Al-Salam Journal for Engineering and Technology
Journal Homepage: http://journal.alsalam.edu.iq/index.php/ajest
e-ISSN: 2790-4822 p-ISSN: 2958-0862

Enhanced Tomato Disease Classification Using Hybrid Deep Learning Approach

Ali Abdullah Mohammed Mohammed[1] *

[1]Altinbaş University Institute of Graduate Studies Information Technologies, Republic of Türkiye.

*Corresponding Author: Ali Abdullah Mohammed Mohammed

DOI: https://doi.org/10.55145/ajest.2025.04.01.015
Received September 2024; Accepted November 2024; Available online November 2024

ABSTRACT: Tomato disease classification is important for agricultural productivity and food security, yet achieving high accuracy stays challenging due to the complexity of disease symptoms. This study proposed a model classification utilizing DenseNet121 combined with an Autoencoder for feature extraction and Simple neural network (SNN) for classifier. The dataset contains 10 classes of tomato diseases. Experimental results shows that the proposed approach achieved a high accuracy of 99%, outperforming the performance of several approaches. The integration of the Autoencoder enhances feature extraction and dimensionality reduction, important for improved classification outcomes. This study highlights the efficacy of the proposed work in achieving state-of-the-art accuracy in tomato disease detection. Future work may focus on refining the model using advanced augmentation techniques and expanding the dataset to enhance its applicability across diverse agricultural conditions.

Keywords: Tomato Disease, Classification, Deep Learning, Machine Learning, DenseNet121

1. INTRODUCTION

Tomato plant is an important global crop contributing much to both the agricultural economy and food supply [1]. Tomato plant is very weak to a wide range of diseases that can severely reduce their produce and value. Early and correct detection of these diseases is key for efficient management. Traditional methods for diagnosing tomato illnesses often depend on visual review via experts, which is time-consuming, subjective, and prone to error. There is a growing need for automated, accurate, and efficient systems to classify tomato diseases at an early stage [2].

The advance of deep learning (DL) techniques has shown good ability in plant disease classification outstanding to their ability to learn and extract important features from difficult image datasets [3]. While advancements, achieving high accuracy in the classification of tomato diseases among multiple classes stays a challenging task [4,5]. This work addressed the accuracy problem in classifying ten different tomato diseases. The problem plays from the similarity in signs around separate diseases and differences in disease appearance due to environmental factors.

This work aims to propose a new hybrid approach from combined DenseNet121 for feature extraction, and an Autoencoder for reduction dimensionality, and a SNN as the classifier. DenseNet121 is chosen for its efficiency in extracting deep features with reduced computational costs, making it suitable for applications in environments with limited resources. The Autoencoder further optimizes the features by reducing redundancy and enhancing relevant patterns, improving the classifier's ability to distinguish among similar diseases. Finally, SNN is utilized for classification tasks to reliable disease identification.

The aim of this method is to proposed a good approach for the automatic classify of tomato diseases via combined of DenseNet121, Autoencoders, and SNN, the proposed model aims to significantly enhance the accuracy and performance of disease recognition systems, finally contributing to sustainable agricultural practices and improved tomato crop management.

This study is arranged as following the related work in (Section 2), approach detailing in (Section 3), while (Section 4) include the discussion and results. Finaly the future work and conclusion in (Section 5).

*Corresponding author: svhhvdd@gmail.com

2. RELATED WORKS

Natarajan et al. [2] proposed automated method for detecting plant diseases utilizing advanced image processing techniques, addressing the limitations of traditional manual inspection. The paper utilized DL model specifically the Faster R-CNN model with a ResNet50 feature extractor, to classify tomato diseases. The technique is trained on 1,090 images, and accurately identifies conditions like leaf curl, early blight, septoria leaf spot, and bacterial spot in complex environments.

Aggarwal et al. [6] proposed a DL method for classifying tomato leaf diseases. Different from traditional methods requiring manual feature extraction, their approach automatically extracts features hierarchically using DL and classifies the images into three categories: no Septoria leaf spot, bacterial spot, and disease. Tested on images taken via handheld cameras or drones, the approaches performance was evaluated utilizing accuracy as the metric, validating its efficiency. The approach supports accurate disease management and decision-making for tomato crops.

Bhatia et al. [7] proposed Extreme Learning Machine (ELM) algorithm to predict Tomato Powdery Mildew Disease (TPMD) and addressed dataset imbalance with techniques resampling such as IMPS, SMOTE, RUS, and ROS. They evaluated ELM models on both the original and resampled datasets utilizing AUC and classification accuracy. The best results were achieved with the IMPS technique, producing a CA of 89.19% and an AUC of 88.57%, show off the efficiency of resampling in improving the model's performance.

Nyalala et al. [8] this study developed a computer vision method utilizing ML to identify the mass and volume of cherry tomatoes. Via capturing depth images and extracting features, they created five regression models. The RBF-SVM (Radial Basis Function-Support Vector Machine) model showed the best performance, achieving high accuracy (0.9706 for 2D features and 0.9694 for all features). The technique, which utilizes a mass-volume relationship, provides an accurate, non-destructive, and efficient approach for grading and sorting cherry tomatoes based on density, volume, or mass.

Liu et al. [9] proposed Yolo V3 algorithm for detecting tomato diseases and pests, optimizing it with bounding box clustering, multi-scale training and multi-scale feature detection. The model achieved 92.39% accuracy with a detection time of 20.39 ms, outperforming SSD, Faster R-CNN, and Yolo V3. It showed strong robustness across several object volumes and resolutions in complex environments, meeting real-time detection requirements. This approach provides an efficient solution for accurately identifying and locating tomato diseases and pests, supporting smarter agricultural practices.

Verma et al.[10] this work examined the severity of Tomato Late Blight disease utilizing 3 CNN methods like Inception V3, SqueezeNet, and AlexNet —analyzing images from the Plant Village dataset across early, middle, and late disease stages. The models utilized feature extraction techniques and transfer learning with extracted features utilized to train a multiclass SVM. AlexNet outperformed the others, achieving accuracies of 89.69% and 93.4% in the two approaches, highlighting its effectiveness in evaluating disease severity.

Hong et al. [11] this study employed transfer learning to decrease training computational costs and data size while classing nine kinds of tomato leaves, including healthy ones. Five deep network structures like DenseNet121_Xception ,ResNet50, ShuffleNet, MobileNet, and Xception —were utilized for feature extraction and compared with varying learning rates. DenseNet-Xception achieved the high accuracy at 97.10%, despite having the most parameters, while ShuffleNet reached 83.68% accuracy with less parameters. The findings support the enhancement of an intelligent tomato diagnosis disease method for mobile devices, aiding pest control decision-making.

Qasrawi et al. [12] they employed ML models to classify and cluster five tomato illnesses. Techniques included hierarchical clustering and image embedding, alongside models like NN, RF, and LR. The clustering model achieved 70% accuracy, while the NN and LR reached 70.3% and 68.9%, respectively. The findings suggest that ML can effectively help Palestinian farmers manage tomato diseases.

Subrol et al. [13] this paper explored image processing applications for the recognition and classification of plant diseases, emphasizing their importance for timely detection. The study focused on five types of tomato diseases. The class complicated texture features, shape, and extracting color from both healthy and diseased images, which were processed after segmentation. These features were then input into a classification tree. This work achieved an accuracy of 97.3% for the six classes of tomato images, indicating the efficiency of their approach.

Putra et al. [14] this work proposed DL model specifically CNNs. The study aimed to improve the disease identification process, which traditionally relies on farmers' visual assessments. A dataset containing images of six different types of diseases was utilized, with 100 images per disease for training and 60 for testing. Three datasets were tested: original RGB images, blending images, and a combination of both. The combined dataset achieved the best performance, yielding a GAR of 96.7%, with a FAR and FRR of 3.3%.

Xian et al. [15] this study utilized the ELM classification algorithm based on a single-layer FFNN, to analyze tomato plant leaf images. Images were pre-processed in the HSV color space, and features were extracted utilizing Haralick textures. The ELM classifier was trained and tested on a subset of the Plant-Village dataset. The results got an accuracy of 84.94%, outperforming other models such as SNN and DT, displaying the efficacy of ELM on plant disease classifier.

Nagamani et al. [16] utilized various ML and DL techniques, counting Fuzzy-SVM, CNN, and R-CNN. They utilized tomato leaves images affected by 6 diseases alongside healthy examples, employing approaches like image scaling, color thresholding, and gradient local ternary pattern for feature extraction. The R-CNN classifier achieved the high accuracy of 96.735%, outperforming another methods. This work highlights the importance of early disease diagnosis in improving agricultural production and reducing future losses.

Javidan et al. [17] proposed ensemble approach to classify tomato leaf diseases, including bacterial spot and late blight, via combination multiple base classifiers. They extracted color, shape features, and texture from RGB images then selected effective features using the relief method. Six ML classifiers SNN, DT, RF, KNN, NB, and discriminative analysis is achieved accuracies ranging from 44.42% to 91.53%. The ensemble methods improved classification accuracy to 93.49% and 95.58%. The proposed framework outperformed DL models like GoogLeNet and AlexNet, demonstrating its efficacy in tomato disease classification.

As above related work studies achieved good results but faced challenges related to limited dataset sizes or class imbalance. Our proposed, via utilizing a larger and more diverse dataset, and incorporating advanced techniques like DenseNet121 for feature extraction, Autoencoders for dimensionality reduction, and SNN for classification, addresses these limitations, important to improved detection accuracy.

3. RESEARCH METHODOLOGY

Figure 1 displays the research method for this proposed that focuses on the tomato disease classification problem across 10 classes using a hybrid DL model. This part outlines the steps included in preparing the dataset, defining the DL architecture, and evaluating the model.

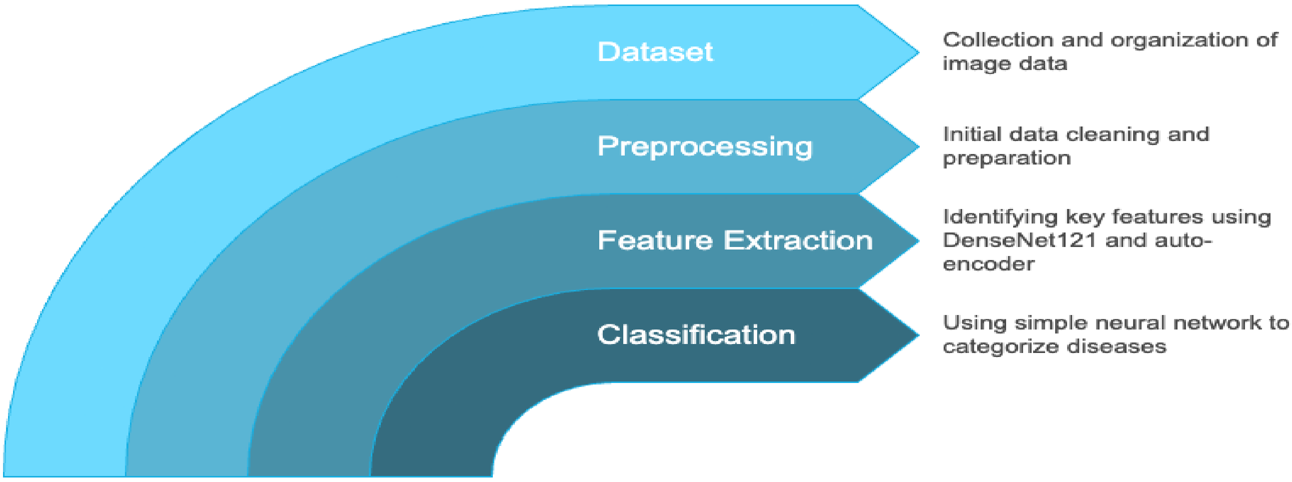

FIGURE 1. - **Research Methodology**

3.1 Dataset details

The dataset comprises 60387 images with 10 different tomato diseases as shown in Figure 2. The images are pre-labeled into respective disease categories. The dataset is separated into train (80%) and test (20%) sets, with stratified sampling to ensure an equal distribution of classes. The dataset is large and diverse and it's suitable for training a disease classification model, but has limitations such as image quality variability, and limited representation of rare diseases and conditions.

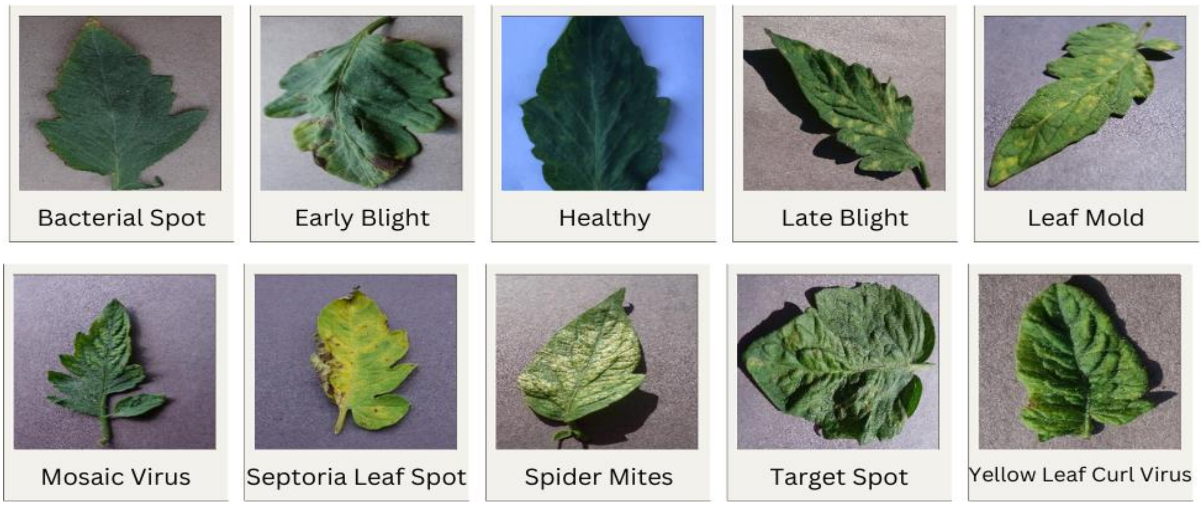

FIGURE 2. - **Sample of dataset**

3.2 Data Augmentation

To improve model generalization, data augmentation is applied using the Image Data Generator class [18]. The training data is augmented with a variety of transformations, as shown in Table 1.

Table 1. - Sample of dataset

An example of a column heading	Column A (*t*)
rescale	1/255
zoom_range	0.2
shear_range	0.2
width_shift_range	0.2
brightness_range	[0.8, 1.2]
rotation_range	0.2
vertical_flip	True
horizontal_flip	True
height_shift_range	0.2

3.3 Model Architecture

The proposed model architecture for tomato disease classification involves a hybrid structure, combining DenseNet121 for feature extraction and the autoencoder for reduction dimensionality, followed by a simple neural network classifier. This architecture leverages transfer learning, autoencoder-based compression, and a multi-layer classifier to deliver a highly accurate system for identifying tomato diseases from leaf images as showing in the Table 2.

Table 2. - Model summary

Component	Details
Base Model	DenseNet121
Input Shape	(224, 224, 3)
Image Size	224 (height, width)
Number of Base Layers	121 (for DenseNet121)
Trainable Layers	Second half of the DenseNet121 layers (after freezing the first half)
Autoencoder	Yes
Autoencoder Input Shape	(224, 224, 3)
Encoded Output Size	128 (Dense Layer)
Global Average Pooling	Yes
Classifier Input Shape	(128,)
Dense Layers in Classifier	1 Hidden Layer (64 units, ReLU activation)
Dropout Rate	0.5
Output Layer	10 units (Softmax activation for 10 classes)
Optimizer	Adam
Learning Rate	0.0001
Loss Function	Categorical Crossentropy
Metrics	Accuracy

3.3.1 DenseNet121 Model

The backbone of the feature extraction process is DenseNet121, a well-known CNN that is pre-trained on the Image Net dataset [19]. This pre-trained model effectively captures hierarchical visual features from input images, making it ideal for the tomato leaf disease class task. The DenseNet121 approach is packed without its top classification layer, as the objective is to use it purely for feature extraction.

The network has two main phases:

Frozen Layers: The initial half of the layers in DenseNet121 are frozen, meaning their weights remain unchanged throughout the training process.

Trainable Layers: allow fine-tuning to adapt to specific features of the tomato leaf dataset, enabling better disease identification in tomato diseases.

3.3.2 Autoencoder

Once the features are extracted via the DenseNet121 model, they are passed through an autoencoder. The part of the autoencoder is to reduce the high-dimensional feature space into a lower-dimensional, high compact image [20]. This is done utilizing a GlobalAveragePooling2D layer, which reduces the feature maps into a single vector via averaging the values in every feature map. This efficiently reduces the number of trainable parameters while maintaining key information.

The autoencoders feature vector undergoes a dense 128-unit layer, improving computational efficacy and reducing overfitting via compressing features into a 128-dimensional space.

3.3.3 Classifier

The SNN is a classifier model that designed to take the 128-dimensional feature vector from the autoencoder and map it to the final disease classifications. The classifier consists of:

Fully connected layer: the dense layer with 64 units, utilizing the ReLU (Rectified Linear Unit) activation function. This layer presents non-linearity into the method, allow it to discover difficult relationships among the compressed features.

Dropout layer: it is help to avoid overfitting via randomly setting half of the units to zero through training, ensuring that the approach does not become overly dependent on individual neurons.

Output layer: The last layer is a fully connected layer including 10 output units, corresponding to the 10 classes of tomato diseases.

3.3.4 Hybrid Model

This work proposed a hybrid approach that combined the autoencoder for feature extraction and the SNN for classifier. It is trained end-to-end, meaning that both elements are optimized at once during training. The hybrid approach is collected with the Adam optimizer, which is known for its efficiency in optimizing DL models. A learning rate of 0.0001 is utilized to balance the speed of meeting with the risk of overshooting the optimal parameters.

3.4 Evaluation

This paper evaluation utilized matrix performance that contained accuracy, recall, precision, and F-score [21-23].

$$Precision = \frac{TP}{(FP + TP)} \tag{1}$$

$$Accuracy = \frac{TP * TN}{total\ number\ of\ cases} \tag{2}$$

$$F - measure = \frac{2 \times (Precision * Recall)}{Precision + Recall} \tag{3}$$

$$Recall = \frac{TP}{FN + TP} \tag{4}$$

4. Result and discussion

In this study proposed a hybrid DenseNet121 with an Autoencoder for feature extraction and SNN for classification, shows high accuracy in classifying ten tomato disease classes. It achieved high precision, F1-score, and recall values of 0.99, 0.99, and 0.99, separately, with a high accuracy of 0.99 as shown in Table3. These results highlight the model ability to correctly classify different disease classes with minimal false positives and negatives. This proposed utilized DenseNet121's architecture, combined with the Autoencoder for dimensionality reduction, enables efficient feature extraction, making it fitting for environments beside reduced computational resources. Compared to previous models, the proposed approach shows large improvement in behaviors the complexity of different tomato disease patterns, implying its potential for real-world agricultural applications.

Table 3.- Results of proposed

	Accuracy	Recall	Precision	F1-score
Proposed	**0.99**	0.99	0.99	0.99

As shows in the Figure 3 the confusion matrix of hybrid approach for disease of tomato classification.

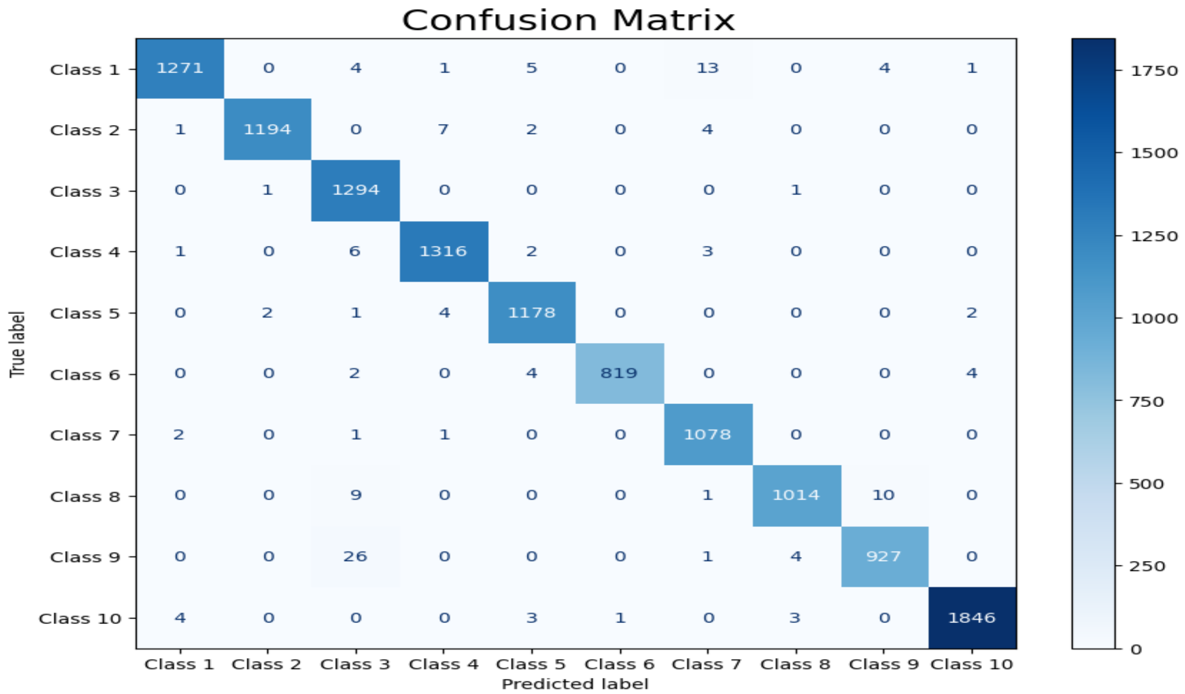

FIGURE 3.- Confusion matrix

The discussion section compared the results of different studies on tomato disease classification, emphasizing their use of different datasets as shown in Table 4. In studies [6] and [15] achieved lower accuracy of 89.19% and 84.94%, respectively, utilizing ELM and similar models. Higher accuracy were recorded via methods like RBF-SVM [8] (97.06%), segmentation-based approaches [13] (97.3%), and CNN models [14] (96.7%). Studies combining advanced architectures like Yolo V3 [9], AlexNet, SqueezeNet, Inception V3 [10], and DenseNet121_Xception [11] showed improved accuracy, with DenseNet121_Xception reaching 97.10%. The proposed model in this study, utilizing DenseNet121 with an Autoencoder for feature extraction and SNN for classification, outperformed all these methods with an accuracy of 99%. The higher accuracy achieved can be attributed to the efficient feature extraction potential of DenseNet121 linked with the dimensionality reduction of the Autoencoder, enhancing classification accuracy. This shows the superiority of proposed approach with different datasets used. The limitations of the proposed model include generalizability to other plant varieties, adaptability to new diseases and environmental variability.

Table 4.- A comparation results

Authors	year	Method	Accuracy
[7]	2020	EL3	89.19%
[8]	2019	RBF-SVM	97.06%
[9]	2020	Yolo V3 algorithm	92.39%
[10]	2020	AlexNet, SqueezeNet, and Inception V3 with SVM	93.4%
[11]	2021	ResNet50, Xception, MobileNet, ShuffleNet, and DenseNet121_Xception	97.10%
[12]	2021	like neural networks, random forests, and logistic regression	70.3%
[13]	2021	segmentation	97.3%
[14]	2020	CNN	96.7%
[15]	2021	ELM	84.94%
[24]	2022	Fuzzy-SVM, CNN	96.735
[17]	2023	ML	95.58%
Proposed Model	2024	DenseNet121 with an Autoencoder for feature extraction and SNN for classification	99%

5. CONCLUSION

This study proposed a tomato disease classification model that contain from DenseNet121 combined with an Autoencoder for feature extraction and an SNN classifier. The model was evaluated on a dataset consisting of ten distinct tomato disease classes that achieved an accuracy of 99%. The proposed approach outperforms various state-of-the-art studies models, showing its efficiency in accurately identifying tomato diseases. The superior performance is attributed to the model's efficient feature extraction and dimensionality reduction capabilities, which enhance classification accuracy. Future work could used data augmentation techniques and optimizing hyperparameters to further improve the model's performance and generalizability across diverse agricultural environments.

FUNDING

None

ACKNOWLEDGEMENT

The authors would like to thank the anonymous reviewers for their efforts.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

REFERENCES

[1] N. K. Trivedi *et al.*, "Early detection and classification of tomato leaf disease using high-performance deep neural network," *Sensors*, vol. 21, no. 23, p. 7987, 2021.

[2] V. A. Natarajan, M. M. Babitha, and M. S. Kumar, "Detection of disease in tomato plant using Deep Learning Techniques," *Int. J. Mod. Agric.*, vol. 9, no. 4, pp. 525–540, 2020.

[3] Y. M. Mohialden, N. M. Hussien, S. A. Salman, A. B. A. Alwahhab, and M. Ali, "Enhancing Agriculture Crop Classification with Deep Learning," *Babylonian J. Artif. Intell.*, vol. 2024, pp. 20–26, 2024.

[4] J. Abdulridha, Y. Ampatzidis, J. Qureshi, and P. Roberts, "Laboratory and UAV-based identification and classification of tomato yellow leaf curl, bacterial spot, and target spot diseases in tomato utilizing hyperspectral imaging and machine learning," *Remote Sens.*, vol. 12, no. 17, p. 2732, 2020.

[5] A. A. Nafea, R. R. Majeed, A. Ali, A. J. Yas, S. A. Alameri, and M. M. AL-Ani, "A Brief Review of Big Data in Healthcare: Challenges and Issues, Recent Developments, and Future Directions," *Babylonian J. Internet Things*, vol. 2024, pp. 10–15, 2024.

[6] A. K. Aggarwal, "Biological tomato leaf disease classification using deep learning framework," *Int J Biol Biomed Eng*, vol. 16, no. 1, pp. 241–244, 2022.

[7] A. Bhatia, A. Chug, and A. Prakash Singh, "Application of extreme learning machine in plant disease prediction for highly imbalanced dataset," *J. Stat. Manag. Syst.*, vol. 23, no. 6, pp. 1059–1068, 2020.

[8] I. Nyalala *et al.*, "Tomato volume and mass estimation using computer vision and machine learning algorithms: Cherry tomato model," *J. Food Eng.*, vol. 263, pp. 288–298, 2019.

[9] J. Liu and X. Wang, "Tomato diseases and pests detection based on improved Yolo V3 convolutional neural network," *Front. Plant Sci.*, vol. 11, p. 898, 2020.

[10] S. Verma, A. Chug, and A. P. Singh, "Application of convolutional neural networks for evaluation of disease severity in tomato plant," *J. Discret. Math. Sci. Cryptogr.*, vol. 23, no. 1, pp. 273–282, 2020.

[11] H. Hong, J. Lin, and F. Huang, "Tomato disease detection and classification by deep learning," in *2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, 2020, pp. 25–29.

[12] R. Qasrawi, M. Amro, R. Zaghal, M. Sawafteh, and S. V. Polo, "Machine learning techniques for tomato plant diseases clustering, prediction and classification," in *2021 International Conference on Promising Electronic Technologies (ICPET)*, 2021, pp. 40–45.

[13] 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)*, 2016, pp. 1242–1246.

[14] I. Putra, R. Fauzi, D. Witarsyah, and I. Putra, "Classification of tomato plants diseases using convolutional neural network," *Int J Adv Sci Eng Inf Technol*, vol. 10, no. 5, pp. 1821–1827, 2020.

[15] T. S. Xian and R. Ngadiran, "Plant diseases classification using machine learning," in *Journal of Physics: Conference Series*, 2021, vol. 1962, no. 1, p. 12024.

[16] H. S. Nagamani and H. Sarojadevi, "Tomato leaf disease detection using deep learning techniques," *Int. J. Adv.*

Comput. Sci. Appl., vol. 13, no. 1, 2022.

[17] S. M. Javidan, A. Banakar, K. A. Vakilian, and Y. Ampatzidis, "Tomato leaf diseases classification using image processing and weighted ensemble learning," *Agron. J.*, vol. 116, no. 3, pp. 1029–1049, 2024.

[18] H. J. Mohammed, A. A. Nafea, H. K. Almulla, S. A. S. Aliesawi, and M. M. Al-Ani, "An Effective Hybrid Model for Skin Cancer Detection Using Transfer Learning," in *2023 16th International Conference on Developments in eSystems Engineering (DeSE)*, 2023, pp. 840–845.

[19] M. Chhabra and R. Kumar, "A smart healthcare system based on classifier DenseNet 121 model to detect multiple diseases," in *Mobile Radio Communications and 5G Networks: Proceedings of Second MRCN 2021*, Springer, 2022, pp. 297–312.

[20] W. El-Shafai *et al.*, "Efficient Deep-Learning-Based Autoencoder Denoising Approach for Medical Image Diagnosis.," *Comput. Mater. Contin.*, vol. 70, no. 3, 2022.

[21] A. A. Nafea, M. S. Ibrahim, A. A. Mukhlif, M. M. AL-Ani, and N. Omar, "An Ensemble Model for Detection of Adverse Drug Reactions," *ARO-THE Sci. J. KOYA Univ.*, vol. 12, no. 1, pp. 41–47, 2024.

[22] H. Tao *et al.*, "Development of integrative data intelligence models for thermo-economic performances prediction of hybrid organic rankine plants," *Energy*, p. 130503, 2024.

[23] A. A. Nafea, A.-M. Manar, K. M. A. Alheeti, M. S. I. Alsumaidaie, and M. M. AL-Ani, "A Hybrid Method of 1D-CNN and Machine Learning Algorithms for Breast Cancer Detection," *Baghdad Sci. J.*, 2024.

[24] S. Ashok, G. Kishore, V. Rajesh, S. Suchitra, S. G. G. Sophia, and B. Pavithra, "Tomato leaf disease detection using deep learning techniques," in *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, 2020, pp. 979–983.