Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 14, Issue. 2 : 2023
ISSN : **1906-9685**

DEEP LEARNING ALGORITHMS FOR IDENTIFICATION OF DISEASE IN TOMOTA LEAVES

K Punnam Chandar Asst.Prof, Dept of ECE, Kakatiya University, T.S, India
K Rajendra Prasad Assoc.Prof, ECE, K L R College of Engineering and Technology, T.S, India
krpece.klr@gmail.com

***Abstract*—Crop productivity and quality can be severely affected by tomato plant diseases, which is a major problem for farmers, especially in areas where tomato production is crucial for economic growth and food security. The necessity for automated solutions is highlighted by the fact that manual illness identification methods are both expensive and inefficient. There has been encouraging progress in an use of DL algorithms, especially CNNs, for the detection and classification of plant illnesses using photographs of their leaves. This study presents a comprehensive analysis of disease identification in tomato leaves using deep learning. Early disease detection is emphasised, the disease structure in tomato plants is described, and the function of deep learning in disease identification is addressed. It also finds research needs, such as the requirement for optimization methods, transfer learning techniques, and scalable federated learning frameworks, and examines the current literature on DL-based solutions for disease detection in tomato plants. At the end of the study, it emphasises how critical it is to fill these gaps in order to have scalable disease detection systems for farming. Our future research will centre around delving deeper into various transfer learning algorithms on various datasets, enhancing model performance with larger datasets, testing the scalability and efficiency of frameworks in real-world scenario.**

Keywords—Plant diseases, agriculture, tomato plants, Crop production, deep learning.

1 INTRODUCTION

A rise in crop production has created the way for more economic growth and development in sub-Saharan Africa. Farmers have recently achieved excellent yields by using contemporary tactics and technology. The majority of tomatoes in Tanzania are grown by small-scale farmers, but that is not the case in the present research[1]. These farmers and the community around them rely on tomato production for both cash and food. Many people who grow tomatoes also live in rural regions, where poverty rates are about 70%. Iringa, Morogoro, and Njombe are among the most common places to grow tomatoes [2]. One crop that suffers from diseases and pests that lead to less yield is tomatoes. Pests and diseases that disproportionately impact tomato cropsinclude early blight, septoria leaf spot, late blight, bacterial wilt, and bacterial wilt [3]. Previous research has utilized machine learning and deep learning techniques, particularly in the agricultural sector , to detect a variety of diseases. This has helped alleviate pest and disease problems, improved crop quality, and increased disease identification and diagnosis methods, all of which contribute to a decreased risk of harm to ecosystems [4]. Tomatoes, like many other plants, are susceptible to diseases caused by bacteria, fungus, and viruses. These insects may appear on many parts of tomato plants, including the fruit itself, as well as on the plant's roots, stems, and leaves. The majority of smallholderfarmers still rely on outdated methods that are based on laboratory observations, which might result in inaccurate diagnoses. There is a significant delay in processing laboratory observation data because of the absence of control and prevention of illness transmission. It might be much more challenging to detect illnesses and pests when there aren't enough expert support consultants.

The process of manually classifying pathogens and parasites is both labor-intensive and inefficient. Consequently, it is imperative to furnish producers with automated AI image-based solutions. The utilisation and endorsement of images as a dependable method for disease identification in image-centric computer vision applications are a result of the accessibility of suitable software packages or tools. In order to process the photos, they use image processing, a smart image identification technique that enhances recognition accuracy, decreases costs, and boosts efficiency in image recognition [5].

An extremely accurate result is the product of deep learning, a computational paradigm that combines sophisticated data analysis with image processing technologies [6]. Deep learning is now seeing extensive use in a variety of applications, such as biological image classification and segmentation, object identification, signal and speech recognition, and many more. Agricultural applications of deep learning methods have recently grown in popularity, especially for the purpose of plant disease detection and classification. The CNN is universally acknowledged as the most efficacious methodology within the realm of deep learning. Various CNN architectures, such as GoogleNet and AlexNet, are presently being implemented to identify and categorise plant diseases [7].

A. *Problem statement*

Plant diseases represent a substantial obstacle, contributing significantly to substantial loss or injury. The potential transmission of the virus from an infected tomato plant to the healthy tomato plants can lead to a reduction in overall farm production and a subsequent decline in the income of the farmers. Therefore, in the agricultural sector, timely detection of plant foliar diseases is critical. Visual inspection is frequently employed for both diagnostic and therapeutic purposes in the field of plant pathology. The cost of specialised advice, which is necessary for this, can be prohibitive for many producers. A method of early detection for plant diseases that is automated will be more effective. AI & ML/DL technologies can be used for automatic disease detection, however many of the DL and ML architectures are large in size and not good in accuracy.

B. *Structure of paper*

The rest of this paper follows as: Sections II and III provide the overview of tomato plant disease and identification. section IV gives the analysis of deep and their types section V provides the literature review. Last section provides the conclusion and future work of this work.

I. TOMATO PLANT DISEASE

Tomato is an essential popular vegetable crop grown in the world. The biological name for tomato is Solanum Lycopersicum. It is a crop of comparatively brief duration but yields significantly, rendering it economically appealing as the cultivated area continues to expand. This condition is highly susceptible to numerous diseases and has a significant negative impact on the quality and yield of tomatoes, in addition to resulting in considerable financial losses. India accounts for over 19.0% of the world's total tomato producing area and 11.1% of its total tomato output. In India, tomatoes make up 8% of the overall vegetable growing area and 12% of the total output [8]. The tomato plant has a lifespan of around 120 days. The flowering or fruiting stage occurs at approximately 45-50 days of the life of the tomato plant. The life cycle of the tomato plant is shown in Figure 1.

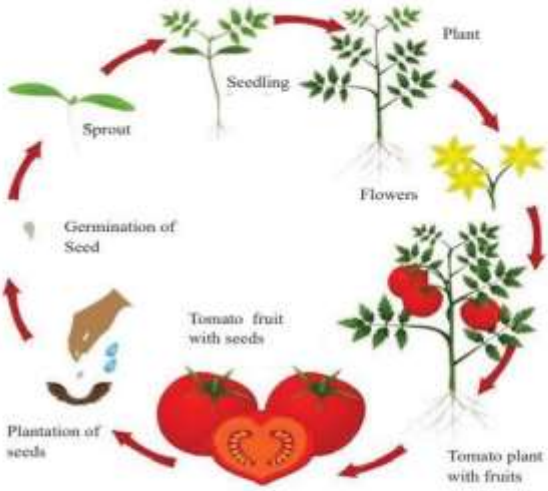

Fig. 1. Life cycle of Tomato plant showing different stages

The tomato life cycle starts from the plantation of seeds, then germination to growing into a sprout, seedling, and further into a plant. Once the plant matures, the flowering stage will be initiated, followed by fruiting. The seeds of the ripe fruits are further used for the next life cycle. The tomato plant in the flowering and fruiting stage is shown in Figure 2. The appearance of yellow flowers on the tomato plant indicates that the plant has begun the process of fruit production. The time required for ripe fruit after the flowers open on the tomato plant varies depending on the variety and several environmental factors. The disease in tomato plants occurs more often at the flowering or fruiting stage when the plant is mature. Farmers may improve their output and decrease yield loss with the use of disease prediction and time management tools.

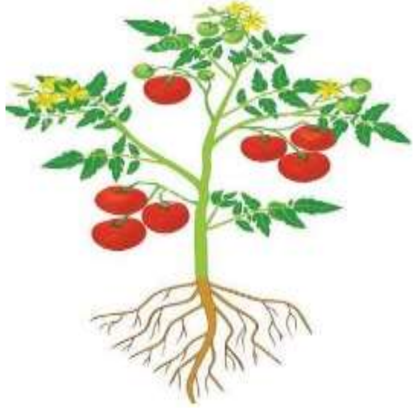

Fig. 2. Tomato plant in flowering and fruiting stage [9]

Plants are the foundation of all living things because they provide food. We must protect the plant from disease to have good food quality and quantity. Plant species are useful in medicine, agriculture, and industry. A few plants are on the verge of extinction; as a result, it is critical to establish a database for plant protection. Agriculture constitutes a pivotal determinant in the economies of numerous nations. It is both a mode of life and a benefit to the nation. Agricultural permits individuals with limited or no prior agricultural experience to cultivate crops and plants [10].

A. Tomato Plant disease category

Crop diseases are classified into two types: airborne and soil-borne. Fungal diseases are common in the airborne type. The affected plant's symptoms are visible in specific parts such as the leaves, stems, and fruit. The effect of soil-borne diseases is most visible on the plant's roots [11]. The plant is affected by a variety of viral and fungal diseases. Weather conditions and seasonal changes cause variations in temperature, humidity, wind speed, and so on. These changes have an impact on plants that are susceptible to certain diseases.

- **Viral diseases:** Plant diseases that arise from infections are notoriously challenging to detect and classify. Moreover, the symptoms exhibited by these pathogens are frequently misconstrued as indications of nutritional deficiency or damage due to the absence of a consistent, predetermined indicator. In addition
to leafhoppers, aphids, and cucumber-crawling insects, whiteflies often transmit viral diseases [12].
- **Fungal diseases:** Foliar diseases that are caused by fungi include powdery mildew, anthracnose, and downy mildew. It initially manifests on grey-green spoty lower foliage that are old or have been saturated with water. These areas become darker and develop fungus as the parasite ages.
- **Bacterial diseases:** Severe maladies in vegetables are caused by pathogens. Instead of entering the vegetation directly, they do so via crop injuries or apertures. A multitude of agricultural implements, pathogens, and pruning and harvesting implements are responsible for crop damage.

2. PLANT DISEASE IDENTIFICATION

Early detection and diagnosis of plant diseases is of the utmost importance in the field of agriculture. The identification of plant diseases through leaf examination is a widely employed method, as the leaves exhibit distinct structural variations that correspond to various types of diseases. An expert must be capable of visually identifying the disease. Pro-found expertise and extensive professional experience regarding the etiology of agricultural diseases [13]. The specialist should also be well-versed in the specifics of disease-related signs and symptoms. In rural areas, manual examination is still carried out today, but it is unable to pinpoint the precise illness and its variations. Larger farms must expend enormous amounts of labour and effort on manual assessment. Additionally, cultivation is an ongoing process that necessitates periodic crop inspections in order to detect diseases. Consequently, the automatic identification of maladies using leaf images necessitates an alternative approach [14].

In recent times, computer vision advancements have introduced a prospect for the expansion and improvement of precise plant protection, as well as the broadening of the market for computer vision applications within the agricultural sector. Conventional machine learning methodologies require domain experts to identify the majority of applied features. This is done to simplify the data and enhance the visibility of patterns for the cognizant algorithms. For the detection and categorization of plant maladies, numerous ML models have been optimised. DL is an advanced subfield of ML that use ANNs with a hierarchical structure to do ML. Deep learning involves training a computer model to identify objects in photos. Deep learning models are trained through the utilisation of extensive labeled datasets and neural network architectures that autonomously acquire features from the data, obviating the necessity for manual feature extraction.

For the detection and categorization of the symptoms exhibited by plant diseases, a multitude of developed and customised DL architectures are integrated with various visualisation techniques. DL algorithms attempt to incrementally learn high-level features from data, which is one of their most significant advantages [9].

3. OVERVIEW OF DEEP LEARNING

DL techniques play a major role in a process of predicting the disease level in the disease prediction system. It is capable of handling large volumes of data faster than machine learning algorithms [15]. Usually, the machine learning algorithm works well than the deep learning algorithm when it is used with a smaller number of datasets. At the same time, deep learning algorithms work well than machine learning algorithms for handling very large volumes of data. But Deep learning algorithm consumes more time since the dataset is trained repeatedly during the learning process. The features of the dataset can be analyzed in depth through repeated learning processes.

A. Convolution Neural Network

CNN has emerged as a popular variant of the standard Artificial Neural Network, with success in tasks involving image processing. In recent times, CNN has demonstrated exceptional progress in various research domains, including NLP, object recognition, face recognition, handwriting recognition, and speech recognition [16]. The mathematical operation that convolution utilizes in neural networks is where the term "convolution" originates. As illustrated in Figure 3, fundamental CNN components typically consist of three layers: convolution, pooling, and entirely connected. These building blocks are discussed below:

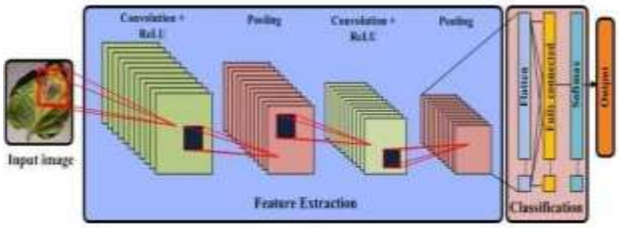

Fig. 3. Basic structure of CNN

B. Artificial Neural Network

A collection of basic, interconnected units termed artificial neurons—the building blocks of an artificial neural network (ANN). In order for impulses to go between neurons, they must first cross specific connections called synapses. Data gathering, processing, analysis, design, configuration, training, simulation, testing, and modifications to weights and biases make up the process. The number of hidden layers and their arrangement are also determined during this stage. There are a plethora of applications for artificial neural networks; for example, in speech recognition, imaging, recognition, optimisation, and many more. These networks frequently give helpful analyses that enable the prediction and identification of new data. Beyond that, it has practical uses in banking, healthcare, commerce, mining, and other areas [17].

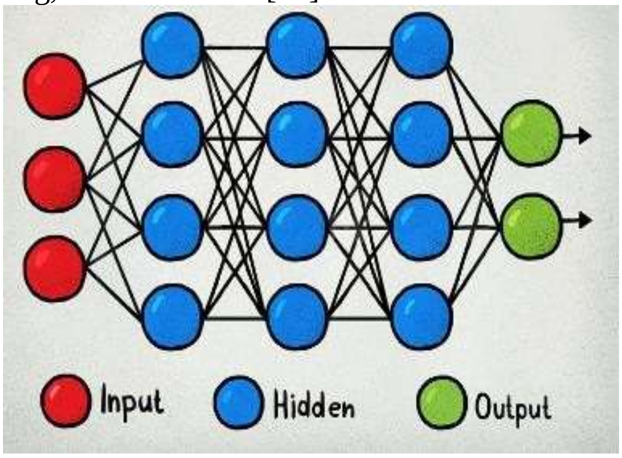

Fig. 4. Artificial neural network

C. Deep Belief Network

DBN is an instruction-based graphical model that acquires the ability to derive a profound hierarchical depiction of the input data. A stack of restricted Boltzmann machines (RBMs), which are two-layer generative stochastic models consisting of a visible-unit layer and a concealed unit layer, comprise the conventional DBN. An RBM requires that its two layers be connected in a bipartite graph, with no lateral connections allowed. All except the first two levels of a DBN use directed connections; instead, the higher-level units train to understand the conditional dependencies among the lower-level units in neighbouring layers. Before training a DBN, there is fine-tuning to be done.

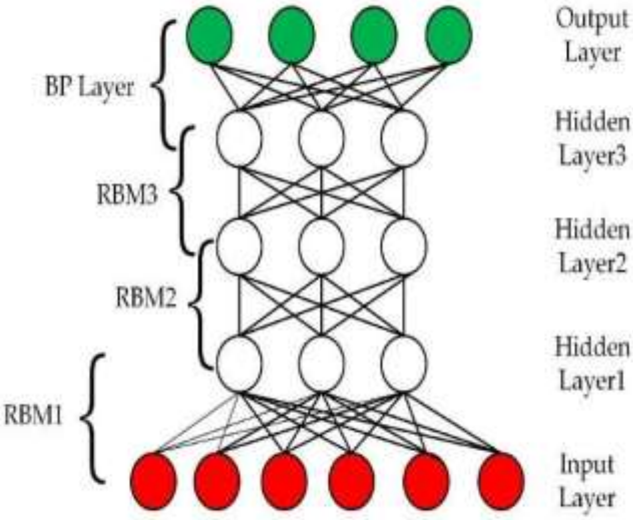

Fig. 5. structure of DBN

D. Recurrent Neural Networks (RNNs)

RNNs are a well-known and widely-used method in the field of deep learning [18]. RNN is utilised primarily in speech processing and natural language processing contexts
[19] [20]. RNN, in contrast to traditional networks, loads data sequentially. This particular attribute is critical for a vast array of applications, as the embedded structure within the data sequence provides valuable information.

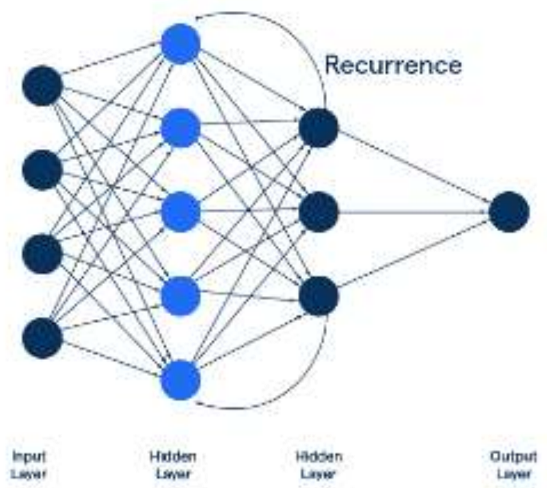

Fig. 6. Recurrent Neural Networks

4. LITERATURE REVIEW

Furthermore, as will be covered later on, other deep learning-based methods for disease detection and classification in tomato plants have been suggested by researchers:

In this paper, Bahrami, Pourhatami and Maboodi, (2024) a comprehensive analysis of different transfer learning algorithms, including VGG19, ResNet-101, and MobileNet- v2 was done on PlantVillage and CCMT datasets. VGG19 demonstrated the greatest performance, with the best results in terms of accuracy, precision, recall, and F1-score on the PlantVillage and CCMT dataset test set being 99.48%, 99.27%, 99.28%, and 92.76%, 92.74%, 95.09%, and 90.86%, respectively. The findings show that VGG19 has a reliable and accurate method of detecting tomato leaf disease[21].

In this paper, Soujanya et al., (2023) the diseased tomato plant leaves were classified using an improved CNN model. The Tomato Leaf Disease Detection dataset on Kaggle was used to identify tomato leaf diseases in our model. This dataset is comprised of 10,000 pieces, with ten separate classes and 1000 samples in each. Using a learning rate of 0.001 and an accuracy of 96% across 100 epochs, the suggested method has achieved promising results on the provided dataset[22].

The study, Trivedi et al., (2023) offers a streamlined federated deep learning framework to classify tomato leaf diseases while ensuring the preservation of sensitive data. The researchers piloted the framework with a single and several clients in both conventional and federated learning environments. Features from different pre-trained models are extracted, and AlexNet is chosen as a baseline because of its 99. 53% precision. Next, IID datasets were tested with FL technique. This strength of the architecture makes it the best option to select for the early tomato leaf disease categorization[23].

This paper, Kumar and Champa, (2023) proposes a deep learning-based model for agricultural disease detection that uses little processing resources while achieving excellent accuracy. The inception v3 network model achieved an impressive average identification accuracy of 98% when evaluated on a publicly accessible dataset of tomato leaves. Findings indicate that this approach has the potential to aid in food security efforts by facilitating the rapid and accurate diagnosis of crop diseases and the subsequent implementation of corrective actions by farmers[24].

This paper, Srivastava, Sisaudia and Meena, (2023) advocates for hybrid method in the use of transfer learning and ELM for classifying tomato leaf diseases. TLMV2-ELM model has MobileNetV2 for feature extraction that gives precise feature vectors which are then classified as ELM. The TLMV2-ELM method is validated using a tomato leaf dataset, as a result the experiment reveals that the approach performs above the current methods with an accuracy of 0. 99% and 0. 06 loss in terms of detecting disease[25].

In this paper, Kibriya et al., (2021) released two models for disease classification in tomato leaves, one based on a CNN and the other on a VGG16. Through the use of deep learning techniques, this suggested study seeks to resolve the issue of disease detection in tomato leaves. Based on 10735 images of leaves in the Plant Village dataset, VGG16 achieved 98% accuracy and GoogLeNet 99.23%. Tomato fields may benefit from the suggested system's early disease detection capabilities, which can therefore help to prevent crop loss[26].

Ref	Model	Dataset	Results	Future Work/Research Gap
Bahrami et al., 2024	Transfer learning (VGG19, ResNet-101, Mobile Net-v2)	PlantVillage and CCMT	VGG19 achieved the highest accuracy 99.48 and 92.76	Further exploration of transfer learning algorithms on different datasets.
Soujanya et al., 2023	CNN model optimization	Tomato Leaf Disease Detection dataset from Kaggle	Achieved 96% accuracy on 10,000 samples for tomato leaf disease detection.	Investigation into improving model's performance with larger datasets.
Trivedi et al. (2023)	Federated deep learning framework	Various datasets, AlexNet as a baseline	The proposed framework achieved 99.53% accuracy	Evaluation of framework's scalability and efficiency in real-world scenarios.
Kumar and Champa, 2023	Inception v3 network	Publicly available tomato leaf dataset	Attained 98% accuracy for crop disease identification	Exploration of model deployment in resource-constrained environments.
Srivastava et al., 2023	Hybrid approach (Transfer learning + ELM)	Tomato leaf dataset	existing methods with 99% accuracy and 0.06 loss.	Investigation into further enhancing hybrid model's performance.
Kibriya et al. (2021)	CNN (GoogLeNet, VGG16)	Plant Village dataset	VGG16 achieved 98% accuracy, GoogLeNet 99.23%	Examination of model robustness across diverse environmental conditions.

A. Research gap

There has been significant progress in the field of tomato leaf disease detection using DL techniques, with many models obtaining high accuracies. Still, the existing literature is lacking in some key areas and has a few significant drawbacks. The first issue is that the results are not applicable to other datasets because most research only looks at how well one model performs. Problems with efficiency and scalability continue, especially in practical deployment settings where limited resources are at a premium. It is also difficult to investigate model resilience and performance under varied environmental circumstances since most research use tiny datasets. To address these limitations and enable effective and scalable disease detection solutions for agricultural applications, more research into optimisation approaches, transfer learning methodology, and the creation of strong federated learning frameworks is necessary.

REFERENCES

[1] J. Ssozi, S. Asongu, and V. H. Amavilah, “The effectiveness of development aid for agriculture in Sub-Saharan Africa,” *J. Econ. Stud.*, 2019, doi: 10.1108/JES-11-2017-0324.

[2] V. Mutayoba and D. Ngaruko, “Assessing Tomato Farming and Marketing Among Smallholders in High Potential Agricultural Areas of Tanzania,” *Int. J. Econ. Commer. Manag.*, 2018.

[3] J. Liu and X. Wang, “Tomato Diseases and Pests Detection Based on Improved Yolo V3 Convolutional Neural Network,” *Front. Plant Sci.*, 2020, doi: 10.3389/fpls.2020.00898.

[4] M. De-Arteaga, W. Herlands, D. B. Neill, and A. Dubrawski, “Machine learning for the developing world,” *ACM Trans. Manag. Inf. Syst.*, 2018, doi: 10.1145/3210548.

[5] R. Wang, M. Lammers, Y. Tikunov, A. G. Bovy, G. C. Angenent, and R. A. de Maagd, “The rin, nor and Cnr spontaneous mutations inhibit tomato fruit ripening in additive and epistatic manners,” *Plant Sci.*, 2020, doi: 10.1016/j.plantsci.2020.110436.

[6] H. Durmus, E. O. Gunes, and M. Kirci, “Disease detection on the leaves of the tomato plants by using deep learning,” in *2017 6th International Conference on Agro-Geoinformatics, Agro-Geoinformatics 2017*, 2017. doi: 10.1109/Agro-Geoinformatics.2017.8047016.

[7] P. Dhiman, A. Kaur, Y. Hamid, E. Alabdulkreem, H. Elmannai, and N. Ababneh, “Smart Disease Detection System for Citrus Fruits Using Deep Learning with Edge Computing,” *Sustain.*, 2023, doi: 10.3390/su15054576.

[8] V. Gupta, V. K. Razdan, S. Sharma, and K. Fatima, “Progress and severity of early blight of tomato in relation to weather variables in Jammu province,” *J. Agrometeorol.*, 2020.

[9] S. A. Wagle, “Detection and Classification of Tomato Plant Disease using Deep Learning Network,” 2023.

[10] S. AlZu’bi, B. Hawashin, M. Mujahed, Y. Jararweh, and B. B. Gupta, “An efficient employment of internet of multimedia things in smart and future agriculture,” *Multimed. Tools Appl.*, 2019, doi: 10.1007/s11042-019-7367-0.

[11] K. Zhang, Q. Wu, A. Liu, and X. Meng, “Can deep learning identify tomato leaf disease?,” *Adv. Multimed.*, 2018, doi: 10.1155/2018/6710865.

[12] H. Orchi, M. Sadik, and M. Khaldoun, “On using artificial intelligence and the internet of things for crop disease detection: A contemporary survey,” *Agriculture (Switzerland)*. 2022. doi: 10.3390/agriculture12010009.

[13] J. Ma, X. Li, H. Wen, Y. Chen, Z. Fu, and L. Zhang, “Monitoring video capture system for identification of greenhouse vegetable diseases,” *Nongye Jixie Xuebao/Transactions Chinese Soc. Agric. Mach.*, 2015, doi: 10.6041/j.issn.1000-1298.2015.03.041.

[14] J. G. Arnal Barbedo, “Digital image processing techniques for detecting, quantifying and classifying plant diseases,” *Springerplus*, 2013, doi: 10.1186/2193-1801-2-660.

[15] J. Ker, L. Wang, J. Rao, and T. Lim, “Deep Learning Applications in Medical Image Analysis,” *IEEE Access*, 2017, doi: 10.1109/ACCESS.2017.2788044.

[16] X. Zhang, J. Zhao, and Y. Lecun, “Character-level convolutional networks for text classification,” in *Advances in Neural Information Processing Systems*, 2015.

[17] I. Veza *et al.*, “Review of artificial neural networks for gasoline, diesel and homogeneous charge compression ignition engine: Review of ANN for gasoline, diesel and HCCI engine,” *Alexandria Engineering Journal*. 2022. doi: 10.1016/j.aej.2022.01.072.

[18] Y. Jiang, H. Kim, H. Asnani, S. Kannan, S. Oh, and P. Viswanath, “LEARN Codes: Inventing Low-Latency Codes via Recurrent Neural Networks,” *IEEE J. Sel. Areas Inf. Theory*, 2020, doi: 10.1109/jsait.2020.2988577.

[19] Ö. Batur Dinler and N. Aydin, “An optimal feature parameter setbased on gated recurrent unit recurrent neural networks for speech segment detection,” *Appl. Sci.*, 2020, doi: 10.3390/app10041273.

[20] A. N. Jagannatha and H. Yu, “Structured prediction models for RNN based sequence labeling in clinical text,” in *EMNLP 2016 - Conference on Empirical Methods in Natural Language Processing, Proceedings*, 2016. doi: 10.18653/v1/d16-1082.

[21] M. Bahrami, A. Pourhatami, and M. Maboodi, “Tomato Leaf Disease Detection Using Transfer Learning: A Comparative Study,” in *2024 13th Iranian/3rd International Machine Vision and Image Processing Conference (MVIP)*, 2024, pp. 1–5. doi: 10.1109/MVIP62238.2024.10491178.

[22] T. Soujanya, S. Padmaja, D. Ramesh, Shabana, and S. Mohmmad, “An Optimized Deep Learning Technique for Enhance Disease Identification in Tomato Leaf to Promote Sustainable Agriculture,” in *2023 International Conference on Evolutionary Algorithms and Soft Computing Techniques, EASCT 2023*, 2023. doi: 10.1109/EASCT59475.2023.10392310.

[23] N. K. Trivedi, H. Maheshwari, R. G. Tiwari, A. K. Agarwal, and

V. Gautam, “Tomato Leaf Disease Classification with Lightweight Federated Learning using Identically Distributed Images,” in *2023 9th International Conference on Signal Processing and Communication, ICSC 2023*, 2023. doi: 10.1109/ICSC60394.2023.10441624.

[24] P. Kumar and H. N. Champa, “Crop Disease Identification in Tomato Leaf using Deep Learning,” in *2023 14th International Conference on Computing Communication and Networking Technologies, ICCCNT 2023,* 2023. doi:10.1109/ICCCNT56998.2023.10306681.

[25] M. Srivastava, V. Sisaudia, and J. Meena, “Tomato Leaf Disease Detection and Classification using MobileNetV2 and Extreme Learning Method: A Hybrid Approach,” in *2023 10th International Conference on Soft Computing & Machine Intelligence (ISCMI)*, 2023, pp. 108–112. doi: 10.1109/ISCMI59957.2023.10458596.

[26] H. Kibriya, R. Rafique, W. Ahmad, and S. M. Adnan, “Tomato Leaf Disease Detection Using Convolution Neural Network,” in Proceedings of 18th International Bhurban Conference on Applied Sciences and Technologies, IBCAST 2021, 2021. doi: 10.1109/ IBCAST51254.2021.9393311.