JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A COMPREHENSIVE SURVEY ON MACHINE LEARNING AND DEEP LEARNING TECHNIQUES FOR TOMATO PLANT LEAF AND FRUIT DISEASE DETECTION

[1]Sharmila M,
[1]Research Scholar,
[1]Department of Computer and Information Science,
[1]Annamalai University, Chidambaram, India

[2]Dr. M. Natarajan
[2]Assistant Professor/Programmer
[2]Department of Computer and Information Science,
[2]Annamalai University, Chidambaram, India

Abstract : **Tomato plant leaf and fruit diseases are a significant concern for farmers and gardeners as they can cause substantial yield losses and affect crop quality. Detecting these diseases early is crucial for implementing timely control measures and minimizing the spread of infections. In recent years, machine learning (ML) and deep learning (DL) techniques have exposed great promise in automating the detection method, providing accurate and efficient disease diagnosis. This article presents a comprehensive review of the application of ML and DL techniques for tomato plant disease detection. The aim of this survey is to investigate the utilization and effectiveness of ML and DL techniques in the detection of tomato plant leaf and fruit diseases. The survey begins by providing an overview of the common diseases affecting tomato plants, highlighting the importance of timely detection and intervention. It then delves into the principles and methodologies of ML and DL, providing a foundation for understanding their applications in disease detection. The survey examines the existing ML and DL techniques available for plant disease detection. Furthermore, the DL approaches, particularly convolutional neural networks (CNNs) are exposed to significant performance in tomato plant disease detection. CNNs can automatically learn hierarchical features in raw image data, enabling accurate disease classification. This survey paper serves as a valuable resource for researchers, practitioners, and stakeholders in the agricultural domain, facilitating the adoption of advanced technologies for early and accurate tomato plant disease detection, leading to improved crop management practices and higher agricultural productivity.**

Keywords— Tomato diseases; Plant disease detection; Machine learning; Computer vision; Deep learning

I. INTRODUCTION

The detection of Plant disease is the most predominant problem in the field of agriculture. Initially, the detection of disease helps to prevent the disease spread between the other plants, ensuing in substantial economic damage [1]. The impact of plant disease differs in the small indications of the losses of complete plantations that have a crucial effect on the farming economy [2]. Globally, Tomatoes are used among the majorly considerable and usually consumed crops. According to recent statistical facts, the production of tomatoes is nearly higher than 180 million metric tonnes around the world, and for exports billion of USD 8.81. Because of the crop's sensitivity to different types of diseases, tomato production is also decreasing [3]. The major reason for reducing tomato crops is tomato leaf diseases and the financial decrease of farmers. The identification of tomato leaf disease is indivisibly connected to agricultural economic action [4]. The detection of tomato leaf diseases is crucial to the rapid way and implementation of suitable control activity to guarantee farmer profitableness as well as tomato production. Traditional disease identification techniques require a manual exploration of diseased leaves utilizing chemical analysis or visual information of impacted areas, which is a time-consuming method and can outcomes in inadequate reliability due to manual faults and lower identification accuracy. Furthermore, exacerbated by the farmer's insufficiency of professional experiences and the lack of agricultural skilled specialists that can detect diseases in remote places delaying the overall production in agriculture. The inattention of this respect shows a crucial risk to global food protection while also permitting major losses for the production of tomato stockholders [5]. Initially, the detection and identification of diseases using the automatic techniques and tools accessible to producers could support mitigation to entirely problems increased. Motivated by the outstanding achievements of Artificial Intelligence (AI) techniques, namely the conventional Machine Learning (ML) algorithms, and Deep Learning (DL) techniques in various fields recently [6].

ML and DL have transformed computer vision (CV), especially in image-based classification and identification [7]. Currently, DL methods are a leading tool to improve these types of automatic techniques to achieve accurate outcomes for real-time plant disease classification and detection [8]. The Convolutional neural networks (CNNs) based DL has proved methods for obtaining effective outcomes in image classification. Despite of comprehensive function that has been provided by the researchers for tomato plant leaf diseases [9], its detection at the initial levels is an even a complicated task owing to the large chrominance resemblance between the unaffected and affected plant areas. Furthermore, the differing plant leaf sizes, presence of noise, light and intensity variations, and also blurred suspicious images have more difficult the process of detection [10]. Thus, there is space for enhancing the performance in conditions of plant disease identification processing time and accuracy. Fig. 1 illustrates the overall process of proposed method.

This article presents a comprehensive review of the application of ML and DL approaches for tomato plant disease detection. The aim of this survey is to investigate the utilization and effectiveness of ML and DL techniques in the detection of tomato plant leaf and fruit diseases. The survey begins by providing an overview of the common diseases affecting tomato plants, highlighting the importance of timely detection and intervention. It then delves into the principles and methodologies of ML and DL, providing a foundation for understanding their applications in disease detection. The survey examines the existing ML and DL techniques available for plant disease detection.

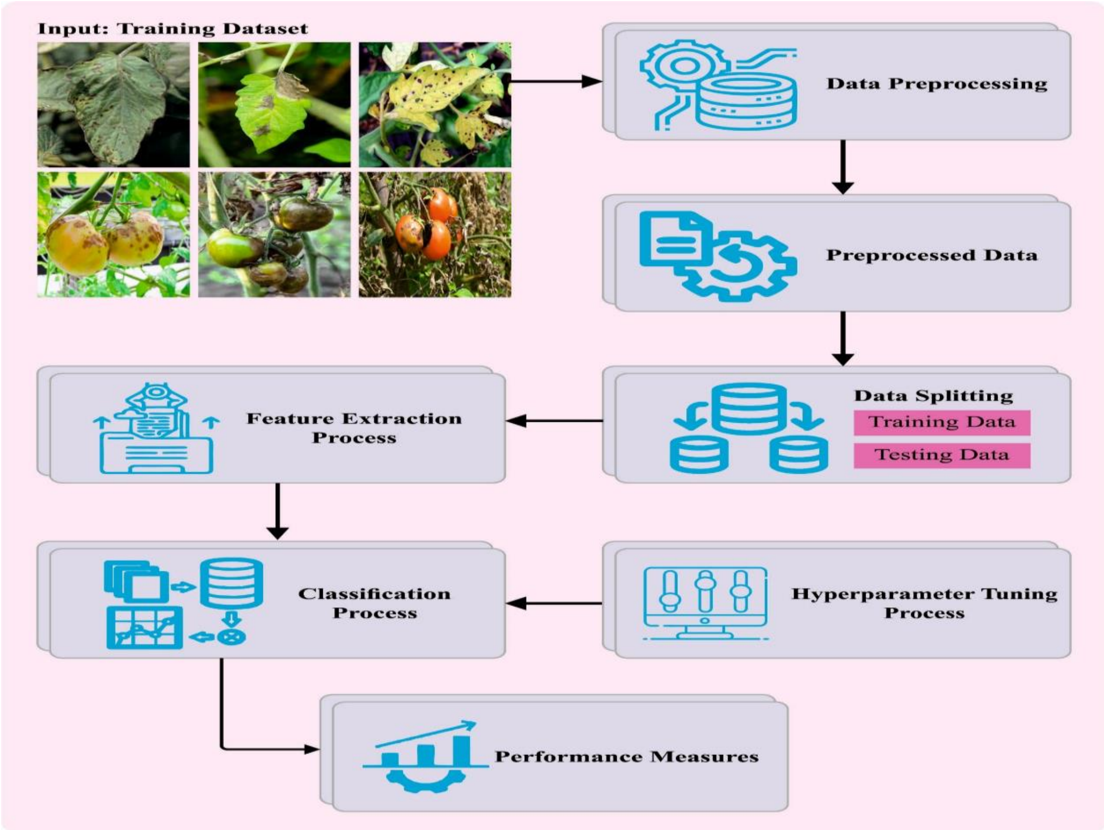

Fig. 1. Overall process of proposed method

II. BACKGROUND INFORMATION

Two structures and connected common workflows are applied for developing AI applications in medical imaging: (i) DL, utilizing end-to-end learning from images or deep feature extraction, and (ü) classic ML, using hand-crafted feature, like radiomic feature mined from segmented imagery; Though DL and ML share general concept like training and supervision, that should be explained before concerning particular characteristics of these two methods.

2.1 Supervised Learning Versus Unsupervised Learning

The prevalent among learning process in AI-related classification systems are supervised learning where training of the classifier model was executed by offering “labeled” training dataset (dataset sample joined to the label of interest or respective class) to the learning systems. The aim of this particular system is to identify a relationship that mapped all inputs of training sets (the dataset) into outputs (the labels). In healthcare sector, input dataset can involve clinical data or medicinal images, whereas the output labels can be, for instance, the disease detection, the condition of patients (e.g., the disease phase at a certain follow-up time), the outcomes after therapy (e.g., survival, recurrence). Once a relation was learned (i.e., training stage), it is utilized for categorizing novel input datasets with unknown labels into one class of interest described in the training stage.

Contrary to supervised learning, no training dataset was joined to any pre-existing label or class of interest in unsupervised learning, probably due to an absence of this data. The learning system was inputted with training datasets, and its objective is to seek unidentified patterns that could divide such datasets into subset of the same sample under certain features. Once the features and these subsets were learned and detected (training stage), new input datasets are categorized into one class of interest that are implicitly described in the process of learning itself (the testing stage).

Related samples of unsupervised and supervised learning methods are presented in this review. It should be noticed that other methods are utilized namely semi-supervised learning where only part of training datasets are considered, making this method a integration of unsupervised and supervised learning.

2.2 Training, Validation, and Testing

As discussed previously, the application of classification method includes two stages, testing, and training. The training stage learns the classifier method itself. The dataset utilized in this stage is named training datasets, self-sufficiently from the usage of an unsupervised or supervised method. To gain a method with generalization capabilities, i. e., well-executing when implemented to novel dataset, the training dataset should be in a great amount and representative of the "general" population, i.e., of the population where system would be tested and, lastly, implemented in a scientific perspective.

In the testing stage, the model learned in the training stage is tested or utilized on novel examples. Data utilized in this stage are termed testing datasets, and the efficiency of the method in properly categorizing these data is termed testing performance. Notably, it is paramount that not any of the samples encompassed in the training dataset was utilized in the testing stage since this could, invalidate the testing performance.

To enhance the learning performance, and if the available examples are adequate, it is beneficial to present a third stage between the testing and the training stages which is known as validation. In this stage, the model parameter learned in the training stage is optimized and tuned for maximizing given metrics. These variables embrace the parameters utilized or their comparative weights. Data utilized in this stage are known as validation datasets, and the efficiency of the method in properly categorizing such data is termed validation performance. It is significant to note that the testing performance indicated the model's final performance, i.e., the one that illustrates the capability of the learned model to work on the population

III. Review of Existing Machine Learning and Deep Learning Models for Tomato Plant Disease Detection

Attallah [11] presents a channel for the automated recognition of tomato leaf ailments by employing three compact CNN. This implements Transfer Learning (TL) for recovering deep aspects from the last CNN and has completely associated layers for a higher condensed and high-lever illustration. Then, this integrates factors from three CNNs to gain from each structure of the CNN. Correspondingly, this enforces a fusion Feature Selection (FS) model for choosing and generating overall lower-dimension feature sets. In [12], the authors presented a model by implementing Digital Image Processing (DIP) for identifying plant ailments from its leaf as the ailment of the plants usually gets exhibited on its leaves. The DIP model comprises three consecutive processes, such as feature extraction, segmentation, and pre-processing. Color, shape, and texture aspects are built from unhealthy leaves. Additionally, the attained aspects are implemented for modelling the classifier of SVM in order to label several ailments.

Deshpande and Patidar [13] introduce an automated identification of plant leaf ailment by implementing Deep CNN (DCNN) to enhance the correlation, feature representation, and Generative Adversarial Network (GAN) for data augmenting to tackle the data variance issue. Nawaz et al. [14] suggested a vigorous DL-based technique known as ResNet-34-based Faster-RCNN for classifying tomato plant leaf ailments. This technique comprises three phases. At first, the doubtful image annotations are generated for specifying the Region of Interest (RoI). Then, ResNet-34 is presented together with the Convolutional Block Attention Module (CBAM) as module for feature extracting of Faster-RCNN for extracting the deep key points. At last, the computer factors are implemented for the Faster-RCNN method that is trained for locating and categorizing the various discrepancies of the tomato plant leaves.

Alruwaili et al. [15] suggest an approach for recognizing tomato plant ailments, called the Real-Time Faster Region CNN (RTF-RCNN) approach by employing both real-time video streams and imageries. Sareen et al. [16] target to identify the initial infestations in tomato plants prior to utilizing a prevalent DL model, that is, CNN. Mukherjee et al. [17] present a Computer Vision (CV) based scheme for the classification of 7 diverse disease classes, known as, early and late blight, bacterial spot, leaf mold, spider mites, Septoria leaf spot, and target spots by implementing maximized MobileNetV2 construction. An altered Gray Wolf Optimization (GWO) model is employed for maximization of MobileNetV2 hyperparameters for enhanced achievement.

Tejashwini et al. [18] aim to identify an effective manner of recognizing tomato plant ailments via the plant leaf patterns, as tomato is an inexpensive and most usually consumed vegetable in India. Pattern recognition in tomato leaves is accomplished by employing CNN. This model can assist agriculturalists in recognizing the ailments in the initial phase which enhances the harvest, thereby reducing the economic losses. Also, the need for insecticide per hectare gets mitigated which supplements the consumer's health privileges and enhances economic returns to the agriculturalists. In [19], the authors suggest applications for smartphones based on DL by implementing CNN that can categorize and identify plant ailments depending on their kinds. Due to these procedures, several agriculturalists have resolved their harvesting issues (plant ailments) and significantly enhanced their harvest and its quality. The utilization of CNN construction DenseNet169 and InceptionV3 allowed us to categorize and identify several ailments of the tomato plants. TL methodology is implemented with a batch size of 23 along with the Adam and RMSprop optimizers.

Gadekallu et al. [20] concentrate on enforcing ML method for categorizing tomato ailment image datasets to actively take needful actions to fight alike farming emergencies. In this article, the datasets are gathered from the public plant-village datasets. The key aspects are extracted from the datasets by employing the fusion primary module evaluation – Whale Optimization model. Additionally, the data extracted are given as input to a Deep Neural Network (DNN) for classifying tomato ailments. In [21], the authors present popular pre-trained CNN methods GoogLeNet, ResNet50, and AlexNet, which are implemented as feature extractors. Also, a DL technique that incorporates Deep Features (DF) extracted from 3 CNN methods is presented. The DF is utilized for training the Support Vector Machine (SVM) classifiers.

Anton et al. [22] propose a model that enforces Image Processing (IP) method for identifying the infected leaf's texture and colour moment by implementing extraction of Gray-Level Co-Occurrence Matrix (GLCM) and CNN models. The most commonly occurring ailments in tomato leaves are leaf mold, leaf curl, late blight, septoria spot, target spot, two spotted spider mites, bacterial spot, early blight, and spider mites. An integration of CNN and GLCM-Colour moments is selected due to their dependability in categorizing and recognizing plant ailments related to utilizing only the CNN. Also, a mixture of CNN and GLCM-Colour moments are utilized in the study. Natarajan et al. [23] present a model that intends to develop an automatic system for identifying ailments in cultivated lands. DL models, particularly with Deep Detectors: ResNet50 and Faster R-CNN with deep feature extractors are employed in categorizing and identifying tomato ailments in plants. Table 1 demonstrates the review of ML and DL approaches for tomato plant disease detection.

Table 1
Review of Existing ML and DL Models for Tomato Plant Disease Detection

Reference	Year of Publication	Aim	Methodology	Dataset	Metrics
Attallah [11]	2023	Automatic detection and classification of tomato leaf diseases	CNN	PlantVillage dataset	$Accu_y$ of 99.92%
Narla, V.L. and Suresh [12]	2023	Multiple Feature-Based Tomato Plant Leaf Disease Classification	SVM	-	$Accu_y$ of 86.6%
Deshpande and Patidar [13]	2023	Automatic plant leaf disease detection	DCNN and GAN	PlantVillage dataset	$Accu_y$-99.74%, $prec_n$- 0.99, $reca_l$-0.99, $F1_{score}$-0.99
Nawaz et al. [14]	2022	DL approach for tomato plant leaf disease	ResNet-34 and Faster-RCNN	PlantVillage dataset	mAP and $accu_y$ of 0.981, and 99.97%
Alruwaili et al. [15]	2022	Using photos and video streaming for detection of plant leaves illness and identification	Faster-RCNN	PlantVillage dataset	$Accu_y$ of 97.42%
Sareen et al. [16]	2022	Identify the early blight disease in tomato plants	CNN	Tomato Early Blight Disease (TEBD) dataset	$accu_y$ of 98.10%
Mukherjee et al. [17]	2022	Detection of the kinds of disease for tomato plant	MobileNetV2 and GWO	PlantVillage dataset	$accu_y$ of 98%
Tejashwini et al. [18]	2022	An effectual manner of recognizing tomato plant diseases	CNN	Plant Diseases Dataset	97–98% of $accu_y$
Hammou and Boubaker [19]	2022	DL based detection and classify plant disease	DenseNet169 and InceptionV3	PlantVillage dataset	100% of $Accu_y$
Gadekallu et al. [20]	2021	ML model for classifying tomato disease image	WOA and PCA	PlantVillage dataset	-
Altuntaş and Kocamaz [21]	2021	Feature Extraction for Recognition of Tomato Plant Disease	CNN and SVM	PlantVillage dataset	$accu_y$ of 96.99%
Anton et al. [22]	2021	Image processing methods for detecting the texture of affected leaf	GLCM and CNN	PlantVillage dataset	$accu_y$ of 99%
Natarajan et al. [23]	2020	DL architectures for pest and disease detection in cultivated land	Faster R-CNN	tomato disease dataset	-
Ahmad et al. [24]	2020	Image-based Recognition and Classification of tomato leaf diseases	VGG Net, ResNet, and Inception V3	tomato leaf disease dataset	-
Kaushik et al. [25]	2020	Recognition of diseases present in tomato leaf utilizing CNNs	CNN and ResNet-50	PlantVillage dataset	$Accu_y$ of 97%

In [24], the authors concentre on recognizing and classifying tomato leaf ailments by implementing CNN models. Four CNN constructions like VGG-19, VGG-16, InceptionV3, and ResNet utilize tuning and feature extraction processes for classifying and identifying tomato leaf ailments. Kaushik et al. [25] present a method that identifies the ailments that exist in the tomato leaf by employing CNN, which is a category under the Deep Neural Network (DNN). Initially, the datasets are segmented prior to identifying tomato leaves. The TL model is employed, in which a pre-training method called ResNet-50 was accustomed and imported accordingly to the classifying issue. To enhance the ResNet method's quality and to improve the outcome that is closer to the actual dominant ailment, data augmenting is utilized.

IV. PERFORMANCE VALIDATION

This section discusses the results offered by different tomato plant disease detection models, as shown in Table 2 and Fig. 2. The result shows that the VGG19 and CNN models show lesser accuracy of 90.42% and 92.21% whereas the ResNet50, SE-ResNet50, AlexNet, and RTF-RCNN models exhibit slightly enhanced accuracy of 97%, 96.81%, 95.32%, and 97.42% respectively. Meanwhile, the TLDCC-CNN, ARDLA-TPLDL, and customized CNN models reported higher accuracy of 99.92%, 99.97%, and 99.30% respectively.

Table 2
Comparative Outcome of Different Tomato Plant Disease detection Approaches

Model	Accuracy (%)
ResNet-50	97.00
Customized CNN	99.30
TLDCC-CNN	99.92
VGG-19 Model	90.42
SE-ResNet50	96.81
ARDLA-TPLDL	99.97
Alex Net	95.32
CNN Model	92.21
RTF-RCNN	97.42

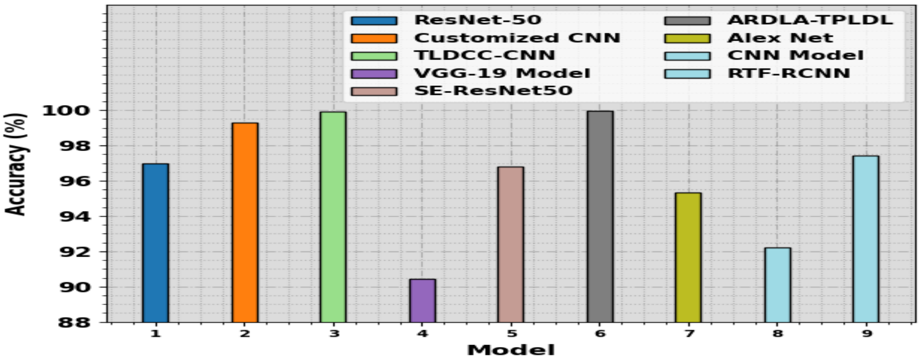

Fig. 2. Comparative outcome of different tomato plant disease detection approaches

V. DISCUSSION AND LIMITATIONS

Although the greater efficiency of the proposed method for detection of tomato leaf diseases, this study take some drawbacks. Initially, this study only inspects 10 various tomato leaf diseases; other types of tomato leaves diseases and other crop diseases could not surveyed. In the future, the author can try to improve the projected approach that is appropriate to other tomato infections and further crop leaf diseases. Future work is to assume further crops containing apples, oranges, potatoes, pepper, grapes, and so on. Other features that are added contain utilizing DL segmentation and recognition methods comprising U-Net, Yolo, R-CNN, faster CNN, and fast R-CNN for detecting and separating among crops and assisting the detection and variation amongst diseases to have same forms. Besides, utilizing image improvement methods to ease the trained method of DL approaches for discriminating among distinct crop diseases. Moreover, additional features are added if employed with other cultures, like gathering images of various species of all the crops planted in several countries. Afterward, learning the DL approaches with these several species to improve its generalizability and enhance its ability for classifying crops of distinct species developed in many cultures. Also, the presented workflow has another major difficulty in exploiting images captured in laboratory environment. But, the presented method is an improved to validate a real world integrative plant disease detection method. However, a lot of experience can be needed to advance the proposed method that is able of categorizing maximal sets of crop infections and automatically identify the disease in several phases in natural settings. Furthermore, this case could not assume recognizing the severity of tomato leaf diseases. In the future work will consider the review of this problem.

VI. CONCLUSION

The purpose of this survey is to investigate the utilization and effectiveness of ML and DL techniques in the detection of tomato plant leaf and fruit diseases. As agriculture faces increasing challenges due to the prevalence of diseases, automated systems using advanced technologies such as ML and DL have emerged as potential solutions for disease detection in crops. The survey explores various CNN architectures like AlexNet, VGGNet, and ResNet, and discusses their applications in the detection of tomato plant diseases. The paper discusses the challenges and opportunities in this field and offers insights for future research directions, such as the development of robust and interpretable models, the integration of multi-modal data sources, and the adoption of TL techniques. By conducting this survey, we aim to gain insights into the current state of knowledge and adoption of ML and DL techniques for tomato plant disease detection. The findings of this comprehensive survey will contribute to the advancement and refinement of automated systems in agriculture, ultimately enhancing crop management and disease control strategies.

REFERENCES

[1] Rahman, S.U., Alam, F., Ahmad, N. and Arshad, S., 2023. Image processing based system for the detection, identification and treatment of tomato leaf diseases. Multimedia Tools and Applications, 82(6), pp.9431-9445.

[2] Shruthi, U., Nagaveni, V., Arvind, C.S. and Sunil, G.L., 2022, February. Tomato Plant Disease Classification Using Deep Learning Architectures: A Review. In Proceedings of Second International Conference on Advances in Computer Engineering and Communication Systems: ICACECS 2021 (pp. 153-169). Singapore: Springer Nature Singapore.

[3] Seth, V., Paulus, R. and Kumar, A., 2023. Tomato Leaf Diseases Detection Using Deep Learning—A Review. Intelligent Systems and Smart Infrastructure: Proceedings of ICISSI 2022, p.118.

[4] Mudgil, R., Garg, N., Singh, P. and Madhu, C., 2022, June. Identification of Tomato Plant Diseases Using CNN-A Comparative Review. In 2022 IEEE World Conference on Applied Intelligence and Computing (AIC) (pp. 174-181). IEEE.

[5] Aishwarya, N., Praveena, N.G., Priyanka, S. and Pramod, J., 2023. Smart farming for detection and identification of tomato plant diseases using light weight deep neural network. Multimedia Tools and Applications, 82(12), pp.18799-18810.

[6] Jasim, Y.A., 2021. High-Performance Deep learning to Detection and Tracking Tomato Plant Leaf Predict Disease and Expert Systems.

[7] Mohanty, R., Wankhede, P., Singh, D. and Vakhare, P., 2022, May. Tomato Plant Leaves Disease Detection using Machine Learning. In 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC) (pp. 544-549). IEEE.

[8] Sagar, S. and Singh, J., 2023. An experimental study of tomato viral leaf diseases detection using machine learning classification techniques. Bulletin of Electrical Engineering and Informatics, 12(1), pp.451-461.

[9] Elsharkawy, M.M., El-Okkiah, S., Elsadany, A.Y., Bedier, M.Y., Omara, R.I., Behiry, S.I., Hassan, S. and Abdelkhalek, A., 2022. Systemic resistance induction of tomato plants against tomato mosaic virus by microalgae. Egyptian Journal of Biological Pest Control, 32(1), pp.1-7.

[10] Saranya, S.M., Rajalaxmi, R.R., Prabavathi, R., Suganya, T., Mohanapriya, S. and Tamilselvi, T., 2021, February. Deep learning techniques in tomato plant–a review. In Journal of Physics: Conference Series (Vol. 1767, No. 1, p. 012010). IOP Publishing.

[11] Attallah, O., 2023. Tomato leaf disease classification via compact convolutional neural networks with transfer learning and feature selection. Horticulturae, 9(2), p.149.

[12] Narla, V.L. and Suresh, G., 2023, January. Multiple Feature-Based Tomato Plant Leaf Disease Classification Using SVM Classifier. In Machine Learning, Image Processing, Network Security and Data Sciences: Select Proceedings of 3rd International Conference on MIND 2021 (pp. 443-455). Singapore: Springer Nature Singapore.

[13] Deshpande, R. and Patidar, H., 2023. Tomato plant leaf disease detection using generative adversarial network and deep convolutional neural network. The Imaging Science Journal, pp.1-9.

[14] Nawaz, M., Nazir, T., Javed, A., Masood, M., Rashid, J., Kim, J. and Hussain, A., 2022. A robust deep learning approach for tomato plant leaf disease localization and classification. Scientific Reports, 12(1), p.18568.

[15] Alruwaili, M., Siddiqi, M.H., Khan, A., Azad, M., Khan, A. and Alanazi, S., 2022. RTF-RCNN: An architecture for real-time tomato plant leaf diseases detection in video streaming using Faster-RCNN. Bioengineering, 9(10), p.565.

[16] Sareen, N., Chug, A. and Singh, A.P., 2022. An image based prediction system for early blight disease in tomato plants using deep learning algorithm. Journal of Information and Optimization Sciences, 43(4), pp.761-779.

[17] Mukherjee, G., Chatterjee, A. and Tudu, B., 2022. Identification of the types of disease for tomato plants using a modified gray wolf optimization optimized MobileNetV2 convolutional neural network architecture driven computer vision framework. Concurrency and Computation: Practice and Experience, 34(22), p.e7161.

[18] Tejashwini, V., Patil, S.S., Mali, S.S., Salina, M.S. and Nayak, J.S., 2022. Convolutional Neural Network-Based Tomato Plant Leaf Disease Detection. In Innovations in Electronics and Communication Engineering: Proceedings of the 9th ICIECE 2021 (pp. 259-269). Singapore: Springer Singapore.

[19] Hammou, D.R. and Boubaker, M., 2022. Tomato plant disease detection and classification using convolutional neural network architectures technologies. In Networking, Intelligent Systems and Security: Proceedings of NISS 2021 (pp. 33-44). Springer Singapore.

[20] Gadekallu, T.R., Rajput, D.S., Reddy, M.P.K., Lakshmanna, K., Bhattacharya, S., Singh, S., Jolfaei, A. and Alazab, M., 2021. A novel PCA–whale optimization-based deep neural network model for classification of tomato plant diseases using GPU. Journal of Real-Time Image Processing, 18, pp.1383-1396.

[21] Altuntaş, Y. and KOCAMAZ, F., 2021. Deep feature extraction for detection of tomato plant diseases and pests based on leaf images. Celal Bayar University Journal of Science, 17(2), pp.145-157.

[22] Anton, A., Rustad, S., Shidik, G.F. and Syukur, A., 2021. Classification of Tomato Plant Diseases Through Leaf Using Gray-Level Co-occurrence Matrix and Color Moment with Convolutional Neural Network Methods. In Smart Trends in Computing and Communications: Proceedings of SmartCom 2020 (pp. 291-299). Springer Singapore.

[23] Natarajan, V.A., Babitha, M.M. and Kumar, M.S., 2020. Detection of disease in tomato plant using Deep Learning Techniques. International Journal of Modern Agriculture, 9(4), pp.525-540.

[24] Ahmad, I., Hamid, M., Yousaf, S., Shah, S.T. and Ahmad, M.O., 2020. Optimizing pretrained convolutional neural networks for tomato leaf disease detection. Complexity, 2020, pp.1-6.

[25] Kaushik, M., Prakash, P., Ajay, R. and Veni, S., 2020, June. 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.