Asian Journal of Computer Science and Technology
ISSN: 2249-0701 (P); 2583-7907 (E)
Vol.12 No.2, 2023, pp.39-47

DOI: https://doi.org/10.51983/ajcst-2023.12.2.3735

Detection and Classification of Plant Diseases in Crops (Solanum lycopersicum) due to Pests Using Deep Learning Techniques: A Review

Tejinder Deep Singh[1] and Ramesh Bharti[2]

[1]Ph.D. Scholar, [2]Professor and Head,
Department of Engineering and Technology, Jagan Nath University, Jaipur, Rajasthan, India
E-mail: tejinderdeepsinghkalsi@gmail.com, ramesh.bharti@jagannathuniversity.org
(Received 3 September 2023; Revised 14 October 2023; Accepted 18 November 2023; Available online 23 November 2023)

***Abstract* - All people have access to food thanks to agriculture, even in areas with rapid population expansion. In order to ensure that the entire population has access to food, early diagnosis of plant diseases is recommended. However, when crops are still maturing, it might be challenging to predict diseases. The goal of this paper is to inform farmers about the use of machine learning to recognize various pest species in various crop plants. Deep learning establishes a continuing, cutting-edge method for analysing images with significant potential and promising outcomes. DL has expanded into the field of agriculture after demonstrating its effectiveness in a number of applications. Here, we reviewed various research articles that used deep learning methods to address diverse research issues in tomato (Solanum lycopersicum) plants. We look at the study areas in tomato plants where deep learning, data preprocessing, transfer learning, and augmentation approaches are performed. studied dataset details, including the number of photos, classes, and train test to validation ratios that were employed. We also look at comparisons made across different deep learning architectures and analyse the results. The results demonstrated that deep learning techniques beat all other image processing methods, however how well DL works depended on the dataset employed.**
***Keywords:* Tomato Leaf Diseases, Deep Learning, Machine Learning, Image Analysis, Classification, Datasets**

I. INTRODUCTION

Recent years have seen agriculture play a significant role in the world economy. The growing stress on the agricultural system is a result of population growth and urbanization, which cause a gradual decline in the total area under cultivation. Intelligent systems based on computer vision are being employed to increase productivity and efficiency in agriculture, accounting for a significant portion of agricultural product maintenance [1]. Artificial intelligence (AI) includes machine learning, which enables computers to learn automatically and get better over time without having to write code explicitly [2]. As DL exhibits promising results in numerous areas, it has most recently expanded into the field of agriculture [3]. One of the DL architectures, CNN, ended up being the best at classifying images and made incredible progress [4]. DL was successfully used to a variety of applications, including scene analysis, semantic segmentation, text analytics, and object detection. The CNN model has two steps: the first is to take a picture of the fruit or crop that piques our attention, and the second is to feed that picture into the model that has been created for further analysis and output. To obtain the promising outcome, a variety of algorithms and approaches are used to well-known CNN architectures as AlexNet, VGGNet, GoogLeNet, ResNet, and SqueezeNet [5]. Transfer learning, data augmentation, hyperparameter tweaking, data pretreatment methods, object detection, and picture segmentation are common methodologies.

The commercially important tomato plant is susceptible to more illnesses than other crops. The leaves of plant diseases can be used to identify them. One of the research areas is the automatic detection, categorization, and severity assessment of plant leaf diseases with the goal of increasing crop productivity. Because there is higher variance in the picture data of the infected tomatoes, the typical machine learning approach cannot extract and classify multi-class tomato diseases. More current research is concentrating on employing convolutional neural network architectures to solve this problem.

Sometimes it's difficult for farmers and gardeners to accurately monitor plant growth. On occasion, tomato plant infections may not be visible, or the plants may grow ugly, disease-filled black blotches at the bottom. The first step in diagnosing a tomato plant disease is to locate afflicted leaf regions. Then, finding insects is made easier by seeing irregularities like brown or black spots and gaps in plants. Tomatoes, potatoes, and closely related vegetables are only permitted to be planted on the same farm once every three years [3]. It's important to start growing any grass or crop before planting tomatoes in order to preserve soil fertility.

Two categories of tomato-related issues can be identified: Five diseases are brought on by insects, whereas sixteen are brought on by bacteria, fungi, or bad agricultural practices. The bacteria Ralstonia solanacearum is the source of the dangerous illness known as bacterial wilt. Diseases can grow more easily in hot climates and with lots of dampness. Bacteria soon establish there and cause the water-conducting membrane of the plant to become slimy. There might still be green leaves, but this affects the plant's vascular system. When examined in cross section, a diseased stem becomes brown and has yellowish stuff pouring out of it [4].

The first step in managing plant diseases and pests is to predict them accurately and quickly. As a result, future risk assessments and management plans will be viable. Statistical analysis and the use of several case studies are also essential for predicting similar diseases and insect pests [5]. In the past, many pest management procedures were carried out by hand, and agricultural experts who were hired used their skills to identify pests through time-consuming and repeated assessments, estimations, and statistical analyses. Modern information technology is vitally needed to support it since outdated technology and fictitious experience make it difficult to categorize diseases and pests accurately and cause errors and omissions in the processing of information [6].

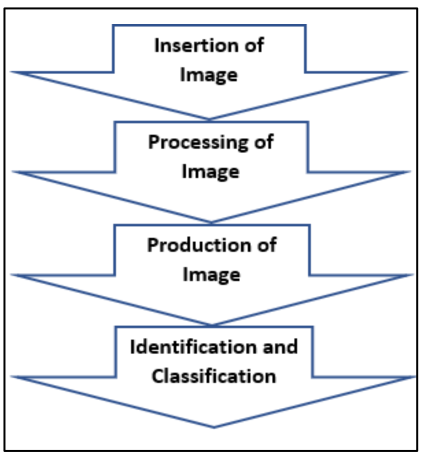

Fig. 1 Traditional Image Processing Techniques

Fig. 1 depicts general procedure for using conventional image recognition processing to recognise plant diseases. Most promising method for closing gap is automatic plant picture identification, which is attracting a lot of interest in fields of botany and computing [7]. In a variety of applications, including plant recognition, facial recognition, and others, an image represents most important information. Numerous studies concentrate on categorization, segmentation, and quality evaluation of plant leaves. A few elementary image processing steps are required for plant leaf recognition in order to recognise and classify plant leaves. This technique includes steps of image capture, pre-processing, feature extraction, and classification [8].

Deep Learning has recently entered agriculture field as it has demonstrated promising results in a variety of applications [12]. Medical experts can forecast plant anomalies with aid of DL approaches based on automated computer-aided diagnostic systems, enabling them to choose best course of action. DL systems function admirably today due to technological advancements, and the system's output helps experts make right decisions.

Deep NN's input layer, several hidden layers, and outcome layer make up its fundamental design. When input data is sent to DNNs, the output is computed sequentially across layers of network. CNN proved to be best at classifying images and made astounding progress. DL was successfully applied to a variety of tasks, including scene analysis, text analytics, and object detection etc. First step in CNN is to take a picture of crop that piques our interest, and then to feed that picture into model that has been created for additional evaluation and output [13].

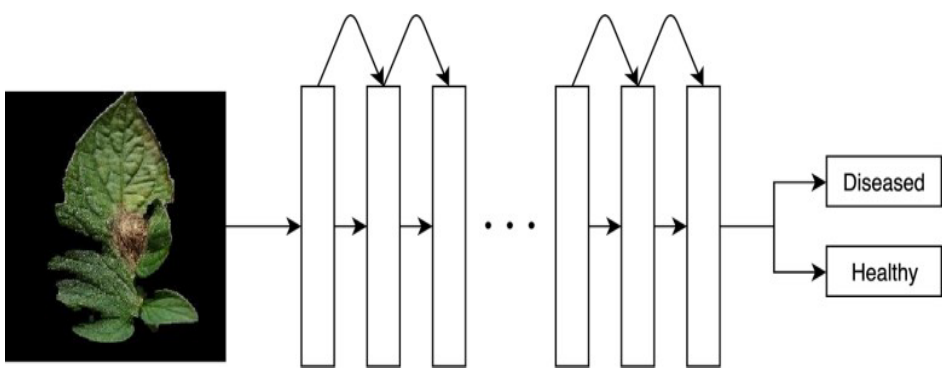

Fig. 2 DL classifier for image classification [14]

II. DEEP LEARNING ARCHITECTURE USED ON TOMATO PLANTS

Deep learning is a multilayered automated learning system that was developed from ANNs and is used to create information that is categorized into unsupervised, supervised, and reinforcement learning. DL models have been used in several applications that have solved a variety of picture recognition issues and improved research outcomes in fields like automatic plant disease identification, natural language processing, and medical diagnosis. DL is a novel method for identifying plant species and leaf diseases. Fig. 3 shows diagram for implementing DL algorithms for identification and categorization of tomato leaf disease. The research on using DL models to identify tomato illnesses from leaf photos is covered in this section.

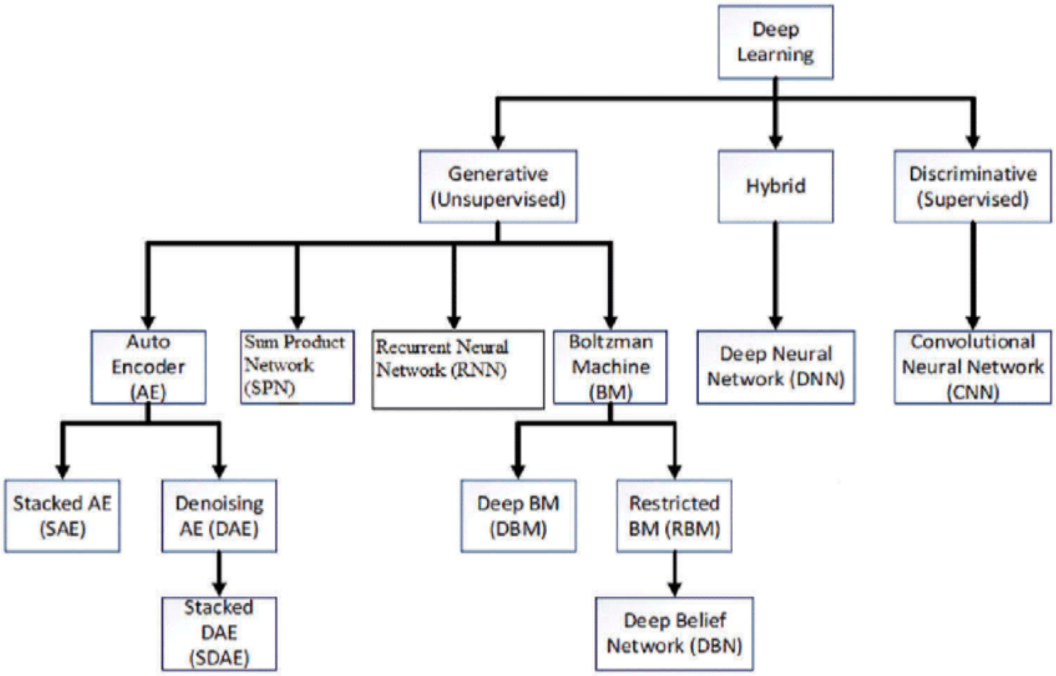

Fig. 3 DL algorithms for categorization of tomato leaf diseases [66]

A. CNN Architecture Used on Tomato Plants

Khan *et al.,* [15] recommended a DL technique that automates diagnosis of tomato leaf ailments. To categorise image datasets based on apparent effects of diseases on plant leaves, CNN is trained from scratch. They trained a deep CNN to recognise early and late blight fungal diseases that affect tomatoes utilising a database made up of leaf pictures collected from various sources. With 97.25 percent accuracy, a DNN sequential model is created, proving viability of suggested system testing on a dataset that combines real- world data with pictures downloaded from Internet and basic data from Plant Village.

Zhang *et al.,* [16] presented a 3-channel CNN to detect tomato leaf disease. They employed 3 convolutional feature extraction models with a fused dense network. With 15.817 images and 8 classes of controlled environments, PlantVillage dataset allowed Multiclass Classifier to achieve accuracy of 91.15 percent. With Layers Custom as predominate technique, simulation is done in Matlab with Top View of images. One of the 3 RGB colour channels was given to every CNN. Suggested model outshined Sparse Representation based Classification, Global-Local Singular Value Decomposition, SVM, and Image Processing Technology by a wide margin.

Brahimi *et al.,* [17] contrasted efficacy of SVM and RF classifiers to AlexNet and GoogleNet CNNs that were trained from scratch and utilising transfer learning to identify 9 tomato leaf diseases. Dataset included 14,828 images and was categorised using a CNN with 99.18% accuracy. CNN models outperformed SVM and RF classifiers and also pre-trained CNNs outperformed CNNs trained from scratch.

Elhassouny and Smarandache [18] showed that deep CNNs can be implemented for identifying plant illnesses on mobile devices. Images from PlantVillage dataset were used to train MobileNets to recognise 10 typical tomato leaf diseases. Model's accuracy was only slightly impacted by optimisation method that was selected. Additionally, despite the cost of a longer training period, greater accuracy could be attained by reducing learning rate. According to learning rate selected, accuracy ranged from 85.9% to 90.3%. considering the prevalence of smart devices, potential for farmers to get the most from this innovation will grow with creation of CNN designs which can be used on mobile devices.

Prabhjot *et al.,* [19] For localization of items, 1610 tomato leaf images representing various classes were taken from PlantVillage database. Modified Mask R-CNN is suggested for recognition of tomato leaves diseases. Proposed model includes a Region CNN with a light head in an effort to reduce computation and storage costs. Effectiveness of computing metrics are enhanced by changing ratios of anchor in RPN network as well as feature extraction topology. To determine whether suggested approach is practically better, it is contrasted to existing models. Proposed model produced accuracy, F-measure and precision of 0.88, 0.912, and 0.98, respectively. Lesion detection period is decreased by two times compared to current classifiers as model's capability enhances with few parameters.

Anandhakrishnan *et al.,* [20] invented a computerized software for identifying tomato leaf diseases employing Deep CNN. 18160 images were used from plant village data set and divided 60% images for training and 40% for testing. 98.40% accuracy was attained for testing set using suggested DCNN model.

Anim *et al.,* [21] suggests ResNet-9 that farmers can use to identify blight disease in potatoes and tomatoes. 3,990 training samples were used from "Plant Village Dataset". Classifier had been trained with hyperparameter values and tested on 1,331 images, following augmentation of training set and hyperparameter optimisation process. 99.25% accuracy, 99.67% precision, 99.33% recall, and 99.33% F-measure were all attained. Saliency maps were used to explain suggested model's assumptions and provide justifications for its predictions, allowing for a thorough understanding of model. ResNet-9 considered leaf shape, diseased and green areas for predictions. Findings may help with development and application of CNN models for classifying tomato and potato leaves images. This modelling framework will be useful for future research, which will test a number of additional variables to identify leaf infections at earlier times for protecting crops.

Islam *et al.,* [23] devised a methodology for categorising tomato leaf diseases depending on output of multiple concurrent CNN with various configurations. Network performs significantly better with using LeakyReLU-Swish, Elu-Swish, and ClippedReLU-Swish activation layers and Batch Normalization-Instance Normalisation layer, accomplishing accuracy 99.0%, 97.5% and 98.0% with training, validation and testing instances.

Sharma *et al.,* [25] introduces deeper lightweight CNN for leaf disease detection across various crops. Passage layer and a series of collective blocks are added in suggested model to obtain attributes. These advantages in feature reuse and propagation help to solve vanishing gradient issue. Point-wise and detachable Convolutional blocks are also used to lower various learning metrics. Citrus, cucumber, grapes, and tomato are publicly accessible datasets used to validate DLMC-Net's performance. Accuracy, error, sensitivity, specificity, F- measure and Mathews correlation coefficient are used in comparison of outcomes of suggested classifier against 7 existing models. Recommended approach has outshined all models with 93.56%, 92.34%, 99.5%, and 96.5% accuracy for citrus, cucumber, grapes, and tomato respectively. It is 2nd best classifier in comparison with 6.4 million trainable metrics needed.

Agarwal *et al.,* [26] created CNN model to find diseases in tomatoes. 3 convolutional with maximum pooling layers, having distinct filters, provided suggested solution. We used data from Plant Village's dataset of tomato leaves for simulation. There are 9 diseased class labels and 1 healthy label in data that contains images. To balance images inside class, data augmentation has been used. Suggested approach's precision for classes ranges from 76% to 100% and accuracy is 91.2%. Suggested model requires 1.5 MB memory, whereas pretrained classifiers require 100 MB storage, showing CNN's benefits over others.

Paymode *et al.,* [28] employed CNN techniques for detecting Multi-Crops Leaf Disease. DL model extracted features from images to classify unhealthy and healthy leaves. For better performance measures, VGG classifier is utilised. For model training and testing, crops leaves pictures dataset is considered. Accuracy, sensitivity, precision and F-measure were computed and tracked. Created model more accurately categorises leaves with disease. Suggested research has 95.71% accuracy for tomatoes and 98.40% accuracy for grapes. Suggested technique directly supports boosting agricultural food production.

Algani *et al.,* [29] presented ACO-CNN model in which ACO was used to examine efficacy of disease detection in plant leaves. CNN is used to remove color, texture, and leaf arrangement from given images. Parameters for measuring effectiveness that were used to analyse suggested methodology showed that recommended approach outperforms existing ones with highest accuracy. The stages of disease detection include image acquisition, separation, removing noise, and classification.

Ngugi *et al.,* [30] suggested removing noise from leaves photos captured using mobile devices by employing CNNs. A leaf would be surrounded by other leaves, stalks, and mulch. These supplementary traits will be removed by segmentation network, leaving only target leaf. Dataset was produced to train and test suggested systems. It is made up of 1,408 tomato leaf images and ground truth masks that go with them that were captured under challenging field settings. They present cutting-edge leaf image segmentation outcomes with mean weighted intersection over union over 0.96 and boundary F1 scores over 0.91.

Particularly, our suggested segmentation network KijaniNet outshines all rivals with 0.9439 boundary F1-measure and mean weighted intersection over union of 0.9766. Suggested method outperforms rival background subtraction computations while requiring neither user input nor imposing restrictions on target leaf's orientation or illumination. Additionally, compared to other methods, all CNN models can segment a 256x256 RGB picture in lesser than 0.12 seconds when running on GPU and lesser than 2.1 seconds on CPU.

Baser *et al.,* [32] uses TomConv model, which employs CNN to classify tomato leaves into ten distinct groups. Publicly accessible dataset PlantVillage, which contains greater than 16000 pictures of healthy and diseased leaves, was employed for this research project. Suggested model is most straightforward of all current cutting-edge classifiers. Images of tomato leaves underwent pre-processing to reduce their size to 150 x 150 pixels. Model consists of a max pooling layer after a 4 layered CNN. It divides corpus into training and validation datasets in 80:20 proportion, trains with 105 iterations for pictures of tomato leaves, and achieves a 98.19% accuracy. Proposed model is contrasted with existing ones based on various factors, including number of classes, layers, and accuracy. Outcomes are encouraging because they outperform all current cutting-edge models.

B. R-CNN Architecture used on Tomato Plants

Fuentes *et al.,* [33] compared the performance of a variety of DL networks for disease categorization in tomatoes. Faster R-CNN, R-FCN, and SSD were some of these. For classification, Front View point is applied to RGB images. Keras framework employs TensorFlow language, with Data Augmentation being main methodology. They discovered a technique for local and global class annotation and data augmentation as their foundation. Outcomes were more accurate and there were fewer false positives.

Natarajan *et al.,* [36] presented an automated system for spotting diseases on cultivated land. To identify and categorise tomato disease in plants, Faster R-CNN with feature extraction is used. Suggested model was trained and tested using a tomato dataset that includes roughly 1090 pictures of early and late stages of tomato diseases. Even in complex plant surroundings, suggested system ResNet50 effectively predicts early blight, leaf curl, septoria and bacterial leafspot.

Alvaro *et al.,* [38] presented DL method for identifying diseases and pests in tomatoes utilising real-time pictures took from cameras. They focus on 3 families of detectors: Single Shot Multibox Detector, Region-based Fully CNN and Faster Region-based CNN. They combined VGG net and Residual Network with every meta- architecture. They also suggest a technique for local and global class annotation as well as data augmentation to improve precision and decrease false positives during training. Tomato Diseases and Pests Database contains pictures consisting of many inter class variations, like infection portion in leaf, is utilised for training and testing models from beginning to end. Suggested method is capable of identifying 9 distinct diseases and pests and is able to handle complex situations that may arise in plant's surroundings.

Nagamani *et al.,* [40] examined ML tools like Fuzzy-SVM, CNN and Region-based CNN to detect tomato leaf disease. Tomato leaves pictures with 6 diseases and healthy samples were used to confirm findings. Images are trained using picture scaling, colour thresholding, flood filling, gradient local ternary pattern, and Zernike moments' attributes. Analysis and comparison of Fuzzy SVM, CNN with R-CNN aims to identify most precise classifier for plant disease detection. When contrasted to other methods, R-CNN achieves 96.735 percent accuracy.

C. Other DL Architectures Used on Tomato Plants

Li *et al.,* [22] suggests a method LMBRNet for identifying tomato leaves diseases classifier that uses Complementary Grouped Dilated Residual feature extraction blocks. To extract distinctive data of tomato illnesses and tomato leaf receptive fields, 4 subsidaries with convolutional kernels of various dimensions were created. Residual connection was used to address network degradation and gradient disappearance issues. Public datasets RS, SIW, and Plantvillage-corn were used to test LMBRNet. All 3 datasets showed high accuracy, with scores of 82.32%, 88.37%, and 97.25% on RS, SIW and Plantvillage-corn, demonstrating LMBRNet's strong generalizability. When applied to specific datasets, LMBRNet outperforms MobileNetV3S and MobileNetV3L. Its (4.1M) metrics are greater than MobileNetV3S (2.9M) and lesser than MobileNetV3L (5.4M) suggesting that, despite having a limited no. of parameters, it has better generalisation.

Sunil *et al.,* [24] put forth Multilevel Feature Fusion Network for categorization of tomato leaf diseases. To categorise leaves images, ResNet50, MFFN, and Adaptive Attention Mechanism are used. Suggested technique accomplished 99.88% training, 99.9% validation and 99.8% test accuracy. It performed better than currently used methods appropriate for dataset. The research offers information on specific pesticides in accordance with the kind of leaf disease.

Astani *et al.,* [28] seeks to identify 13 tomato diseases quickly and accurately in farms and labs through 260 ensemble techniques created with feature extraction. Accuracy and precision of suggested method were assessed under laboratory and outdoor conditions with various challenges using two databases, Plantvillage and Taiwan tomato leaves. Best ensemble classifier identify diseases with 95.98% accuracy based on background clutter, multiple leaves, brightness changes, disease similarity, and shadow conditions. Comparison among 260 suggested ensemble models in recommended methodology and various DL models was conducted. Proposed approach performed better than most advanced DL model.

Wspanialy *et al.,* [31] trained a disease model to recognise previously unidentified tomato leaf diseases, and its severity forecasting can yield outcomes that are comparable to human assessment. Leaves shape has predictive ability for disease detection. Future gathering data initiatives can increase diversity of datasets through reducing accidental bias, in backgrounds, by having a better understanding PlantVillage information set drawbacks and its image capturing methods.

One could conceptualise diseased-healthy binary classifier as a healthy leaf predictor. In addition to being able to identify diseases that haven't been trained on before, such a classifier can assist in reducing effort needed to create an extensive data set for identifying general disease. This study also presented a brand-new dataset of proportional disease severity with annotations and an associated classifier. Ordinal categories work better for diseases brought by viruses and insects, while proportional area measures work best for estimating severity of bacterial and fungal diseases. By incorporating classifiers into automatic examining system, lowering expenses and error, and boosting accuracy, the findings can be put into practise.

Guo *et al.,* [34] implemented a tomato leaf illness detection system on Android mobile using AlexNet model for identifying diseases accurately in their early, middle, and late phases.

Fuentes *et al.,* [35] suggested deep architecture with a targeted feature extraction to identify plant illnesses. It was created to spot diseases in every picture. It was confirmed on tomato plant diseases dataset and pests that they independently gathered and successfully applied to challenging real-world scenarios.

Monika *et al.,* [37] conducted research between 2019 and 2020. Aphids Myzus persicae and Macrosiphum euphorbiae, serpentine leaf miner Liriomyzia trifolii, fruit borer Helicoverpa armigera, whitefly Trialeurodes vaporariorum and aphids Myzus persicae and Macrosiphum euphorbiae were all observed during surveys. Low hills were home to aphid species M. persicae, while mid hills were found to have tomato infestations by M. euphorbiae. In Himachal Pradesh's mid-hills contrasted to low-hills, more tomato pests infestations were noted.

Ashok *et al.,* [39] Suggested methodology that links input image pixel intensity and contrasts it with trained image instance using CNN for feature extraction. By lowering error relative to training set, all adjusting metrics of leaf parts are optimised. This study suggests using image processing methods on the basis of segmentation and clustering to detect tomato diseases. Leaf picture is classified using an image classifier that uses ANNs, fuzzy logic, and hybrid algorithms to distinguish between disease-affected and healthy leaves. Accuracy of suggested method is 98%.

Bhandari *et al.,* [41] In addition to healthy leaves, this study seeks to visually recognise 9 infectious diseases in tomato leaves, including, early and late blight, leaf mould, 2-spotted spider mite, Septoria leaf and bacterial spot and mosaic virus. Without segmenting dataset, they used EfficientNetB5, with 10 cross folds. Classifier produced 99.84%, 98.28% and 99.07% accuracy for training, validation and testing data. It is suggested to use Gradient-weighted class activation mapping & locally interpretable model related discussions for integration into agricultural practise as well as for forecasting effectiveness.

Tian *et al.,* [42] proposed DL classifier based on private and public datasets of tomato leaf images for identifying diseases. VGG16, InceptionV3, and Resnet50 were trained and evaluated. To identify 9 different diseases and healthy tomato leaves, they installed trained model into Android application called TomatoGuard. TomatoGuard performed better than APP Plantix with 99% testing accuracy.

Martins *et al.,* [43] created ML classifier for assessing severity of leafminer fly attacks in tomatoes. Database included pictures of pest signs on tomato leaves that were taken in the field. Acquired pictures were manually annotated into 3 groups, including background, leaves and leafminer fly symptoms. For a multiclass categorization, metrics like accuracy, precision and recall contrasted 3 classifiers and 4 distinct backbones. U- Net classifier with Inceptionv3 produced best outcomes, according to a comparison of segmentation outcomes. Best classifier for estimating symptom severity had lower RMSE values and was FPN with ResNet34 and DenseNet121 backbones.

Bouni *et al.,* [44] Finding and controlling plant illnesses, which have certain effect on food production, population health, plant quality and productivity, is a significant challenge in agriculture. It requires time to accurately identify different plant diseases with the naked eye. Managing tomato diseases necessitates constant attention throughout crop lifecycle and accounts for a sizeable portion of overall cost of production. They used automation and pretrained DNN to classify tomato diseases.

Plant disease monitoring can be done using digital image processing. DL has significantly outperformed more traditional methods in digital image processing. This article uses transfer learning and a deep CNN to predict tomato diseases. AlexNet, ResNet, VGG-16 & DenseNet form the core of CNN classifier. Adam and RmsProp approach analyzes relative performance of networks, showing that DenseNet with RmsProp methodology obtains significant outputs having 99.9% accuracy.

Tarek *et al.,* [63] assessed ResNet50, InceptionV3, AlexNet, MobileNetV1, MobileNetV2, and MobileNetV3, that were trained on ImageNet dataset. MobileNetV3 Small and MobileNetV3 Large has 98.99% and 99.81% precision respectively. To assess each model's effectiveness, detection duration on tomato leaves pictures was calculated on workstation where all models had been employed.

To construct IoT system for detecting tomato diseases, classifiers were also installed on Raspberry Pi 4. On workstation and Raspberry Pi 4, MobileNetV3 Small has shown 66 ms and 251 ms latency, respectively. MobileNetV3 Large had 348 ms latency on Raspberry Pi 4 and 50 ms on workstation.

TABLE I TOMATO LEAVES DISEASE RECOGNITION USING DL APPROACHES

Reference	Approach used	Dataset	Performance Parameter
Kim *et al.,* (2017) [33]	Faster R-CNN, ResNet	5000 field pictures 9 pests diseases classes	mAP = 0.8306 Accuracy =85.98%
Boukhalfa *et al.,* (2017) [17]	AlexNet, GoogLeNet	Plant Village	Accuracy = 99.185% Precision= 98.529% Recall= 98.532% F-measure= 98.518%
Smarandache *et al.,* (2019) [18]	MobileNets	PlantVillage	Accuracy= 90.3%
Yoon *et al.,* (2018) [45]	Faster R-CNN, VGG16 feature extraction	8927 self-gathered pictures, 9 anomalies and 1 background class	mAP = 96%
Gunes *et al.,* (2017) [46]	AlexNet, SqueezeNet	Plantvillage	Accuracy= 94.3%
Okura *et al.,* (2019) [47]	Modified Inceptionv3	PlantVillage	Accuracy =97.1%
Huang *et al.,* (2019) [16]	Custom 3 channel CNN	PlantVillage (15,817 Images/ 8 Class Controlled Environment)	Accuracy= 91.16%
Ramesh *et al.,* (2018) [48]	VGG16 & AlexNet	Plant Village, 6 tomato diseases	Accuracy = 96.2%
Sharma *et al.,* (2019) [49]	S-CNN	PlantVillage, 17,000 Real pictures 10 Classes	Accuracy = 98.6%
Khamparia *et al.,* (2019) [50]	ResNet	PlantVillage Subset	Accuracy = 99.4%
Wang *et al.,* (2019) [51]	Mask R-CNN & ResNet101	1,430 Images 11 Classes	Accuracy = 99.64%
Abu *et al.,* (2019) [52]	LeNet	PlantVillage 9,000 pictures 6 Classes Control Environment	Accuracy = 99.84%
Suryawati *et al.,* (2018) [53]	VGG	PlantVillage 18,160 instances 10 Classes	Accuracy = 95.24%
Dadios *et al.,* (2018) [54]	AlexNet	4,923 pictures 4 Classes	Accuracy = 95.75%
Tuncer *et al.,* (2018) [55]	LeNet classifier & LVQ	Plant Village 500 photos 5 Classes Control Environment	Accuracy = 86%
Meng *et al.,* (2018) [56]	ResNet & SGD	5,550 Plant Village photos, 8 Classes	Accuracy = 96.51%
Koolagudi *et al.,* (2018) [57]	LeNet	PlantVillage18,160 pictures,10 Classes	Accuracy = 94.85%
Fuentes *et al.,* (2018) [58]	Refinement Filter Bank Based ResNet	8,927 real instances 10 Classes	Accuracy = 96%
Zeng *et al.,* (2018) [59]	HoResNet Based ResNet	PlantVillage 10,478 pictures 6 Classes Control Environment	Accuracy = 91.79%
Rangarajan *et al.,* (2018) [60]	AlexNet VGG16	Plant Village 13,262 pictures 6 Classes	Accuracy = 97.49% Accuracy = 97.23%
Durmus *et al.,* (2017) [61]	AlexNet SqueezeNet	54,306 photos 38 Classes Control Environment	Accuracy = 95.65% Accuracy = 94.3%
Atabay *et al.,* (2017) [62]	ResNet	Plant Village 19,742 instances 10 Classes	Accuracy = 97.57%
Yamamoto *et al.,* (2017) [63]	AlexNet	18,149 pictures 9 Classes Control Environment	Accuracy = 78%

IV. CONCLUSION

The agricultural sector has recently faced numerous challenges. This article examines new research on tomato leaf disease detection using artificial intelligence. This study investigates various ML and DL methods used to classify tomato leaf diseases. In this study, a number of related research publications have been analysed with an emphasis on dataset, pre-processing techniques used, algorithms, and accuracy. According to a review of the literature, the DL model outperforms more conventional approaches like machine learning and neural networks for diagnosing tomato illnesses from photos of the leaves. Early detection of tomato plant diseases reduces costs by preventing unnecessary pesticide application to plants. Deep learning employing hyperspectral imaging is a novel emerging method that is suggested for early identification of tomato leaf disease. The severity of tomato plant diseases has grown over time as they have spread to neighbouring plants. This has made it possible to forecast and classify tomato leaf diseases throughout their whole life cycle using specialized DL classifiers. To hasten convergence and boost prediction accuracy, CNN classifier properties at both low and high levels can be combined. Using drones and agricultural robots to automatically take pictures of plant leaves and categorize plants with disease in the future.

REFERENCES

[1] V. Pallagani, V. Khandelwal, B. Chandra, V. Udutalapally, D. Das and S. P. Mohanty, "DCrop: A deep- learning-based framework for accurate prediction of diseases of crops in smart agriculture," In *Proceedings of the 2019 IEEE International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS),* Rourkela, India, 2019.

[2] H. S. Abdullahi, R. Sheriff and F. Mahieddine, "Convolution neural network in precision agriculture for plant image recognition and classification," In *Proceedings of the 2017 Seventh International Conference on Innovative Computing Technology (INTECH),* Luton, UK, pp. 1-3, 16-18 August 2017.

[3] M. Altalak, M. A. Uddin, A. Alajami, and A. Rijg, "Smart Agriculture applications using deep learning technologies: A survey," *MDPI,* Vol. 12, pp. 5919, 2022.

[4] A. A. Ahmed and G. H. Reddy, "A mobile-based system for detecting plant leaf diseases using deep learning," *Agri Engineering,* Vol. 3, pp. 478-493, 2021.

[5] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," *Computational Intelligence and Neuroscience,* Vol. 2016, 1-11.

[6] S. Arivazhagan, R. N. Shebiah, S. Ananthi and S. V. Varthini, "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features," *Agricultural Engineering International: CIGR Journal,* Vol. 15, pp. 211-217, 2013.

[7] S. Khan and M. Narvekar, "Novel fusion of color balancing and superpixel based approach for detection of tomato plant diseases in natural complex environment," *Journal of King Saud University - Computer and Information Sciences,* 2020.

[8] A. Kumar, M. Vani, "Image based tomato leaf disease detection," In *Proceedings of the 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT),* Kanpur, India, pp. 1-6, 30 December 2019.

[9] S. M. Patel, M. B. Jain, S. S. Pai and S. D. Korde, "Smart agriculture using IoT and Machine Learning," *International Research Journal of Engineering and Technology,* 2021.

[10] A. Gupta, D. Nagda, P. Nikhare and A. Sandbhor, "Smart crops prediction using IoT and Machine Learning," *International Journal of Engineering Research and Technology,* Vol. 9, No. 3, pp. 18-21, 2021.

[11] Yogesh, Ashwani Kumar Dubey, Rajeev Ratan and Alvaro Rocha, "Computer vision based analysis and detection of defects in fruits causes due to nutrients deficiency," *Cluster Computing,* Vol. 23, pp. 1817-1826, 2020.

[12] S. Zhao, Y. Peng, J. Liu and S. Wu, "Tomato leaf disease diagnosis based on improved convolution neural network by attention module," *Agriculture,* Vol. 11, No. 7, pp. 651, 2021.

[13] A. Bhujel, N. E. Kim, E. Arulmozhi, J. K. Basak, H. T. Kim, "A lightweight Attention-based convolutional neural networks for tomato leaf disease classification," *Agriculture,* Vol. 12, No. 2, pp. 228, 2022

[14] C. Jackulin and S. Murugavalli, "A comprehensive review on detection of plant disease using machine learning and deep learning approaches," *Measurement: Sensors,* Vol. 24, Dec. 2022.

[15] Saiqa Khan and Meera Narvekar, "Disorder detection in tomato plant using deep learning," In *Advanced Computing Technologies and Applications: Proceedings of 2nd International Conference on Advanced Computing Technologies and Applications - ICACTA 2020, Springer,* Singapore, pp. 187-197, 2020.

[16] S. Zhang, W. Huang and C. Zhang, "Three-channel convolutional neural networks for vegetable leaf disease recognition," *Cognitive Systems Research,* Vol. 53, pp. 31-41, January 2019.

[17] M. Brahimi, K. Boukhalfa and A. Moussaoui, "Deep learning for tomato diseases: classification and symptoms visualization," *Applied Artificial Intelligence,* Vol. 31, No. 4, pp. 299-315, 2017.

[18] A. Elhassouny and F. Smarandache, "Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks," In *Proc 2019 Int Conf Comput Sci Renew Energies, ICCSRE,* pp. 1-4, 2019.

[19] Prabhjot Kaur, Shilpi Harnal, Vinay Gautam, Mukund Pratap Singh and Santar Pal Singh, "An approach for characterization of infected area in tomato leaf disease based on deep learning and object detection technique," *Engineering Applications of Artificial Intelligence,* Vol. 115, pp. 105210, 2022.

[20] T. Anandhakrishnan and S. M. Jaisakthi, "Deep Convolutional Neural Networks for image based tomato leaf disease detection." *Sustainable Chemistry and Pharmacy,* Vol. 30, pp. 100793, 2022.

[21] Anim-Ayeko, Alberta Odamea, Calogero Schillaci and Aldo Lipani, "Automatic Blight Disease Detection in Potato (Solanum tuberosum L.) and Tomato (Solanum lycopersicum, L. 1753) Plants using Deep Learning," *Smart Agricultural Technology*, pp. 100178, 2023.

[22] Mingxuan Li, Guoxiong Zhou, Aibin Chen, Liujun Li, and Yahui Hu, "Identification of tomato leaf diseases based on LMBRNet." *Engineering Applications of Artificial Intelligence,* Vol. 123, pp. 106195, 2023.

[23] Islam, M. P., K. Hatou, T. Aihara, S. Seno, S. Kirino, and S. Okamoto. "Performance prediction of tomato leaf disease by a series of parallel convolutional neural networks." *Smart Agricultural Technology,* Vol. 2, pp. 100054, 2022.

[24] C. K. Sunil, C. D. Jaidhar and Nagamma Patil, "Tomato plant disease classification using Multilevel Feature Fusion with adaptive channel spatial and pixel attention mechanism," *Expert Systems with Applications*, pp. 120381, 2023.

[25] Vivek Sharma, Ashish Kumar Tripathi and Himanshu Mittal, "DLMC-Net: Deeper lightweight multi-class classification model for plant leaf disease detection," *Ecological Informatics,* Vol. 75, 102025, 2023.

[26] Mohit Agarwal, Abhishek Singh, Siddhartha Arjaria, Amit Sinha and Suneet Gupta, "ToLeD: Tomato leaf disease detection using convolution neural network." *Procedia Computer Science,* Vol. 167, pp. 293-301, 2020.

[27] Paymode, S. Ananda, and Vandana B. Malode, "Transfer learning for multi-crop leaf disease image classification using convolutional neural network VGG," *Artificial Intelligence in Agriculture,* Vol. 6, pp. 23-33, 2022.

[28] Mounes Astani, Mohammad Hasheminejad and Mahsa Vaghefi, "A diverse ensemble classifier for tomato disease recognition." *Computers and Electronics in Agriculture,* Vol. 198, 107054, 2022.

[29] Abd Algani, Yousef Methkal, Orlando Juan Marquez Caro, Liz Maribel Robladillo Bravo, Chamandeep Kaur, Mohammed Saleh Al Ansari and B. Kiran Bala, "Leaf disease identification and classification using optimized deep learning," *Measurement: Sensors,* Vol. 25, 100643, 2023.

[30] C. Ngugi, Lawrence, Moataz Abdelwahab and Mohammed Abo-Zahhad, "Tomato leaf segmentation algorithms for mobile phone applications using deep learning," *Computers and Electronics in Agriculture,* Vol. 178, 105788, 2020.

[31] Wspanialy, Patrick, and Medhat Moussa, "A detection and severity estimation system for generic diseases of tomato greenhouse plants." *Computers and Electronics in Agriculture,* Vol. 178, 2020.

[32] Preeti Baser, Jatinderkumar R. Saini, and Ketan Kotecha, "Tom Conv: An Improved CNN Model for Diagnosis of Diseases in Tomato Plant Leaves," *Procedia Computer Science,* Vol. 218, pp. 1825-1833, 2023.

[33] A, Fuentes, S. Yoon, S. C. Kim and D. S. Park, "A robust deep-learning based detector for real-time tomato plant diseases and pests recognition," *Sensors,* Vol. 17, No. 9, 2022.

[34] X. Guo, T. Fan and X. Shu, "Tomato leaf diseases recognition based on improved multi-scale AlexNet (in Chinese)," *Transactions of the Chinese Society of Agricultural Engineering,* Vol. 35, No. 14, pp. 162-169, 2019.

[35] A. Fuentes, S. Yoon and D. S. Park, "Deep learning-based techniques for plant diseases recognition in real-field scenarios. In: Advanced concepts for intelligent vision systems - 20th international conference, pp. 3-14, 2020.

[36] Natarajan, V. Anantha, Ms Macha Babitha, and M. Sunil Kumar, "Detection of disease in tomato plant using Deep Learning Techniques." *International Journal of Modern Agriculture,* Vol. 9, No. 4, pp. 525-540, 2020.

[37] M. Monika Singh, P. L. Sharma and I. K. Kasi, "Incidence of major insect pest infesting tomato in low and mid hills of Himachal Pradesh," *MDPI,* Vol. 11, pp. 1888-1890, 2022.

[38] Alvaro Fuentes, Sook Yoon, Sang Cheol Kim, and Dong Sun Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," *Sensors,* Vol. 17, No. 9, 2022.

[39] Surampalli Ashok, Gemini Kishore, Velpula Rajesh, S. Suchitra, SG Gino Sophia, and B. Pavithra, "Tomato leaf disease detection using deep learning techniques," In *2020 5th International Conference on Communication and Electronics Systems (ICCES), IEEE,* pp. 979-983, 2020.

[40] H. S. Nagamani and H. Sarojadevi, "Tomato Leaf Disease Detection using Deep Learning Techniques," *International Journal of Advanced Computer Science and Applications,* Vol. 13, No. 1, 2022.

[41] Mohan Bhandari, Tej Bahadur Shahi, Arjun Neupane, and Kerry Brian Walsh, "BotanicX-AI: Identification of Tomato Leaf Diseases Using an Explanation-Driven Deep-Learning Model," *Journal of Imaging,* Vol. 9, No. 2, pp. 53, 2023.

[42] Kai Tian, Jiefeng Zeng, Tianci Song, Zhuliu Li, Asenso Evans, and Jiuhao Li, "Tomato leaf diseases recognition based on deep convolutional neural networks," *Journal of Agricultural Engineering,* Vol. 54, No. 1, 2023.

[43] Martins Crispi, Guilhermi, Domingos Sárvio Magalhães Valente, Daniel Marçal de Queiroz, Abdul Momin, Elpídio Inácio Fernandes-Filho, and Marcelo Coutinho Picanço, "Using Deep Neural Networks to Evaluate Leafminer Fly Attacks on Tomato Plants," *Agri Engineering,* Vol. 5, No. 1, pp. 273-286, 2023.

[44] Mohamed Bouni, Badr Hssina, Khadija Douzi, and Samira Douzi, "Impact of Pretrained Deep Neural Networks for Tomato Leaf Disease Prediction," *Journal of Electrical and Computer Engineering,* 2023.

[45] A. F. Fuentes, S. Yoon, J. Lee and D. S. Park, "High-performance deep neural network-based tomato plant diseases and pests diagnosis system with refinement filter bank," *Front Plant Science,* Vol. 9, pp. 1-15, 2018.

[46] H. Durmus, E. O. Gunes and M. Kirci, "Disease detection on the leaves of the tomato plants by using deep learning," In *6th Int Conf Agro-Geoinformatics, Agro-Geoinformatics,* 2017.

[47] Y Toda and F. Okura, "How convolutional neural networks diagnose plant disease," *Plant Phenom,* pp. 1-14, 2019.

[48] A. K. Rangarajan, R. Purushothaman and A. Ramesh, "Tomato crop disease classification using pre-trained deep learning algorithm," *Procedia Computer Science,* Vol. 133, pp. 1040-1047, 2018.

[49] P. Sharma, Y. P. S. Berwal and W. Ghai, "Performance analysis of deep learning cnn models for disease detection in plants using image segmentation," *Information Processing in Agriculture,* Vol. 7, No. 4, pp. 566-574, December 2020.

[50] A. Khamparia, G. Saini, D. Gupta, A. Khanna, S. Tiwari and V. H. C. de Albuquerque, "Seasonal crops disease prediction and classification using deep convolutional encoder network," *Circuits, Systems, and Signal Processing,* Vol. 39, pp. 818-836, 2020.

[51] Q. Wang, F. Qi, M. Sun, J. Qu and J. Xue, "Identification of tomato disease types and detection of infected areas based on deep convolutional neural networks and object detection techniques," *Computational Intelligence and Neuroscience,* Vol. 15, 2019.

[52] B. A. M. Ashqar and S. S. Abu-Naser, "Image-based tomato leaves diseases detection using deep learning," *International Journal of Academic Engineering Research (IJAER),* Vol. 2, pp. 10-16, 2019.

[53] E. Suryawati, R. Sustika, R. S. Yuwana, A. Subekti and H. F. Pardede, "Deep structured convolutional neural network for tomato diseases detection," In *2018 International Conference on Advanced Computer Science and Information Systems (ICACSIS),* pp. 385-390, 2018.

[54] R. G. de Luna, E. P. Dadios, A. A. Bandala, "Automated image capturing system for deep learning- based tomato plant leaf disease detection and recognition," In *TENCON 2018-2018 IEEE Region 10 Conference,* pp. 1414-1419, 2018.

[55] M. Sardogan, A.Tuncer, Y. Ozen, "Plant leaf disease detection and classification based on cnn with lvq algorithm," In *2018 3rd International Conference on Computer Science and Engineering (UBMK),* pp. 382-385, 2018.

[56] K. Zhang, Q. Wu, A. Liu and X. Meng, "Can deep learning identify tomato leaf disease?," *Advances in Multimedia,* pp. 1-10, 2018.

[57] P. Tm, A. Pranathi, K. Sai Ashritha, N. B. Chittaragi, S. G. Koolagudi, "Tomato leaf disease detection using convolutional neural networks," In *2018 Eleventh International Conference on Contemporary Computing (IC3),* pp. 1-5, 2018.

[58] A. F. Fuentes, S. Yoon, J. Lee, D. S. Park, "High-performance deep neural network based tomato plant diseases and pests diagnosis system with refinement filter bank," *Frontiers in Plant Science,* Vol. 9, pp. 1162, 2018.

[59] W. Zeng, M. Li, J. Zhang, L. Chen, S. Fang, J. Wang, "High-order residual convolutional neural network for robust crop disease recognition," In *Proceedings of the 2Nd International Conference on Computer Science and Application Engineering, CSAE '18,* ACM, New York, NY, USA, Vol. 5, pp. 1-101, 2018, DOI: 10.1145/ 3207677.3277952.

[60] A. K. Rangarajan, R. Purushothaman, A. Ramesh, "Tomato crop disease classification using pre- trained deep learning algorithm," *Procedia Computer Science,* Vol. 133, pp. 1040-1047, 2018.

[61] H. Durmus, E. O. Günes, M. Kirci, "Disease detection on the leaves of the tomato plants by using deep learning," In *2017 6th International Conference on Agro Geoinformatics,* pp. 1-5, 2017. DOI: 10.1109/Agro-Geoinformatics.2017.8047016.

[62] H. A. Atabay, "Deep residual learning for tomato plant leaf disease identification," *Journal of Theoretical and Applied Information Technology,* Vol. 95, pp. 866, 2017.

[63] K. Yamamoto, T. Togami, N. Yamaguchi, "Super-resolution of plant disease images for the acceleration of image-based phenotyping and vigor diagnosis in agriculture," *Sensors,* Vol. 17, 2017.

[64] Hesham Tarek, Hesham Aly, Saleh Eisa, and Mohamed Abul-Soud, "Optimized deep learning algorithms for tomato leaf disease detection with hardware deployment," *Electronics,* Vol. 11, No. 1, pp. 140, 2022.

[65] Taye and Mohammad Mustafa, "Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions," *Computers,* Vol. 12, No. 5, pp. 91, 2023.

[66] Selvaganapathy, Shymala Gowri, Mathappan Nivaashini, and HemaPriya Natarajan, "Deep belief network based detection and categorization of malicious URLs," *Information Security Journal: A Global Perspective,* Vol. 27, No. 3, pp. 145-161, 2018.