to be a good solution, and recently with the advent of Artificial Intelligence (AI) and Deep Learning (DL) it has been possible to find a more efficient solution. This paper offers a thorough evaluation of DL frameworks for the early detection and classification of tomato leaf disease. examination of several methods, including hybrid DL models, Vision Transformers (ViTs), Convolutional Neural Networks (CNNs), transfer learning models, and their accuracy and performance. The study also explores and discusses commonly used agricultural datasets, preprocessing strategies, feature extraction techniques, and performance assessment measures (such as accuracy (ACC), precision (PRE), recall (REC), F1-score (F1), and ROC-AUC). Furthermore, recent advancements in Explainable AI (XAI), Edge AI and small DL models for Smart Agriculture applications were highlighted. Lastly, challenges, limitations and future directions of real-time tomato disease detection systems are discussed.**

Keywords—Tomato Leaf Disease, Deep Learning, Precision Agriculture, Image Classification, Explainable AI (XAI).

I. Introduction

In order to sustain human existence and supply necessary food resources, the agricultural sector is crucial. Both human health and the global farming industry depend heavily on the health of plants and prompt and accurate identification of plant diseases. A major issue for the agricultural sector is the presence of pests and illnesses that affect plants. Agricultural quality and productivity are jeopardized by pests and plant diseases, which can result in substantial food and financial losses [1]. Bacteria, viruses, fungi, and environmental stressors can cause a wide range of diseases in tomatoes.

In addition to being widely used in agriculture, tomatoes are useful in everyday kitchens. Despite fact that tomato consumption has grown dramatically in recent years, a number of diseases, poor soil, climate change, and other environmental issues have hindered tomato production [2]. Organic factors cause tomato leaf diseases (TLD). Rainfall, inappropriate fertilizer, chemical toxicity, and temperature imbalances, inadequate nourishment, and other non-living factors can cause plant diseases. Vitamin C, potassium, vitamin K, folate, and many more minerals and vitamins are abundant in tomatoes. There are a number of pests that can damage tomatoes, including bacterial spots, early and late blossom curl viruses, spider mites, leaf mold, target spot, and tomato mosaic virus. Farmers may find it challenging to accurately diagnose illnesses due to a lack of knowledge.

It is essential to identify TLD early and accurately. It assists farmers in acting quickly to stop spread of disease. There is little doubt that larger yields and better harvests are produced. Automating disease diagnosis using AI and image processing presents a fresh approach to a persistent agricultural issue, given growing need on the rise of precision farming and ecologically sustainable farming methods [3]. The number of skilled workers needed in agricultural areas for disease monitoring and detection was lowered to ML and DL. Precision agriculture advances as plant image collections improve, because algorithms have more photos to analyze, which enhances early disease identification and control and yields more accurate detection results. In the beginning, researchers employed manual approaches such as backpropagation networks, SVMs, RFs, KNNs, and NB to extract features and categorize diseases. Tomato plant diseases may be detected using DL. Because DL employs several neural network convolution techniques, it can achieve object identification and disease categorization more accurately than ML. Among the DL algorithms are CNNs, RNNs, GANs, LSTMs, and others. TLD identified and categorized utilizing images and DL.

This review paper aims to examine and assess various methods, including models, for diagnosing plant diseases using ML and DL. This review focuses on the following objectives:

- To study various diseases of tomato and their effect on agricultural productivity.
- To research various ML and DL methods used for tomato leaf disease diagnosis and classification.
- To assess CNNs, Vision Transformers, Hybrid DL models, and Transfer learning models' performance.
- To learn about commonly used agricultural dataset, pre-processing techniques, and Feature extraction techniques.

- ACC, PRE, REC, F1, and ROC-AUC are used to compare current models. To learn about latest developments in smart agriculture, like Explainable AI (XAI), Edge AI and lightweight DL models.

A. *Structure of the Paper*

The paper is organized as follows: Section II includes information on categorization of diseases affecting tomato leaves and need to detect them early. Section III presents DL models including CNNs, transfer learning, Vision Transformers and hybrid models. Section IV presents the literature review and compares and contrasts the current models. Lastly, Section V presents limitations and future research directions.

II. CLASSIFICATION AND ANALYSIS OF TOMATO LEAF DISEASES

The tomato (Solanum lycopersicum) is grown worldwide and has a substantial economic impact because of its superior nutritional value and adaptability in both unprocessed and processed versions. However, a number of diseases that affect different plant parts, such as leaves, stems, and fruits, often pose a barrier to tomato production. Fungal, bacterial, and viral infections are main causes of these diseases, which cause farmers to suffer large financial losses, reduced fruit quality, and severe production losses. Fig. 1 (a) shows how insect-vectored viral infections like TYLCV and TSWV frequently enter young apical leaves. (b) Fungal infections (such early blight and septoria) and bacterial diseases (like bacterial spot and speck) mostly affect leaves (c) Secondary bacterial and fungal diseases harm fruits. (d) Bacterial wilt is especially dangerous for stems and vascular structures.

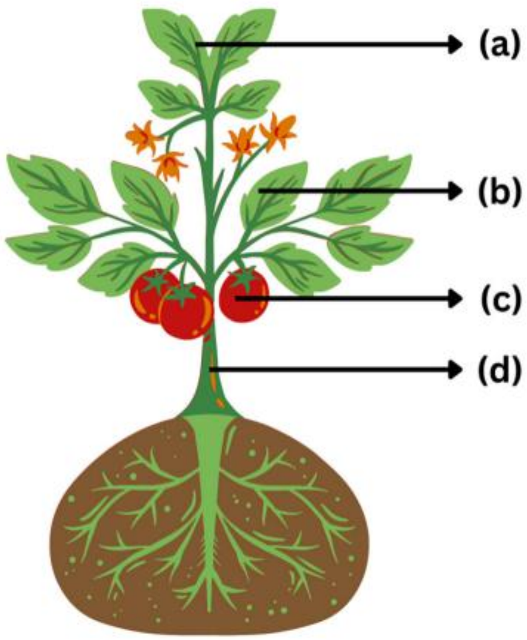

Fig. 1. Schematic diagram of the tomato plant showing disease-prone regions by type of pathogen

A. *Disease Type and Detection Stage*

Fig. 2 and Table I illustrate the nine types of disorders and healthy classes found in tomatoes: Diseases affecting the healthy class include target spot, early light, septoria leaf spot, mosaic virus, bacterial spot, leaf mold, yellow leaf curl virus, two-spotted spider mite, and others. The deadly tomato plant disease known as late blight affects the leaves of the plants.

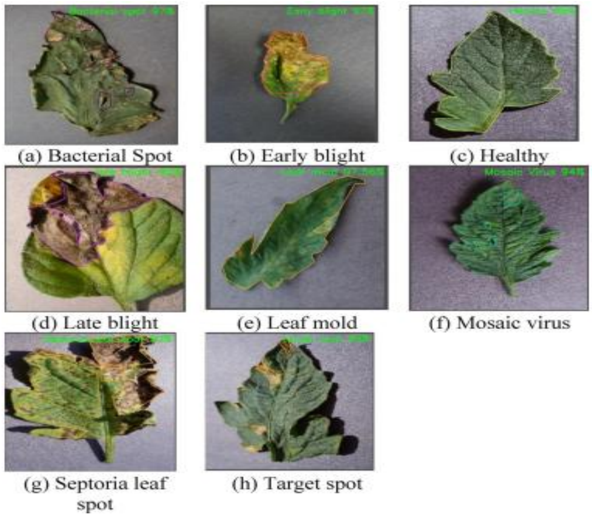

Fig. 2. Detection of tomato leaf diseases

- **Viral Diseases:** Once a plant becomes infected, viral infections like ToMV and YLCV are difficult to eradicate. Plant cells are infected by viruses. They are hard to manage and spread quickly. Nonetheless, virus's spread is manageable. The contaminated plants can be removed and destroyed right away to accomplish this. This stops additional spread to healthy plants in the vicinity.
- **Fungal Diseases:** If caught early, fungal infections like EB and LB can occasionally be successfully treated. Fungicides can stop or delay disease progression. This works particularly well in the beginning.
- **Bacterial Diseases:** From infected plants, bacterial infections are hard to eradicate. As with viral infections, early identification primarily aids in stopping their spread. It is not intended to treat the diseased plants.
- **Bacterial Spot:** Bacterial infections are defined as spots caused by the Xanthomonas bacteria. It can lead to crop damage and leaf loss when accompanied with high temperatures, heat, and rain.
- **Early blight:** Bacteria or fungus are the root of early blight. Little black spots first appear on elder leaves. Infected leaves may turn dry and dead and adhere to the stem, or they may turn brown and fall off.
- **Late Blight:** Late blight is caused by fungal pathogen viruses. Late blight in leaves manifests as Water-soaked, asymmetrical lesions with a lighter halo ring.
- **Leaf Mold:** According to science, Leaf Mold is a fungus that grows best in moist environments [24] and elevated relative humidity levels (over 85%). The diseases are shown by yellow spots on the top leaf surface.
- **Septoria Leaf spot:** The fungal disease known as Septoria Leaf Spot damages leaves. After first fruit has developed, it often appears on lower leaves. Each leaf has several dots and many circular sections with dark brown edges. When there are several leaf lesions, the leaves eventually become yellow, brown, and wither.
- **Two-spotted spider mite:** Tomato leaves get white markings due to the two-spotted spider mite. After many days of intense insect feeding, plant leaves develop diseased patches and become yellow or grey before dropping off.

- **Target spot:** The optimal temperature range for tomato development is 68 to 82 degrees Fahrenheit, with up to 16-hour intervals between leaf wetness. It causes leaves to develop round, necrotic lumps.
- **Target Mosaic virus:** One of main reasons for crop loss brought on by tomato mosaic virus is the yellowing and shrinkage of tomatoes. Symptoms include curled, deformed, or unusually tiny leaves.
- **Yellow leaf curl Virus:** In short, tropical and subtropical regions, the Yellow Leaf Curl Virus results in significant financial losses. This disease is spread by a species of insect called fungus gnats.

TABLE I. SUMMARY OF MAJOR TOMATO PLANT DISEASES

Disease	Causal Organism	Category	Key Symptoms	Transmission	Geographical Impact
Bacterial Spot	Xanthomonas spp.	Bacterial	Dark leaf spots, yellowing	Seeds, rain splash, tools	Warm and humid regions
Early Blight	Alternaria solani	Fungal	Brown concentric spots, leaf drop	Airborne spores, soil	Worldwide tomato farms
Late Blight	Phytophthora infestans	Fungal	Water-soaked lesions, decay	Wind and infected plants	Cool and humid areas
Leaf Mold	Cladosporium fulvum	Fungal	Yellow spots, mold growth	Airborne spores	Greenhouses and humid climates
Septoria Leaf Spot	Septoria lycopersici	Fungal	Small brown lesions, wilting	Water splash, debris	Wet and warm regions
Two-Spotted Spider Mite	Tetranychus urticae	Pest	White spots, yellow leaves	Wind and infected plants	Hot and dry regions
Target Spot	Corynespora cassiicola	Fungal	Circular necrotic spots	Spores and rain splash	Tropical regions
Tomato Mosaic Virus	ToMV	Viral	Mosaic leaves, distortion	Contact and seeds	Worldwide
Yellow Leaf Curl Virus	TYLCV	Viral	Yellow curled leaves, stunting	Whiteflies	Tropical and subtropical areas

B. Importance of Early Detection

TLD must be identified early for a number of reasons:

- **Preventing Disease Spread:** Early disease detection enables prompt action, which helps stop diseases from spreading to healthy plants [4]. For example, growers can uproot and destroy damaged specimens when ToMV-infected plants are identified early. Viruses cannot spread by vectors or mechanical transfer because of this.
- **Reducing Economic Losses:** By maintaining agricultural output and quality, prompt action can significantly lessen financial losses. Immediate treatment is essential in preventing massive losses caused by diseases such as late blight. In order to reduce damage, early identification allows for use of appropriate fungicides and cultural methods.
- **Enhancing Treatment Effectiveness:** The stage of the disease at which a treatment is implemented frequently affects how successful it is. In general, early-stage therapies are more successful. Additionally, compared to therapies, they demand less extensive resource input. in a later stage of the disease. For instance, using fungicides as soon as Early Blight signs appear can successfully stop the disease's development.
- **Promoting Sustainable Agriculture:** Sustainable farming operations are facilitated by prompt disease identification. Reducing the need for excessive chemical inputs is facilitated by effective management[5]. As a result, farming has less of an influence on the environment. Moreover, it fosters ecological equilibrium.

C. Agriculture Datasets

The primary issue that most researchers in this discipline deal with is scarcity of datasets [6]. This would significantly impact and restrict ML research for identification of plants and categorization of diseases using leaf images. A brief summary of five publicly accessible datasets utilized in several investigations is shown in Fig. 3:

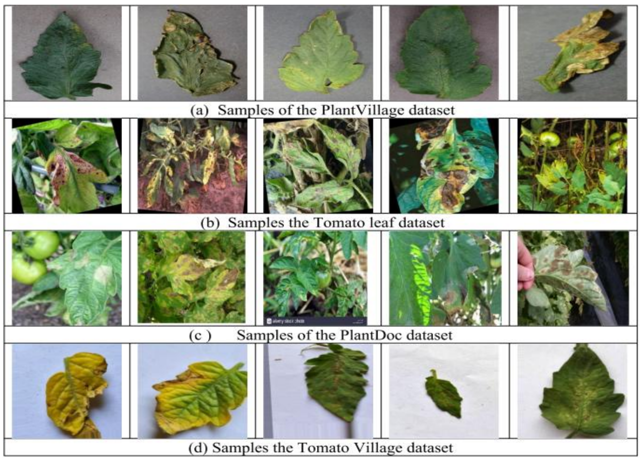

Fig. 3. Tomato leaf dataset with unhealthy images.

- **Plant Village:** Plant Village has been one of the most popular and openly available databases for more than 10 years, used by researchers to find and classify leaf illnesses. The initial compilation was released in 2015 and encompasses fourteen different plant species, encompassing apple, blueberry, cherry, corn, grape, orange, peach, bell pepper, potato, raspberry, soybean, squash, strawberry, and tomato. On it, may shows 54,305 pictures of both healthy and diseased leaves. There are 22 separate disease categories because 1 to 10 distinct disease categories are associated with each species.
- **PlantDoc and Cropped PlantDoc:** The PlantDoc dataset is a non-laboratory collection of images and data on leaf disease detection. The majority of dataset's images show diseases contracted in the field. There are 2,598 images of leaves, 13 different kinds of plants, and 17 diseases that are identical to those in Plant Village. For a mix of species and diseases, there are 38 classifications. Thus, PlantDoc is far smaller than Plant Village.
- **Taiwan Tomato:** The 622 photos of Taiwanese tomato leaves in this dataset are divided into six groups: 1 category for health and 5 categories for

sickness. It has a plain backdrop, a complex background, a single leaf, and several leaves.

- **Tomato-Village:** The majority of tomato infections in Gehlot et al.'s attempt to anticipate leaf miners, spotted wilt virus, and other field-based tomato diseases, and nutrient-deficient diseases were the causes in Rajasthan, India's Jodhpur and Jaipur districts. This new database was made sense there were no available datasets that contained these categories. These images may show a single disease (with a single label) or several diseases (with several labels). 2,103, 1,106, and 22 of the 3,231 photos have one disease, two diseases, and three diseases. As needed for multiclass classification, the multilabel version of dataset includes all 3,231 images with one or more diseases per image, whereas multiclass variation has 2,103 images, each of which depicts a distinct disease.
- **Field Plant:** Featuring 5,170 annotated photos of field-collected leaves, Field Plant is a data collection on plant diseases that is relatively, gathered from plantations in Cameroon, 10th largest producer of tomatoes in world. The dataset focuses on a number of diseases that affect three tropical crops: maize, tomatoes, and cassava.

D. Data Preprocessing

In order to make images uniform, in agricultural image analysis, preprocessing is an essential step for DL since it removes noise and emphasizes important visual information [7]. In this instance, effects of background's intricacy, lighting, resolution, and orientation were removed by preprocessing, if left unchecked, can affect model convergence and prediction accuracy. To highlight the characteristics associated with the diseases, this process involved enlarging images, increasing contrast, and rescaling pixel intensities.

1) Label Encoding

Since DNN designs work with numbers, first, integer indices were used to replace category class labels. The next step was to transform integer indices into one-hot encoded vectors while the model evolved. This encoding technique produces equal gradient propagation to each node in the output layer and is compatible with the softmax activation function. Equation (1) provides a precise mathematical definition of the transformation.

$$y_{encoded} = OneHotEncoded(y), y \in \{0,1, \ldots .C-1\} \quad (1)$$

where C is total number of disease classifications.

2) Image Standardization

The form of the input tensor was the same for every model since all images were scaled during preprocessing to input size of chosen backbone architectures (either 224 × 224 or 299 × 299 pixels). Next, Equation (2)s min–max scaling was used to normalize pixel intensities to the [0, 1] range.

$$I_{scaled} = \frac{I}{255} \quad (2)$$

Equation (3) was used as an additional normalizing step in the dataset-wise standardization process.

$$I_{normalized} = \frac{I-\mu}{\sigma} \quad (3)$$

Where global dataset mean and standard deviation are represented by μ and σ.

3) Adaptive Contrast Refinement

Adaptive gamma correction using a randomly selected gamma value from the interval [0.8, 1.2] was utilized to enhance minor disease-related visual signals. Equation (4) provides a mathematical definition of the transformation.

$$I_{enhanced} = I_{scaled}^{\gamma} \quad (4)$$

An image is brighter when the gamma value is less than 1.0, and darker when it is more than 1.0. This selective contrast enhancement can improve feature extraction by making lesions more noticeable while preserving their natural appearance.

4) Feature Extraction

The automated categorization of leaf diseases relies heavily on feature extraction, which transforms raw image data into relevant feature representations that capture disease-specific patterns. The current study uses deep CNNs to extract features at several hierarchical levels because multiscale pattern identification in the spatial and texture domains may not be suitable for conventional handcrafted approaches.

E. Performance Evaluation of Tomato Leaf Disease Classification

A DL model's accuracy is frequently evaluated against a gold standard in order to gauge its performance. The predictive efficacy of a model can be found by dividing the proportion of correct forecasts by the total number of predictions. Equation (5) for it is:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (5)$$

Accuracy is frequently employed as a metric for the efficacy of a deep learning model, particularly when classification is the objective. This statistic finds the percentage of correct predictions out of the total number of forecasts, which is a measure of the model's accuracy in forecasting good events. Equation (6) can be used to obtain it.

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

The assessment statistic "recall" is widely used by DL models, especially when addressing categorization problems. It measures percentage of positive cases in dataset that model correctly classifies. In simple terms, it determines how many predictions are correct, as a percentage of all positive cases in dataset. It is mathematically represented in Equation (7):

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

A common assessment metric for DL models, is F1 score, particularly for classification difficulties. It is a method for finding a balance between memory and accuracy and is comparable to the harmonic mean of two. Finding the rarer set of data classes or dealing with uneven datasets are two situations when it is useful. It evaluates in Equation (8):

$$F1 - Score = 2 * \frac{(Precision*Recall)}{Precision+Recall} \quad (8)$$

A ROC curve displays TPR and FPR for different threshold values on y-axis and x-axis, respectively. How well a classifier performs overall is shown by AUC. Better performance is indicated by high numbers, values around 1 are better.

III. Advanced Deep Learning Frameworks for Tomato Disease Classification

DL is a branch of AI's ML that allows computers to find patterns in very large datasets. In agriculture, DL is garnering significant attention, and various applications are being investigated. A use case involves monitoring crops, where DL algorithms can track their growth and development. This other application is in weed detection and is already being developed using optical sensors. The valuable insights that DL models can provide from high-resolution and large numbers of images are well-suited to smart farming and precision agriculture systems.

A. *Convolutional Neural Networks (CNNs)*

ML and DL are also widely used in Agriculture, particularly for detecting diseases in crops, such as leaves. CNNs are one of the most popular applications for leaf disease detection [8]. CNNs are naturally capable of employing many convolutional filters to extract pertinent characteristics from images. The initial stage was to take detailed pictures of the leaves of tomato plants, encompassing both well-nourished and diseased specimens. The assembled photos are quite good in showing various diseases affecting tomato plant. The images were resized and preprocessed for CNN analysis. The CNN model, which has convolutional, pooling, and fully connected layers, was given this dataset. Following training, model's capacity to categorize plant leaf diseases was evaluated using an alternative validation set.

B. *Transfer Learning Algorithms*

Transfer learning techniques allow a model created for one task to be used to another activity that is comparable but distinct. This may be especially helpful when a job is similar to one that has already been completed or when there is no labeled data available for the work [9]. It can be very time- and resource-efficient in utilizing the knowledge and features acquired by a pre-trained model.

1) *VGG16*

A straightforward yet effective CNN for feature extraction is the VGG16. Its sixteen layers consist of thirteen three completely linked layers, as well as convolutional layers. The VGG16 model's modest 3 × 3 convolutional filters allow it to maintain great picture resolution with a reasonable set of model parameters. The architecture is particularly good at identifying complicated aspects because of its consistent design, which facilitates the learning of hierarchical features. Since TLD may frequently be detected from very small visual variations, VGG16 is a suitable model for their detection and has demonstrated effectiveness in a variety of classification challenges.

2) *DenseNet121 Model*

The DenseNet family, which Huang et al. announced in 2017, includes the well-known CNN architecture DenseNet121. The network's high degree of connectedness between layers allows for more accurate and seamless information transmission. Each of the several dense blocks that make up convolutional layers in DenseNet121 are closely connected to each other.

This research uses a pre-trained DenseNet121 model to detect tomato illnesses. Usually, transfer learning is carried out, in this instance, the large ImageNet dataset was used to extract weights. Two batch normalization layers, two completely connected layers housing 512 and 256 neurons, comprise new set of layers, and global average pooling layer was used in place of top layer of pretrained model. Using ReLU activation technique, a new layer was constructed once second layer was finished to serve as an activation layer.

3) *ResNet50V2 Model*

CNN, such as ResNet50V2, are utilized in computer vision analysis, image classification, plant disease classification, and other applications. As is typical in transfer learning, weights learned on a large image dataset were used to initialize pretrained model. A fresh set of layers replaced pretrained model's top layer. In order to train the network for a different picture classification job, a classifier was added to the pretrained ResNet50V2 model. The output of the pretrained model is averaged along the height and width axes by the GlobalAveragePooling2D layer, which minimizes the spatial dimensions of the feature maps. As a consequence, most significant aspects of input image are encoded in a fixed-length feature vector.

The feature vector is looked at through two fully connected layers of 512 and 256 neurons, respectively. This creates a high-level representation that holds the discriminative information for a certain image classification Task.

4) *Vision Transformer*

In the DL field, a novel architecture for image categorization called Vision Transformer (VIT) has drawn a lot of interest. VITs employ transformer-based design, which has proven quite effective in NLP applications, in contrast to conventional CNNs.

The VIT architecture is made up of a number of essential elements. Initially, a series of fixed-sized patches is created from the input image. An embedding layer is used to translate each patch to a higher-dimensional feature space after it has been flattened into a 1D vector. After that, a transformer encoder receives these patch embeddings and captures contextual relationships between patches using self-attention techniques.

C. *Hybrid Deep Learning Models*

To increase prediction accuracy and resilience, hybrid deep learning models combine many architectures or methods. These models combine CNNs with additional models such ensemble models, attention networks, transformers, and LSTM. Hybrid frameworks blend benefits of different frameworks to achieve optimal performance in feature extraction/classification. For instance, CNN-LSTM models can capture both spatial and sequential information, and CNN-transformer models fuse local and global feature learning. In general, hybrid DL approaches are more precise and exhibit better generalization for tomato disease identification than individual approaches.

D. *Rise of Deep Learning in Plant Pathology*

Disease diagnosis in agriculture has been revolutionized by recent advances in AI, especially DL [10]. The accurate detection and classification of plant diseases using leaf pictures is a common use of convolutional neural networks (CNNs). An advantage of SE models for automated plant health monitoring is their ability to detect intricate visual patterns, such as color, texture, and lesion shape.

Despite their widespread use, high processing needs of classic GPUs and cloud servers with a lot of processing power are sometimes required for DL models. These limitations hinder its application in field situations, especially when resources are limited. Consequently, lightweight designs. Researchers are paying more attention to systems like MobileNet, EfficientNet-Lite, and SqueezeNet.

E. Edge AI and Lightweight Deep Learning

The term "AI at edge" describes the process of applying AI models directly to devices such as smartphones or microcontrollers (such as the Raspberry Pi and Jetson Nano) without relying on a cloud or Internet connection. In the agricultural sector, edge AI lessens reliance on cloud connectivity, expedites the identification of diseases, and maintains its utility even in outlying farming areas. By reducing model size and energy consumption without compromising performance, researchers are using model compression methods to facilitate edge deployment, such as knowledge distillation, quantization, and pruning. Additionally, models based on transformers for the detection of plant diseases, such ViT (Vision Transformer), are being made lighter.

F. Explainable Artificial Intelligence (XAI) in Agriculture

The aim of XAI, is to create AI systems that can give concise, intelligible explanations for decisions and predictions. Ensuring AI systems are open and accountable is one of its main objectives so that consumers can trust and comprehend the results. Ensuring open and responsible AI systems is its primary objective so consumers can trust and comprehend the decisions that made [11]. It used two popular explainable AI techniques, LIME and SHAP, to provide both regional and global justifications for forecasts produced by proposed model. SHAP offers an integrated framework for determining feature relevance. LIME creates an interpretable model using a local linear approach.

1) SHAP

A ML framework called Shapley Additive exPlanations (SHAP) gives a thorough comprehension of contributions each feature makes to output of a model. Shapley values, a measure of an attribute's overall marginal contribution to the complete set of attributes, are computed across almost all subsets of attributes using cooperative game theory. SHAP values are a suitable and trustworthy way to assign certain properties to the model's prediction.

2) LIME

LIME is one of the most widely used model-independent techniques for elucidating specific black-box model predictions. This method has been shown to be a useful tool in ML, allowing the approximation of complex models using locally interpretable models around each data point. This is helpful for understanding the model's individual behavior.

3) Grad CAM

An interpretive technique used in computer vision to view and understand the decision-making processes of CNN is called Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM employs gradients from last convolutional layer to determine each feature map's relevance, in contrast to earlier methods that depend on feature analysis in final convolutional layer. This results in a heatmap showing important areas of image that had a big impact on model's classification decision.

G. Comparative Analysis of Existing Models

The diagnosis of plant diseases is crucial for assessing crop quality, including nutrient retention, grain richness, and yield potential. The objective of the piece is to give an extensive analysis of computational techniques used in plant disease classification and identification systems. A number of smart algorithms have contributed significantly to the accurate diagnosis.

TABLE II. MODEL ACCURACY COMPARISON

Study	Models	Accuracy
[12]	Deep CNN with VGG model	99.53
[13]	RCNN	98.1
[14]	DenseNet	99.9
[15]	InceptionV3	89.33
[16]	CNN–VGG1	96.8
[17]	MobileNetV2	98.05
[18]	DenseNet+C-GAN	97

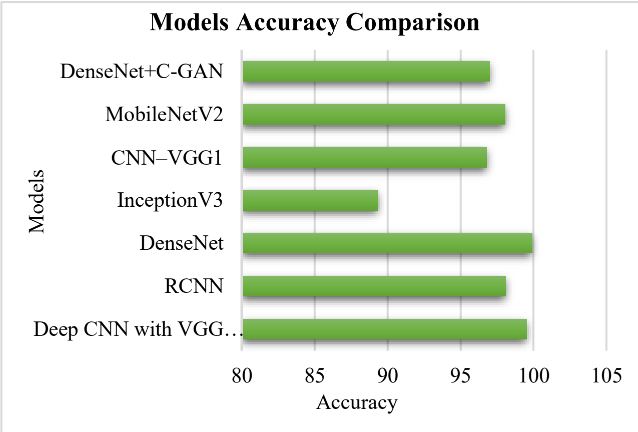

Fig. 4. Models accuracy graph of tomato leaf disease

The relative accuracy of various DL models for categorizing TLD is displayed in Table II and Fig. 4. The Deep CNN model using VGG model had an accuracy rate of 99.53%, while DenseNet model had the highest acc. of 99.9%. The other two models, RCNN and MobileNetV2, performed well as well, with accuracies exceeding 98%. Among them, the lowest accuracy (89.33%) was achieved by the InceptionV3 network, which shows that it has a relatively poor classification capability. Overall, the results show that CNN-based advanced architectures are good in detecting accurately and efficiently diagnosing problems affecting tomato leaves.

IV. LITERATURE REVIEW

The most recent methods for detecting diseases in tomato leaves using ML and DL are summarized in Table III.

Saurav et al. (2026) Tomato leaf condition categorization on EB, SLS, and healthy leaves using VGG16 with transfer learning. Multiple models were tested and trained with an own-created tomato leaves data set and the VGG16 model had the best acc of 98.2%, and prec (98.2%), rec (98.2%), and F1(98.2%). With a test time of 24.19 seconds and a memory footprint of 33.37 MB, model was also effective, that it is suitable for use in real-time [19].

Nagila et al. (2025) investigated efficacy of different ML algorithms in categorizing TLD using diverse image sources. The algorithms examined were SVM, CNN, and RF. To improve accuracy of categorization, used a soft-voting classifier based on results of various algorithms, creating a hybrid model. The soft voting classifier exhibited exceptional enhancement in precision and resilience, surpassing the performance of the separate models to a large degree, with 97.13 accuracy [20].

Verma and Kaur (2025) aim to identify diseased leaf in Tomato plant. As higher-quality characteristics are collected, DL approaches aid in improving disease classification. Four DNN architectural models—AlexNet, DenseNet, Inception, and Xception are used in research on Tomato Leaf Disease dataset. Each model extracts the features based on their architecture and produces the classification results with train-test-validation mechanism. Among all models, Exception and AlexNet models outperform other models in terms of accuracy metrics, with respective values of 95% and 90% [21].

Srivastav et al. (2024) first use data augmentation and picture annotation tools to build the Tomato leaf disease dataset, which includes both standardized laboratory photos as well as complicated images captured in field. In light of this, propose A new deep CNN-based model utilizing MobileNet architecture for tomato leaf disease detection. Finally, a hold-out testing dataset with 962 pictures of wilted tomato leaves was used, suggested MobileNet model is trained to recognize these five common TLD. Experimental results show that suggested framework's detection performance is 95.79% mAP [22].

Bahrami et al. (2024) conducted a various method, DL algorithms provide automatic, accurate, and robust leaf disease detection algorithms. With acc, prec, rec, and F1 of 99.48%, 99.27%, 99.28%, 99.27%, and 92.76%, 92.74%, 95.09%, 90.86%, respectively, VGG19 outperformed the other models Plant Village and CCMT datasets. The results determine that VGG19 can detect tomato leaf disease precisely and robustly [23].

Kaur and Shalu (2023) presented a comparative study of leaf disease diagnosis in tomato plant using ML techniques. A InceptionV3 based ML model has been proposed in order to diagnose leaf disorders in tomatoes at an early stage and further protect the plant from other diseases, 81% classification accuracy is provided by the suggested method [24].

Jagatheeswari and Rao (2022) researched classification of tomato plant leaf diseases in real-life using A ML system augmented by metaheuristics that offers valuable details for the upkeep of tomato plants. Problems with feature optimization are resolved via metaheuristics. To ascertain the best method for categorizing plant diseases, this study compares supervised ML with image processing. Experiment shows that 88.26% of tomato a RF classifier with Plant leaf diseases, may be correctly classified using an equilibrium optimizer [25].

TABLE III. COMPARATIVE ANALYSIS OF EXISTING TOMATO LEAF DISEASE DETECTION TECHNIQUES

Authors	Technique	Objective	Methods	Key Findings	Limitations / Future Work
Saurav et al. (2026)	VGG16 with Transfer Learning	To classify TLD and healthy leaves accurately	Used transfer learning on VGG16 with a self-created tomato leaf dataset containing EB, SLS, and healthy leaves	Achieved 98.2% acc, prec, rec, and F1 with low memory usage and reduced testing time	Limited disease categories considered; future work can include larger datasets and real-time field deployment
Nagila et al. (2025)	CNN, SVM, RF, Soft Voting Hybrid Model	To compare ML algorithms for TLD classification	Implemented CNN, SVM, RF, and hybrid soft-voting classifier on multiple tomato image datasets	Hybrid soft-voting model achieved 97.13% accuracy with improved robustness	Requires more diverse environmental conditions and larger-scale validation
Verma and P. Kaur (2025)	AlexNet, DenseNet, Inception, Xception	To identify diseased tomato leaves using deep learning	Preprocessing, segmentation, and classification using four deep neural network architectures	Xception achieved 95% accuracy and AlexNet achieved 90% accuracy	Performance can be enhanced with larger datasets and advanced augmentation techniques
Srivastav et al. (2024)	MobileNet based Deep CNN	To detect common TLD in laboratory and field conditions	Data augmentation, image annotation, and MobileNet-based disease classification	Achieved 95.79% mAP using 962 diseased leaf images	Limited dataset size; future work may focus on real-time mobile deployment
Bahrami et al. (2024)	VGG19, ResNet-101, MobileNet-v2	To assess transfer learning models for reliable detection of tomato diseases	Comparative analysis on PlantVillage and CCMT datasets using transfer learning	The PlantVillage dataset yielded the maximum accuracy of 99.48% for VGG19.	Performance dropped on complex datasets; future work should improve generalization in field environments
Kaur and Shalu (2023)	InceptionV3	Early detection of TLD	Comparative review and implementation of the InceptionV3 model	Achieved 81% classification accuracy	Lower accuracy compared to recent models; future work can integrate advanced CNN architectures
Jagatheeswari and Rao (2022)	Equilibrium Optimizer with Random Forest	To improve tomato leaf disease classification using optimization techniques	Applied metaheuristic optimization for feature selection and RF classification	Achieved 88.26% classification accuracy	Accuracy can be improved with deep learning and larger real-world datasets

A. Deep Analysis on Literature Review

The literature review reveals that DL models offer an extremely precise and effective method of identifying TLD. Previous techniques such as SVM, KNN and RF were not successful because they rely on manual feature extraction. Recent studies primarily focus on CNNs, hybrid models like VGG16, DenseNet, and MobileNetV2, and transfer learning, which achieve high classification accuracy. The researchers also highlighted the need for agricultural datasets, like Plant Village and pre-processing and data augmentation. But, most of the models are tested on the controlled dataset, which plays a limited role in the real world. Hence, lightweight and explainable deep learning frameworks are key future research areas.

V. CONCLUSION AND FUTURE WORK

Tomato crop is one of the most vulnerable crops to fungal, bacterial and viral diseases and is a key component in global food production. To reduce crop losses and increase output, early disease diagnosis is crucial. The authors of this paper covered a number of DL frameworks, including CNN, transfer learning models, Hybrid models and vision transformers for the categorization of TLD. The DenseNet, VGG and MobileNetV2 models were able to classify with high accuracy and were deemed good potential for automated disease diagnosis. The DL techniques enhance the detection speed, minimize the manual workload, and aid precision agriculture applications. However, several limitations still exist. Most of studies are based on laboratory datasets where background is simple, so this will not be the case in real-world performance. Challenges include high computational cost, lack of diversity in the data, and limited interpretability of the models. The lightweight Ness and explainability of models for mobile and edge computing should be the focus of future research. Integration of IoT, drones, and transformer-based architectures can further enhance real-time disease monitoring and smart farming systems.

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