International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

COPY RIGHT

IJIEMR Transactions, online available on 12th September 2024. Link

https://ijiemr.org/downloads.php?vol=Volume-13&issue=issue09

DOI:10.48047/IJIEMR/V13/ISSUE09/02

Title: "REVIEW OF THE LITERATURE ON MACHINE LEARNING TECHNIQUES FOR TOMATO LEAF DISEASE DETECTION"

Volume 13, ISSUE 09, Pages: 16- 24

Paper Authors
Mansi Verma, Dr. Amrita Kumari, Dr. Ashish Saini

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

REVIEW OF THE LITERATURE ON MACHINE LEARNING TECHNIQUES FOR TOMATO LEAF DISEASE DETECTION

[1]Mansi Verma, [2]Dr. Amrita Kumari, [3]Dr. Ashish Saini

[1]Research Scholar, Department of Computer Science and Engineering, Quantum University Roorkee India.

[2]Department of Computer Science and Engineering, Quantum University, Roorkee, India

[3]Department of Computer Science and Engineering, Quantum University, Roorkee, India

mansiverma550@gmail.com amrita.cse@quantumeducation.in ashish.cse@quantumeducation.in

ABSTRACT

—The most popular vegetable crop grown extensively in Indian agricultural lands is the tomato. Although the tropical environment of India is perfect for its growth, normal tomato plant growth is influenced by a number of other elements as well as specific climatic circumstances. In addition to these weather patterns and natural calamities, plant disease seriously threatens agricultural productivity and is a significant source of financial loss. The results of the conventional disease detection techniques for tomato crops were unsatisfactory, and the time it took to find infections was long. Earlier illness detection can produce better outcomes than current detection techniques. Therefore, deep learning approaches based on computer vision technology could be used for early disease detection. The disease categorization and detection methods suggested for tomato leaf detection are thoroughly examined in this research. This report also evaluates the advantages and disadvantages of the proposed approaches. This paper ultimately suggests using hybrid deep- learning architecture for early tomato leaf disease detection.

Index Terms—Machine Learning, CNN, Deep Learning, R- CNN, Leaf Disease Detection

INTRODUCTION

In the agricultural area, plant diseases are regarded as a serious crisis that hinder the growth of agriculture and cause significant financial losses for farmers. Tomatoes are grown on hectares all throughout India and are one of the major crops there. A survey found that over 20 different tomato diseases have an impact on tomato productivity and quality, which costs agriculturalists a significant amount of money [1]. The tomato plant's leaves, roots, fruits, and stems are all impacted by the illnesses. Plants that have phonological changes in their leaves develop abnormally, get discolored, sustain damage, and eventually die. Early blight, spider mites, leaf mold, target spot, mosaic virus, yellow curl virus, and other conditions are among the ailments that affect tomato leaves [2].

It is challenging and less accurate to identify and detect tomato leaf diseases with the naked

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

eye in limited areas, even with the assistance of agricultural professionals. The agricultural specialists' crop inspections cost more money and take more time, and the farmers and agriculturalists lack the means to get in touch with them [3]. AI and machine learning principles, which help with automatic diagnosis of tomato leaf disease using computerized systems for monitoring huge tomato fields, are a result of recent advances in computing technology.

Technological developments in computers have improved plant protection as an application in agriculture. The growth of machine learning from its early stages to the present is illustrated in Fig. 1. With current breakthroughs and concepts, these machine learning (ML)-based techniques have led to significant advancements in numerous domains. Plant illnesses were classified using digital image processing methods in the early days of disease detection systems.

The most recent method claims that deep learning with neural networks improves categorization and accuracy because of their automatic numerous feature extraction steps [4]. Then, when compared to all other conventional classification algo- rithms, the Convolutional Neural Network (CNN), a popular machine learning methodology, performs better in DNN.With the use of their most recent meta architectures, such as VGGNet, LeNet, ResNet, etc., Deep CNN has significantly improved and achieved the best classification performance when trained to detect tomato leaf disease.

The well-known segmentation and object identification ar- chitectures, such as Mask R-CNN, FCN, SSD, and R-CNN, were designed for improved detection but required a lot of time to provide better results. Subsequently, the hybrid design suggested by Deep CNN was extended to improve the accuracy and performance of Convolutional Neural Networks. CNN is mostly used for object detection, recognition, seg- mentation, classification, and other tasks for which it performs incredibly well with a reasonable amount of labeled data. Additionally, CNN's advancements led to the creation of

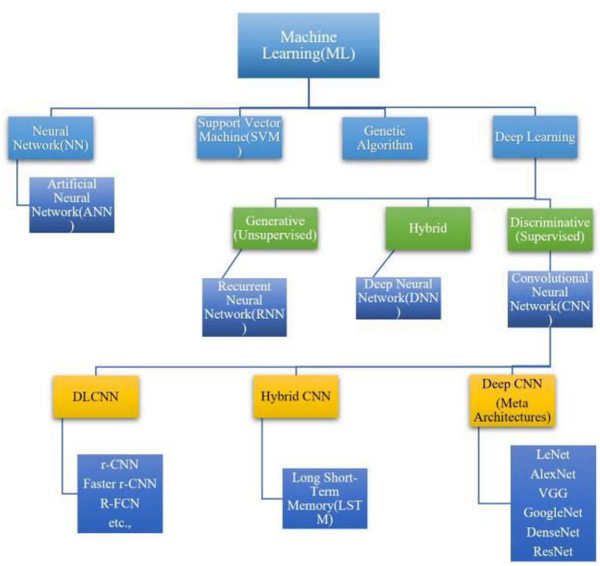

Fig. 1. Concepts of Machine Learning

hybrid CNN, which has Long Short-Term Memory (LSTM). CNN has several benefits, including multitasking, hierarchical learning, automatic feature extraction, etc.

LITRATURE SURVEY

A method for detecting plant diseases using a neural net- work and the k-means clustering algorithm was proposed by
H. Al-Hiary et al. This trained model is able to identify plant diseases both in terms of detection and classification. It offers an exact accuracy ranging from 83% to 94% . Benefits include accurate illness detection requiring less computer work. It is discovered that the merits recognition rate has decreased [5]. K-means clustering for segmentation and ANN for leaf disease detection and classification were proposed by Dheeb Al Bashish et al. The diseases were identified by this suggested model 93% of the time. Among its benefits is its exceptional ability to identify illnesses. Among the drawbacks are the need
for finer segmentation and feature extraction [6].
The ANN classifier was introduced by Anand.H. Kulkarni et al. for the purpose of classifying and identifying damaged leaves. Images input are filtered and segmented using the gabor filter. The suggested model achieves 91% accuracy. Among the merits are the development of effective categorization and recognition. Better classifiers that can be applied to increase recognition rates are among the merits [7].
A Support Vector Machine (SVM) classifier was proposed by S. Arivazhagan et al. This suggested model has an accuracy of 94%. Benefits include the ability to automatically identify and categorize leaf disease. NN classifiers, which can be utilized to get better performance, are among the demerits [8]. SVM with various kernel functions was proposed by Usama Mokhtar et al. to identify tomato leaf diseases with a 99.5% excellent annotation rate. Among the merits are dependable and efficient outcomes. A high volume of inputs that lowers performance is one of the demerits [9].
A deep learning method using the AlexNet and GoogleNet architectures was proposed by Sharada.P. Mohanty et al. to improve disease diagnosis. The accuracy of this GoogleNet- trained model is 99.35%. One of its many merits is how quickly the suggested DNN classifies data. One of the draw- backs is that extensive training is necessary [10].
A method for deep convolutional neural networks was proposed by Srdjan Sladojevic et al. The accuracy of this trained model is 96.3% [4]. Among its advantages is the suggested methodology's ability to produce a more accurate classification. Drawbacks include the need for augmentation and fine-tuning in order to increase accuracy .
A classification tree model based on supervised learning approaches was proposed by H. Sabrol [11]. This classification tree receives the characteristics that were derived from the segmented image and uses 97.3% accuracy to classify tomato plant diseases. Accurate classification tree findings are among the merits. The most recent classification methods are among the demerits.
Convolutional neural networks were proposed by Mo- hammed Brahimi et al. to improve

categorization. CNN’s automatic feature extraction from unprocessed input images is significant. The trained model therefore attains 99.18% ac- curacy [12]. Among the merits are excellence in performance. One can minimize the size of the deep neural network (dNN) and compute efficiently.

Alvaro Fuentes et al. presented an object recognition tech- nique that combined the most recent deep CNN feature extractors with Faster r-CNN, R-FCN, and SSD algorithms [13]. R-CNN with VGG-16, the suggested model, produced superior recognition outcomes. The benefit is a decrease in false positives during the training stage. Performance lag is the demerit.

SqueezeNet and AlexNet, two Deep Learning-based net- work designs, were proposed by Halil Durmas et al. for the diagnosis of tomato leaf disease. With a classification accuracy of 95.65%, AlexNet performed better. One benefit of squeezeNet is its low computational overhead and light weight. Long training periods and small batch sizes are advantages [14].

VGG16 model based on CNN network proposed by Jia Shijie et al. When it comes to image categorization and localization, the VGG performs well. Overall classification accuracy is attained at 89% [15]. One merit of the suggested paradigm is its high efficacy. Only used, comparatively high- quality test images are among the merits.

A CNN-based machine learning model was proposed by Santosh Adhikari et al. Data augmentation minimizes over- fitting when the model is being trained. A total accuracy of 89% is therefore attained. Data augmentation that results in improved performance is one of its merits [16]. Drawbacks include the need for transfer learning in order to categorize all diseases.

CNN-based architectural models with deep learning were proposed by Konstantinos P. Ferentinos. After training and fine-tuning, the VGG model attained a high success rate of 99.53%. Among its advantages are the suggested method’s greater robustness and great potential [17]. One of its draw- backs is that it is limited to using the same database for training input values.

The VGGNet model was proposed by Endang Suryawati et al. With an accuracy of 95.24%, the suggested model provides strong support for disease detection. Among the virtues is model correctness. One of the model’s shortcomings is its lack of resilience [18].

Pre-trained deep learning-based architectures were proposed by Aravind Krishnaswamy Rangarajan et al. for the catego- rization of tomato diseases. In the shortest amount of time, the AlexNet model was able to attain 97.49% classification accuracy [19]. Better accuracy in a shorter amount of time is one of its merits. Among the drawbacks include decreased accuracy and a rise in mini-batch size.

A.M. Belal Ashqar suggested deep CNN models that are full-color and grayscale. This suggested model uses a full- color representation and achieves 99.84% accuracy. While the color model learned to recognize damaged leaves, the gray- scale model merely learned the shape and patterns of the leaf. Extremely attainable merits are among them. One of the merits is that recognition is a little off [20].

The deep neural network optimization techniques were proposed by Keke Zhang et al. With the ResNet approach, the best SGD yields the highest accuracy of 97.28%. Among its benefits is the time and computing resource savings from fine-tuning [21]. Good performance is then attained. Merits require a lot of time.

A CNN-based LeNet model was proposed by Prajwala TM et al. An accuracy of 94–95% was attained on average by the suggested model. Among the benefits include precise identi- fication requiring less computing work [22]. Various learning rate optimizers that can be applied to enhance performance are among the demerits.

A trained model based on CNN and F-RCNN was proposed by Robert G. de Luna et al. The suggested approach achieves a 91.67% performance rate. Transfer learning identifying high accuracy model increases is one of the merits. Retraining the CNN for optimal performance is one of the drawbacks [23].

A CNN model utilizing the LVQ algorithm was proposed by Melike Sardogan et al. The suggested approach produced an average classification accuracy of 86%. Among the benefits is the prompt and efficient identification of plant leaf disease. The categorization rate presents a hurdle in this case [24].

The CNN-based INAR-SSD model for deep learning was proposed by Peng Jiang et al. The suggested model used real- time input photos to detect diseases with excellent accuracy. A 78.80% detection rate is attained. Superior performance and increased real-time accuracy are among its merits [25]. One of its drawbacks is that the object detection method is application-specific and rarely gets better.

The object detection models with deep CNN architectures were proposed by Qimei Wang et al. 99.64% performance and a better detection rate are demonstrated by the mask R-CNN with ResNet-101 [26]. Accurate and prompt performance is a merit. Drawbacks include the longer training time of Mask- RCNN compared to R-CNN.

A Convolutional Neural Network-based methodology was proposed by Karthik R. et al., and it reached 98% classification accuracy. Among its advantages is a high detection rate in comparison to current techniques. Among the rewards are the most recent CNN method for earlier outcomes [27].

A CNN-based technique was proposed by Surampalli Ashok et al., and it reached 98% classification accuracy. Among the merits are excellence in performance. Recent classifiers and algorithms that can be applied for best outcomes are among its strengths [28].

Deep CNN in conjunction with a ResNet-50 model-based architecture was proposed by Nithish Kannan E et al., [29] and it achieved 97% accuracy. Among its merits is a trained model that uses data augmentation to boost efficiency. High configuration hardware, which is crucial for training, is one of the drawbacks.

A Deep Learning CNN-based model, proposed by Thair

A. Salih et al., attained a 96.43% classification accuracy. Among the benefits are quick detection and identification. Long training and picture resolution determination times are among the merits [30].

Crop diseases are a significant factor that, when they dam- age crops, can lower crop output by 20–30%, according to Park et al. [1]. These crop illnesses significantly affect yield as a whole. Farmers frequently rely on professional guidance or own experience to diagnose ambiguous circumstances. The technology assesses and makes predictions about possible ailments by sending a smartphone-captured image of a leaf to an analytical engine. Their technique for diagnosing diseases consists of three fully connected neural networks and two convolutional neural networks. Utilising a central processing unit (CPU), the model's accuracy stands at 89.7%.

Plant diseases have been identified by Dandawate et al. [2] as a significant contributor lowering agricultural productivity, both in terms of quantity and quality. The diagnosis and treatment of these illnesses present substantial hurdles for farmers. The test results show that the system has an average accuracy of 93.79% in classifying sick leaves.

Using a convolutional neural network (CNN), Militante et al. [3] created a trained model that could identify and detect 32 distinct plant species and diseases with a 96.5% accuracy rate. Real-time picture analysis was used to test the model's ability to recognise and detect plant diseases. With a 96.5% accuracy rate, their suggested method provides farmers with a useful tool for identifying and categorising plant diseases.

An RCNN with a res101 basis that is quicker was proposed by Yang Zhang et al. A 98.54% mAP accuracy is attained [31]. Among its merits is the fact that this suggested method for detecting agricultural diseases detects diseases more quickly than the original, quicker RCNN. Only one leaf disease is visible in the provided photograph, which is a drawback.

We infer from the study that plant leaf disease detection was the primary application of CNN approaches. With Object Detection models, the classification process was noticeably

TABLE I

COMPARISON TABLE OF DIFFERENT MODEL ACCURACY

Author Name	**Accuracy**	**Technique Used**	**Limitation**
N. S. Kumar, et.al	94%	Neural Net- work	Recognition rate de- clined
Mokhtar, Usama, et. al	99.55%	Support Vec- tor Machine	large scale of inputs decrease performance
H. Sabrol and K. Satish	97.3%	Decision Tree Method	latest classification techniques can be used
P. Tm, A. Pranathi et. al	94-95%	CNN-based LeNet model	various learning opti- mizers can be used to improve performance
B. A. Ashqar and S. S. Abu- Naser	99.84%	CNN with full model color	Lacking ofdisease

			recognition
Qimei Wang et al.	99.84%	R-CNN with ResNet 101	Requires long time and high configura- tion hardware

quicker and the detection rate was increased in Deep CNN approaches. These implementations show that to boost the model's performance and overall accuracy, CNN needs an extra model. We draw the conclusion that the current models perform better based on the survey. Nevertheless, such models were unable to identify illness at an earlier stage. Therefore, a hybrid model for tomato leaf disease early detection is required.

CONCLUSION

In the area of agriculture, leaf disease detection is important and calls for increased accuracy to detect illnesses in real- time. Compared to other models, the early leaf detection model can help detect disease earlier. The survey of leaf disease detection algorithms and current detection algorithm approaches is described in the paper. The contribution of the suggested approach and its detection limits are also covered in the paper. The leaf detection model and the importance of early detection models are introduced in this study.

REFERENCES

[1] N. S. Kumar, J. Sony, A. Premkumar, R. Meenakshi, and J. J. Nair, "Transfer learning-based object detection models for improved diagnosis of tomato leaf disease," Procedia Computer Science, vol. 235, pp. 3025– 3034, 2024.

[2] Z. Ullah, N. Alsubaie, M. Jamjoom, S. H. Alajmani, and F. Saleem, "Effimob-net: A deep learning-based hybrid model for detection and identification of tomato diseases using leaf images," Agriculture, vol. 13, no. 3, p. 737, 2023.

[3] M. S. Alzahrani and F. W. Alsaade, "Transform and deep learning al- gorithms for the early detection and recognition of tomato leaf disease," Agronomy, vol. 13, no. 5, p. 1184, 2023.

[4] 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, no. 1, p. 3289801, 2016.

[5] H. Al-Hiary, S. Bani-Ahmad, M. Ryalat, M. Braik, and Z. Alraham- neh, "Fast and accurate detection and classification of plant diseases," International Journal of Computer Applications, vol. 17, 03 2011.

[6] D. Al Bashish, M. Braik, and S. Bani-Ahmad, "Detection and clas- sification of leaf diseases using k-means-based segmentation and," Information technology journal, vol. 10, no. 2, pp. 267–275, 2011.

[7] A. H. Kulkarni and A. Patil, "Applying image processing technique to detect plant

diseases," International Journal of Modern Engineering Research, vol. 2, no. 5, pp. 3661–3664, 2012.

[8] 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, no. 1, pp. 211–217, 2013.

[9] U. Mokhtar, M. A. Ali, A. E. Hassenian, and H. Hefny, "Tomato leaves diseases detection approach based on support vector machines," in 2015 11th International Computer Engineering Conference (ICENCO),
pp. 246–250, IEEE, 2015.

[10] S. P. Mohanty, D. P. Hughes, and M. Salathe´, "Using deep learning for image-based plant disease detection," Frontiers in plant science, vol. 7,
p. 1419, 2016.

[11] H. Sabrol and K. Satish, "Tomato plant disease classification in digital images using classification tree," in 2016 international conference on communication and signal processing (ICCSP), pp. 1242–1246, IEEE, 2016.

[12] 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.

[13] 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, p. 2022, 2017.

[14] H. Durmus¸, E. O. Gu¨nes¸, and M. Kırcı, "Disease detection on the leaves of the tomato plants by using deep learning," in 2017 6th International Conference on agro-geoinformatics, pp. 1–5, IEEE, 2017.

[15] J. Shijie, J. Peiyi, H. Siping, et al., "Automatic detection of tomato diseases and pests based on leaf images," in 2017 Chinese Automation Congress (CAC), pp. 2537–2510, IEEE, 2017.

[16] S. Adhikari, D. Unit, B. Shrestha, and B. Baiju, "Tomato plant diseases detection system," in 1st KEC Conference Proceedings, vol. 1, pp. 81– 86, 2018.

[17] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and electronics in agriculture, vol. 145, pp. 311– 318, 2018.

[18] 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, IEEE, 2018.

[19] A. K. Rangarajan, R. Purushothaman, and A. Ramesh, "Tomato crop disease classification using pre-trained deep learning algorithm," Proce- dia computer science, vol. 133, pp. 1040–1047, 2018.

[20] B. A. Ashqar and S. S. Abu-Naser, "Image-based tomato leaves disease detection using deep learning," 2018.

[21] K. Zhang, Q. Wu, A. Liu, and X. Meng, "Can deep learning iden- tify tomato leaf disease?," Advances in multimedia, vol. 2018, no. 1,

p. 6710865, 2018.

[22] P. Tm, A. Pranathi, K. SaiAshritha, N. B. Chittaragi, and S. G. Koolagudi, "Tomato leaf disease detection using convolutional neural networks," in 2018 eleventh international conference on contemporary computing (IC3), pp. 1–5, IEEE, 2018.

[23] R. G. De Luna, E. P. Dadios, and 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, IEEE, 2018.

[24] M. Sardogan, A. Tuncer, and 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, IEEE, 2018.

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

[26] Q. Wang, F. Qi, M. Sun, J. Qu, and J. Xue, "Identification of tomato disease types and detection of infected areas based on deep convolu- tional neural networks and object detection techniques," Computational intelligence and neuroscience, vol. 2019, no. 1, p. 9142753, 2019.

[27] R. Karthik, M. Hariharan, S. Anand, P. Mathikshara, A. Johnson, and R. Menaka, "Attention embedded residual cnn for disease detection in tomato leaves," Applied Soft Computing, vol. 86, p. 105933, 2020.

[28] S. Ashok, G. Kishore, V. Rajesh, S. Suchitra, S. G. Sophia, and B. Pavithra, "Tomato leaf disease detection using deep learning tech-ctronics Systems (ICCES), pp. 979–983, IEEE, 2020.

[29] M. Kaushik, P. Prakash, R. Ajay, S. Veni, et al., "Tomato leaf disease detection using convolutional neural network with data augmentation," in 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp. 1125–1132, IEEE, 2020.

[30] T. A. Salih et al., "Deep learning convolution neural network to detect and classify tomato plant leaf diseases," Open Access Library Journal, vol. 7, no. 05, p. 1, 2020.

[31] Y. Zhang, C. Song, and D. Zhang, "Deep learning-based object detection improvement for tomato disease," IEEE access, vol. 8, pp. 56607–56614, 2020.