International Journal on Advanced Science Engineering Information Technology

Vol.15 (2025) No. 1
ISSN: 2088-5334

Leaf Disease Detection in Plant Care using CNN Architecture: AlexNet and ResNet-50 Models

Husnul Ajra [a,b], Mazlina Abdul Majid [a,*], Md. Shohidul Islam [a], Dahlan Abdullah [c]

[a] *Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA), Pekan, Kuantan, Malaysia*
[b] *Bangabandhu Sheikh Mujibur Rahman Science and Technology University, Gopalganj, Bangladesh*
[c] *Department of Informatics, Faculty of Engineering, Universitas Malikussaleh, Indonesia*
*Corresponding author: *mazlina@umpsa.edu.my*

***Abstract*—Global agricultural productivity is integral to fulfilling basic nutrition needs and economic growth. Moreover, plants are essential in protecting the environment and food chain balance. However, plant growth and health naturally depend on whether they are affected by various diseases. Agricultural cultivators in remote regions often lack precise information on effective disease detection methods, leading to significant crop losses. Manual observation is an unreliable technique for disease detection, making it challenging to identify and address issues promptly. Accurate disease detection through analyzing leaf images can be a crucial tool for quickly and easily noticing and solving potential issues in digital cultivating. This paper proposes a method for disease detection in plant care using the image dataset of tomatoes and potatoes to help cultivators better manage plant health. The approach leverages image analysis of plant leaves, employing AlexNet and ResNet-50, two well-known convolutional neural network models. This approach has utilized a dataset from Kaggle that includes images of tomato and potato plant leaves to explore leaf diseases. Hence, to detect leaf disease early, processes have been performed that involve preparing images, augmenting them, identifying important features, and classifying them through AlexNet and ResNet-50, including model evaluation using accuracy as the metric. According to experimental results, the proposed work achieves an overall 95.9% accuracy of the AlexNet and 97.3% accuracy of the ResNet-50 for identifying leaf diseases. It contributes to agriculture by providing an effective method for detecting plant leaf diseases and taking timely preventive measures for plant health.**

***Keywords*—AlexNet; detection; leaf disease; plant care; ResNet-50.**

Manuscript received 6 Marc. 2024; revised 21 Jul. 2024; accepted 19 Dec. 2024. Date of publication 28 Feb. 2025.

I. INTRODUCTION

The vitality and health energy of all living beings in the world are closely linked to the nutritional quality of crops and vegetables [1]. The growth of a country's economy is vital not just for financial reasons but also for protecting the environment and the balance of the food chain, which naturally depend on the growth, health, and quality of plants [2]. The economy's performance is heavily reliant on agriculture, particularly plant health care. However, conventional farming practices and various cultivation factors influence the quality and quantity of crops [3]. Crops and vegetables are vulnerable to diseases in different climates and environments, leading to significant losses for cultivators worldwide [4]. The reduction in global crop production due to leaf disease has become a major concern in the agricultural industry at present. The primary challenge is to effectively recognize leaf diseases in crops and implement appropriate measures to increase production rates while maintaining quality [5]. Failure to promptly detect and manage leaf diseases can lead to negative impacts on both crop profit and quality, ultimately affecting cultivators' financial claims. In this case, to accurately recognize diseases in crops, it is important to analyze the leaves of two specific crops: tomato and potato. These crops are widely consumed and are crucial in providing essential nutrients to the human body. Therefore, it is critical to monitor and maintain their health to ensure the continued availability of these vital nutrients.

In recent times, deep learning approaches have led to the achievement of significant advancements in computer vision, particularly in the early diagnosis of leaf illnesses in the context of plant care. The existing applications of deep learning models [6], namely ResNet-50 and AlexNet for accurate identifications and classifications of leaf diseases, can be a crucial step in preventing agricultural deterioration.

In this case, these systems detect plant diseases but do not suggest preventive instructions or measures. This paper aims to bridge the existing gap by developing a graphical user interface with disease detection and demonstrating preventive measures for diseases while improving detection accuracy. Different types of crops and vegetable leaves are susceptible to various diseases [7], including bacterial, fungal, and viral infections. Some of the most familiar crop diseases contain Bacterial Blight, Powdery Mildew, Anthracnose, Downy Mildew, Alternaria Alternata, Black Mold, Cercospora Leaf Spot, and Rust. When the potato and tomato plant leaf get infected, it exposes visible symptoms such as variations in texture, shape, size, and color.

However, most of the disease signs are microscopic in nature, making it impossible for humans to identify the diseases without the aid of technology. Leaf disease detection algorithms primarily rely on the classification of the status of healthy and unhealthy leaves, as well as the identification of disease families from unhealthy leaves through the application of convolutional neural networks [8]. Fig.1 presents the basic concepts of the disease detection approach for plant leaves. Detecting disease symptoms of leaves is a crucial task in agriculture, and it requires the development of an efficient technique that leverages scientific knowledge and experience on a large scale. The leading purpose of this work is to develop a plant care management scheme for plant healthcare facilities using the convolutional neural networks (CNN) approach [9], through which it can rapidly detect leaf diseases. In this paper, it has been accumulated tomato and potato plant leaf images from Kaggle datasets to develop effective leaf care management for detecting disease symptoms.

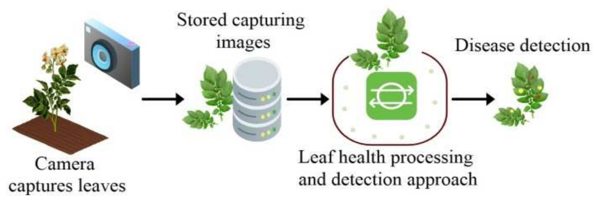

Fig. 1 Basic concepts of Leaf disease detection system

However, tomato and potato leaves can be captured as images using a standard digital or high-quality camera. The collected images are then put through a process that helps to enhance and analyze the images [10]. Detection of plant diseases involves a sequence of image processing strategies, namely acquisition, preprocessing, segmentation, re-storing, augmenting, feature extracting, and classification of leaves. During the preprocessing phase of image processing, RGB leaf images undergo color conversion to remake them into gray images. To enhance the contrast of these image samples while clearing various noises, multiple contrast enhancement methods are employed. Further modifications are made using image augmentation techniques such as cropping, flipping, and rotating to align the images. The aligned images are then analyzed for various properties, including color details, edges, and portions. The color image area can be analyzed using a classification algorithm to identify leaf diseases. This study utilizes the AlexNet and ResNet-50 methods, which are distinct pre-trained classification models [11]. These models are able to categorize healthy and unhealthy leaf images and identify different disease families from unhealthy leaf images. In the field of agriculture, there are several existing systems that can identify various plant leaf diseases, but these systems lack the ability to offer preventive measures for plant healthcare. To address this gap, this paper also introduces a system that can not only notice diseases but also provide preventative measures employing a graphical user interface mechanism.

As such, this work conveys the following contributions.

a. This paper provides a system for detecting leaf diseases in plant care management by conducting leaf image processing and employing AlexNet and ResNet-50 models.
b. This study presents two algorithms to detect leaf disease families in the proposed framework.
c. This paper equips a crafted evaluation metric procedure and presents the overall classification accuracy for leaf disease detection.

The remaining sections are organized as follows: Section II shows an insight into the existing state of the art for disease classification with detection. And expounds on the materials and methods employed in this study, which contains a schematic scenario, dataset description, preprocessing, image augmentation, and feature extraction. Additionally, it introduces an interface for diagnosing leaf diseases and presents two algorithms, namely Alexnet and Resnet-50 models of CNN for disease detection and classification. Section III illustrates the experimental setup and evaluation metrics and provides an exhaustive analysis of the accuracy results obtained. Finally, the conclusion is presented in Section IV.

A. Related Work

The most crucial matter for cultivators is to detect and control plant leaf diseases. In this section, it has been presented a synopsis of the current research-related work. The aim of these related studies is to meticulously review the key issues and deep learning models of existing literature concerning the leaf disease detection of plants or vegetables. Kiran and Chandrappa [12] utilized certain classifiers, namely linear discriminant analysis, SVM, DTC, logistic regression, random forest classifier, and KNN, including image pre-processing, segmentations, and feature extractions, to develop an automatic system for recognizing and classifying leaf diseases. The results showed that SVM achieved relatively well due to its capability to manage multiple classes, while the random forest classifier reached the highest accuracy by effectively detecting and classifying diseases from online images. Convolutional Neural Networks (CNN) were presented by Hasan et al. [13] for the detection of fish diseases. The authors demonstrated a 94.44% accuracy rate in identifying diseases in 90 images that contained both two types of diseases and healthy leaves. They also mentioned that a larger dataset and more studies could improve the performance of the models. Adem et al. [14] proposed an updated arrangement of the hybrid approach by fine-tuning the parameters of deep learning architectures with image processing to accurately identify spot disease of leaves of sugar beet plants and its severity.

The study used imaging-based expert approaches and a dataset of 1024 image samples to conduct high accuracy and ultimately minimize the time and potential errors associated with manual detection methods. Trivedi et al. [15] utilized CNN to accurately express and classify tomato diseases in modern agriculture. For this purpose, they used datasets comprising 3000 pictures of tomato leaves containing healthy and nine diseases. Also, the proposed model's predictions proved to be 98.49% accurate, demonstrating its efficacy in mitigating the effects of diseases and improving crop yield. The MEAN-SSD model offered by H. Sun et al. [16] was utilized to detect diseases in apple leaves using a light-weight CNN structure. Specifically, the model was constructed using data augmentation and annotation technology, where the MEAN block module, through the introduction of the GoogLeNets Inception module, increased the recognition speeds and reduced the model sizes. The model was trained in 5 standard disease image samples of apple leaves to attain high accuracy and provide a useful solution for disease detection.

Elaraby et al. [17] suggested using deep learning to detect plant diseases and to categorize leaf illnesses in five crops. The authors utilized a public image dataset of healthful and diseased crop leaves collected under pragmatic settings to identify plant illnesses in five crops, which were separated into 25 distinct types of classes. A deep CNN called AlexNet and Particle Swarm optimization were utilized in the training process, resulting in 98.83% accuracy, sensitivity of 98.78%, precision of 98.67%, specificity of 98.56%, and F-score of 98.47% for illustrating the feasibility of the proposed strategy. Abbas et al. [18] utilized a deep learning-constructed technique that uses a DenseNet121 model and a Conditional Generative Adversarial Network (C-GAN) to recognize diseases of tomato. The models are trained on real and synthetic pictures of the PlantVillage dataset by employing transfer learning to categorize tomato leaf images into ten classes of illnesses. Uğuz et al. [19] formulated a deep CNN to classify olive leaves into healthy, aculeus olearius, and peacock spot-affected leaves. The study used transfer learning on VGG19 and VGG16 models and operated experiments including and not including data augmentation. This work also designed a web-based application. Results showed low error rates in identifying olive peacock spot and aculus olearius.

Xu et al. [20] employed a multi-scale convolution structure, SoftMax classification, and capsule network module to identify crop insect pests for agricultural crop production and quality. It is also needed to find better results using the presented model in classifying images with mixed environments for controlling crop pests using intelligent technology. Sakkarvarthi et al. [21] utilized CNN, a deep learning strategy, to identify and classify diseases of tomato leaves. Their technique outperformed other pre-trained models, such as VGG19, ResNet 152, and InceptionV3, and achieved 88.17% testing accuracy. After conducting a thorough study, we have compiled a comprehensive comparison of disease detection synopses from various corresponding works, which have been demonstrated in the Table I. This table highlights several approaches to plant disease detection using various techniques and models for different types of plants. However, there are significant gaps and deficiencies in existing research.

TABLE I
SYNOPSIS OF RELATED WORKS

Ref.	Model/ Techniques	Plant Name	Diseases Type	Accuracy
[22]	Deep CNN	citrus	Huanglongbing, bacterial canker, black spot,	94.37 %
[23]	Resnet-18	Sugarcane	bacterial, brown and red stripes, ring spot	97.26%
[24]	Resnet101	Olives	Anthracnose	96.46%
[25]	deep CNN	cucumber	downy and powdery mildew, anthracnose	96.11%
[26]	Resnet	citrus	leaf disease	95.83%
[27]	CNN	Plant	Leaf disease	94.5%
[19]	CNN, transfer learning	Olive leaves	Aculus Olearius, Peacock spot disease	95%
[28]	CNN, M-Net	rice	leaf disease	90%
[21]	Deep CNN	tomato	leaf disease	88.17%
[13]	CNN	Fish	Fish diseases	94.4%

Most existing studies detect plant diseases but fail to provide any preventive instructions or measures for farmers. This leaves a critical gap in the practical application of these studies in agriculture. Besides, some studies of this table struggle with achieving high accuracy due to issues like blurred image edges, noise, and large background interference. In accordance with this, the research question has been raised to detect leaf diseases and provide a user-friendly graphical interface with preventive instructions regarding diseases detected in plant leaves. By addressing this question, the research aims to develop a more accurate, efficient, and practical system for detecting plant diseases and providing preventive measures, thereby enhancing digital farming practices and supporting farmers in increasing crop yield and quality.

II. MATERIALS AND METHODS

This section introduces a way to diagnose plant diseases that can make these things easier for farmers and ensure healthier plants. It will overcome the disease-related complexity of plant leaves using disease detection techniques and ensure that the plants are well taken care of health. Fig. 2 illustrates the schematic of a proposed scenario for detecting leaf diseases and implementing preventive plant healthcare. This system involves the collection of raw leaf image samples and the application of various image processing techniques with the CNN method. This work has used the image samples of potato and tomato leaves from the Kaggle datasets. So, in order to detect unhealthy and diseased leaves, the process involves applying image preprocessing and augmenting, feature extracting, and classification techniques on a dataset. These techniques help to enhance the images, extract relevant features, and classify the leaves based on their characteristics, enabling the detection of any abnormalities.

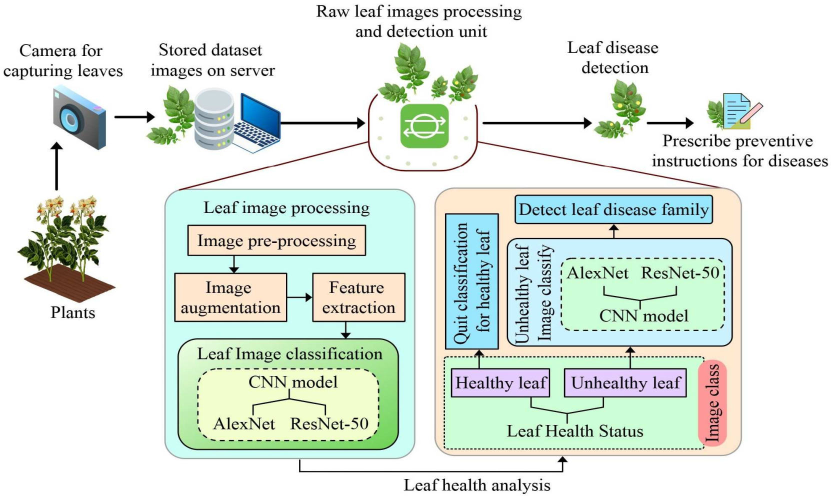

Fig. 2 Scenario of leaf disease detection system

The CNN architecture is constructed to train a dataset of leaf image samples and extract data from it. Here, this system uses CNN architectures, namely AlexNet and ResNet-50, for leaf disease classification and detection. It also includes a design of prescribed preventive instructions for leaf diseases. The method follows a step-by-step procedure for identifying leaf disease families.

A. Dataset of Leaf Images

Accurate and reliable datasets, whether quantitative or qualitative, are indispensable for assuring the credibility of research and the effectiveness of data analysis or field studies. In the case of analyzing the health of plant leaves, standard smart cameras or high-resolution digital cameras can be used to collect leaf images for such datasets. However, as leaf samples of potato and tomato plants, we have got the dataset of leaf images from the online source Kaggle for the disease detection performance analysis, which includes images of healthier or unhealthier leaves. The dataset comprises more than 9473 leaf images of potato plants and tomato plants, which represent healthy and unhealthy conditions. The database mainly included healthy and unhealthy leaf image samples of tomato plants and potato plants, whereas unhealthy leaf image samples contain leaf diseases such as the tomato early and late blight and the potato early and late blight. For this work, a dataset of 9473 images has been split into training and testing samples, whereas 70% is considered as training samples, along with the residual 30% being used as testing samples. These images are all standardized to 256 by 256 dimensions, with vertical and horizontal resolutions of 96 dpi, along with a bit depth of 24. All leaf images in this work have been kept in the .jpg file format. This study has employed image processing techniques, including different learning models, to examine the effects of different backgrounds of plant leaves and recognize leaf diseases.

B. Preprocessing

Image preprocessing [29] is one of the most effectual approaches in health status classification and disease detection of potato and tomato plant leaves, where it prepares data from the raw leaf images for succeeding processing. In this case, the process described involves converting raw input image datasets of leaves into a desired form to enhance the quality of image samples of plant leaves. This transformation supports the elimination of unwanted parts, noise, and blur from the leaf image samples for better image processing. There are several phases, namely data cleaning and reduction, data integration, and data transformation for leaf image processing, which occur in this approach. Fig. 3 demonstrates these phases for leaf image processing. During data cleaning, the process involves identifying and eliminating any unwanted noise or distortion that may be contained in the data. Additionally, it manages any missing data points and rectifies any inconsistencies that may be present in the data [18]. In the integration step, it is common to encounter heterogeneous and multiple data or data redundancy in datasets of plant leaf images. For these contexts, data retrieval procedures are used to resolve conflicts and create a unified replica of the image data. However, when dealing with an oversized dataset, the computational complexity and storage space can increase because of the distinct feature dimensions.

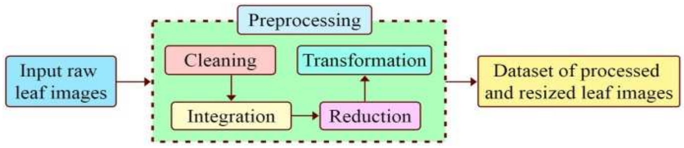

Fig. 3 Preprocessing of leaf images

Subsequently, the reduction in redundant data features plays a significant role in enhancing the efficiency performance of leaf image processing. This process involves reducing the complexity of redundant, unnecessary, and less significant attributes from a large type dataset by focusing on the original feature space. Furthermore, data transformation involves several operations, such as data assembly, data smoothing, feature structure, data discretization, and normalization. It performs a crucial role in improving the reliability of data attributes in diverse data assessment units and structures, as well as in image data transformation. The leaf images from the dataset undergo resizing in order to facilitate the analysis of training and testing datasets. So, the utilization of preprocessing procedures enables the preparation of datasets that can accurately determine leaf diseases by analyzing datasets of plant leaf images.

C. Image Augmentation

Image augmentation is a strategy used in data preparation that involves changing and enhancing the leaf image representation to minimize overfitting [30] This is achieved by applying a series of operations such as rotation, scaling, flipping, and cropping to the original image to generate multiple variations of the same image. These variations are then utilized to train the deep learning models, which helps to increase their accuracy and generalization capability. To enhance the efficacy of the model simplification and transform the leaf images into RGB, training and testing samples of leaf images are augmented through the color transformation approach. Accordingly, the augmented images of plant leaves are generated to enhance the performance of the model while keeping a consistent dimension and quality of pictures in both healthier and unhealthier leaf data.

D. Feature Extraction

The approach of feature extraction is a critical step in which the features or values derived from the leaf image data are grouped together. This process is significant as it enables the identification of key patterns, shapes, and characteristics present in the leaf image data of potatoes and tomatoes, which is used for further analysis and classification. The extracted features provide valuable information on the leaf images, making subsequent image processing considerably easier. A unique class label is assigned to the plant leaf image based on its distinctive features to characterize it. Feature extraction involves the automatic learning of relevant features from plant leaf images, such as shape, color, morphology, texture, and edges, which are then utilized to recognize and classify leaf diseases [31]. The extracted features are fed into a classifier for further processing, which enables the appropriate classification of distinct types of leaf diseases. By employing this extraction technique, this work is able to accurately classify and detect different leaf disease families.

E. CNN Model for Classification and Detection

The main aim of this work is to employ the Convolutional Neural Network (CNN) [32] for analyzing leaf images of tomato and potato plants with the intent of categorizing the health status of the leaves from a given dataset and identifying leaf diseases from unhealthy leaves. This study utilizes two novel deep learning techniques, AlexNet [26] and ResNet-50 architectures [33], to arrange the learning mechanism and accurately recognize distinct types of plant leaf diseases. In the context of image processing, these architectures have been engaged for leaf disease classification and rely on trained and tested data of image samples to classify the various groups of leaf diseases. In accordance, Fig. 4 demonstrates the samples of the health status of potato and tomato leaves.

However, this work effectively manages complex classification processes [34] by utilizing pre-trained deep-learning network models such as ResNet-50 and AlexNet. These models handle the category tasks associated with plant disease identification such as early and late blight disease families for potato and tomato plants. To initiate the learning process, the AlexNet model is first fitted with a set of pre-trained data samples of plant leaves. The design of AlexNet possesses a whole of eight layers, which hold more than one million samples, including five convolutional layers and another three completely connected layers.

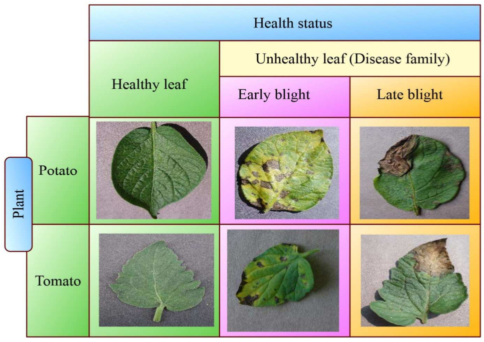

Fig. 4 Health status of potato and tomato leaves

Accordingly, max-pooling is performed in some convolutional layers. The input image size of this network is 227 × 227 × 3. The convolutional window size of the first layer, 11 × 11, has been operated because of large input data. Then, the size of the second convolutional layer contains 5 × 5. Next, the size of the convolutional layer has been taken on 3 × 3 consecutively. To actually train the leaf data samples, it has been transferred the class-specific layers along with the recent last layer, and according to the whole network is fine-tuned.

Algorithm 1 Identification of the healthy and unhealthy status of plant leaves

Input: Leaf images of Tomato and Potato
Results: Ensure healthy and unhealthy plant leaves
Set procedures for plant leaf health status
Dataset (l samples), $D_l = \{i_1, i_2, i_3, ...i_n\}$
Initialize corresponding parameters
if Apply pre-processing technique on D_l **then**
  Perform data cleaning, integration, reduction, transformation on D_l
  Resize D_l images into 256×256 size.
end if
function leafHealthStatus
if Load ResNet50 model and AlexNet model **then**
  net1 = ResNet50() *or* AlexNet()
  D_{tr}, D_{te} = split(D_l)
  liSize = net1.Layers().InputShape
  if Perform image augmentation **then**
    $D_{atr} \leftarrow$ augmentedliStore(liSize, D_{tr}, gray2rgb)
    $D_{ate} \leftarrow$ augmentedliStore(liSize, D_{te}, gray2rgb)
  end if
  if Apply feature extraction process **then**
    $F_{tr} \leftarrow$ active(net1,D_{atr}, featureLayer)
    $F_{te} \leftarrow$ active(net1,D_{ate}, featureLayer)
  end if
  Classifier1 = fitclassErrorCorrect(F_{tr}, D_{tr}.Labels, Learner)
  lPredictLabel = predict(Classifier1,F_{te})
end if
leafHealthStatus $\leftarrow$ findHealthClass(P_H, P_{UH}, T_H, T_{UH}, lPredictLabel)
end function
Get healthy leaf and unhealthy leaf

Moreover, the ResNet-50 model is utilized in CNN to stimulate the learning process. This is achieved by equipping the model with pre-trained data samples of images. ResNet-50 architecture contains 50 layers as CNN. These layers are precisely designed to conduct deep learning tasks in the case of image classification. With its unique architecture, ResNet-50 is able to achieve high levels of accuracy in various sample detection tasks. This model receives image the input size of 224×224×3. It performs a convolutional layer with a kernel size of 7x7 and 64 filters, pursued by a max-pooling layer with a kernel size of 3x3. The model employs a technique of stacking several identity mappings convolutional layers that are initially inactive, bypassing them, and reutilizing the activations generated by the preceding layer.

TABLE II
SYNOPSIS OF CORRESPONDING PARAMETERS

Notation	Description	Notation	Description
l	Leaf	n	Number of Leaf Images
i	Image	D_{atr}	Augmented training set
D	Dataset	D_{ate}	Augmented test set
D_{tr}	Training set	F_{tr}	Training features
D_{te}	Test set	F_{te}	Test features
P	Potato	T	Tomato
H	Healthy	UH	Unhealthy
B_E	Early blight	B_L	Late blight

Algorithm 2 Detection of the disease family from unhealthy leaves

Input: Unhealthy leaf images of Tomato and Potato
Results: Detect leaf disease family
Set procedures for plant leaf disease detection
Initialize related parameters
Quit classify healthy leaves $D_{H_l} = \{(P_H, T_H)\}$
Allow classify $D_{UH_l} = \{(P_{UH}, T_{UH})\}$ to detect disease
function leafDiseaseFamily
if Conduct ResNet50 model and AlexNet model **then**
  net2 = ResNet50() *or* AlexNet()
  $D_{tr_{UH}}$, $D_{te_{UH}}$ = split(D_{UH_l})
  $UHli$Size = net2.Layers().InputShape
  if Employ image augmentation **then**
    $D_{atr_{UH}} \leftarrow$ augmentStr($UHli$Size, $D_{tr_{UH}}$, gray2rgb)
    $D_{ate_{UH}} \leftarrow$ augmentStr($UHli$Size, $D_{te_{UH}}$, gray2rgb)
  end if
  if Perform feature extraction process **then**
    $F_{tr_{UH}} \leftarrow$ active(net2,$D_{atr_{UH}}$, featureLayer)
    $F_{te_{UH}} \leftarrow$ active(net2,$D_{ate_{UH}}$, featureLayer)
  end if
  Classifier2 = fitclassErrorCorrectOutput($F_{tr_{UH}}$, $D_{tr_{UH}}$.Labels, Learner)
  UHlPredictLabel = predict(Classifier2,$F_{te_{UH}}$)
end if
leafDiseaseFamily $\leftarrow$ detectDiseaseClass(P_{BE}, P_{BL}, T_{BE}, T_{BL}, UHlPredictLabel)
end function
Leaf disease family detection
Prescribe instructions on leaf disease family

For both models, it works with 6631 training leaf image samples. These models run on 2842 testing leaf image samples to classify them within two distinct image classes: healthier and unhealthier leaves. For potato plants, there are 658 samples for healthy leaves and 743 samples for unhealthy leaves, and there are 721 samples for healthy leaves and 720 samples for unhealthy leaves for tomato plants, available for analysis and evaluation. Then, the above-mentioned models are utilized on unhealthy leaf image samples to classify them into distinct disease families, namely late blight and early blight for potatoes and tomatoes. Consequently, these procedures can effectively identify and segregate leaf disease groups from the images of tomato and potato plant leaves. The procedure for identification of the healthy and unhealthy status of plant leaves is presented in Algorithm 1. In accordance, the approach for detection of the disease family from unhealthy leaves is illustrated in Algorithm 2. The specified notations and descriptions of corresponding parameters for Algorithms 1–2 are indicated in TABLE II. In this case, the system will broadcast the correctly classified images of potato plant and tomato plant leaves for disease detection. Identification of plant leaf diseases through this method can offer precise guidance to growers regarding the types of leaf diseases and their respective remedies.

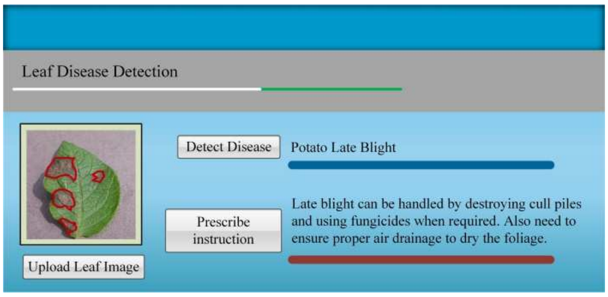

Fig. 5 An interface for diagnosing leaf diseases

A plant care management influences the practices of controlling the quantity and quality of crops and vegetables. Fig. 5 introduces an interface for diagnosing leaf illnesses of potato and tomato plants. This type of interface prevents the spread of diseases, ultimately directing to healthier and more abundant harvests. The leaf disease classification system has been integrated with a graphical application that enables farmers to obtain information about the disease affecting their plant leaves. The interface is programmed to identify the specific leaf disease family from a set of leaf images and provide instructions to farmers on how to prevent further damage. The system is designed to enhance the awareness of plant health among farmers and promote effective disease management.

III. RESULTS AND DISCUSSION

This study focuses on improving the accuracy of leaf disease detection for tomato and potato plants utilizing deep learning models, specifically AlexNet and ResNet-50. The goal of this work is to reduce the number of erroneous classifications in order to effectively manage plant leaf health. The study utilized a dataset of healthy and unhealthy leaf image samples, and experimental results indicate the successful classification of plant leaf images to detect disorders with high accuracy. This study has set an evaluation procedure environment by creating the system demonstration for disease detection that utilized an Intel(R) Core i5 desktop CPU-3.20GHz, 64-bit OS, Windows 10, x64-based processor, 8GB RAM. The design of the proposed work has been carried out using MATLAB 2018a programming environment. To enhance the performance of disease detection for plant leaves, a deep learning framework has been utilized, incorporating the AlexNet and ResNet-50 models. Through this equipped design, the experiment has yielded promising results in terms of implementation and effectiveness.

In this text, various standard metrics are engaged to evaluate the ability of classification models on potato and tomato leaf images for disease detection. These metrics offer a comprehensive reflection to assess the quality of the models and provide valuable insights into their classification efficacy. By analyzing these metrics, experts can determine the strengths and constraints of the model and make informed decisions to improve its accuracy and precision. For detailing the health status of potato and tomato leaves by applying models, the mathematical calculations for the evaluation metrics are specified by equations as follows:

$$Acc = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \quad (1)$$

$$TC_{Acc} = \frac{T_p}{T_p+F_p} \quad (2)$$

$$OC_{Acc} = \frac{T_p}{T_p+F_n} \quad (3)$$

$$F1-Score = \frac{2 \times TC_{Acc} \times OC_{Acc}}{TC_{Acc}+OC_{Acc}} \quad (4)$$

In this context, T_p, F_p, T_n, and F_n denote "true positive", "false positive", "true negative", and "false positive", respectively, which are employed to estimate the performance of models by exploiting the confusion matrix. In equation (1), Acc is defined by accuracy, which represents the ratio between the number of correctly classified predictions and the total number of predictions. TC_{Acc} is specified by precision for the target class in equation (2), which is the ratio between the number of image samples as true positive to the summation of the number of image samples of true positive and false positive. In equation (3), OC_{Acc} is prescribed by the recall for output class, which is estimated as the proportion of the number of image samples as true positive to the summation of the number of image samples of true positive and false negative. Besides, equation (4) represents the $F1-Score$.

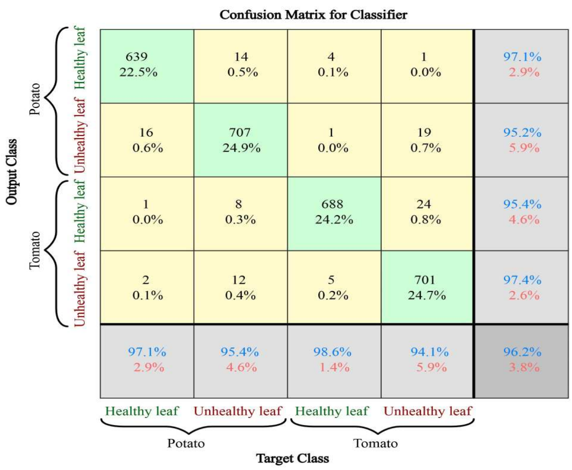

Fig. 6 Confusion Matrix used in H and UH leaf samples for AlexNet

A confusion matrix is utilized to introduce the performance of deep learning model classifiers and their visualization for health status classification and disease detection from plant leaf images. The confusion matrix estimates the value of the target class and output class performance regarding distinct classification labels based on healthy and unhealthy leaves. After analyzing the results of AlexNet and ResNet-50 models, it can be observed that the confusion matrix indicates a relatively high accuracy in identifying healthy and unhealthy leaves through correctly classified diagonal line cells. However, there were some instances where the model incorrectly predicted the status of a few leaves, as indicated by the remaining cells. Hence, Fig. 6 illustrates the results of the evaluation of standard metrics for healthier and unhealthier leaves, utilizing the AlexNet model, where the performance of the model is presented through a confusion matrix. TABLE III demonstrates the classification results of healthier and unhealthy leaves based on the target class and output class using AlexNet. Based on the overall determinations for healthy and unhealthy leaf categories, it appears that the classification accuracy of this model is 96.2%, while the remaining 3.8% are classified incorrectly.

TABLE III
PERFORMANCE MEASUREMENT IN H AND UH LEAF SAMPLES USING ALEXNET MODEL

Status label	Number of leaf images	Correctly classified images	OC_{Acc}	TC_{Acc}
P_H	658	639	97.1%	97.1%
P_{UH}	743	707	95.2%	95.4%
T_H	721	688	95.4%	98.6%
T_{UH}	720	701	97.4%	94.1%

Consequently, employing the Resnet-50 model, Fig. 7 demonstrates the evaluation results of standard metrics for healthier and unhealthier leaves of tomato and potato plants, where the performance of the model is illustrated through a confusion matrix with regard to output class and target class. TABLE IV shows the classification results for the status of the healthier and unhealthy leaf samples based on the target class and output class using Resnet-50. Based on the overall findings for healthy and unhealthy leaf groups, it appears that the classification accuracy of this model is 97.5%, while the remaining 2.5% samples are diagnosed incorrectly.

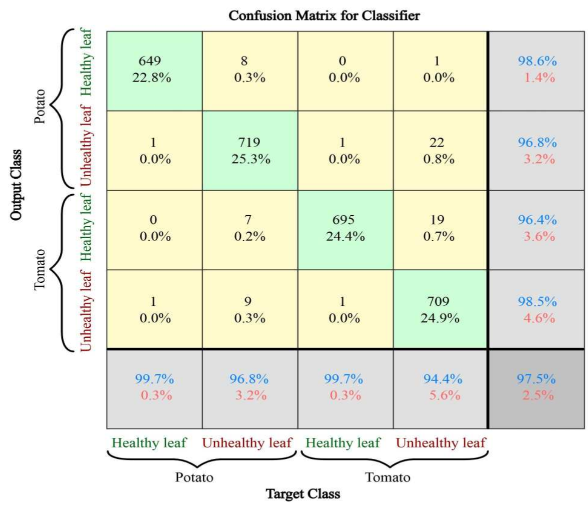

Fig. 7 Confusion Matrix used in H and UH leaf samples for ResNet-50

TABLE IV
PERFORMANCE MEASUREMENT IN H AND UH LEAF SAMPLES USING RESNET-50 MODEL

Status label	Number of leaf images	Correctly classified images	OC_{Acc}	TC_{Acc}
P_H	658	649	98.6%	99.7%
P_{UH}	743	719	96.8%	96.8%
T_H	721	695	96.4%	99.7%
T_{UH}	720	709	98.5%	94.4%

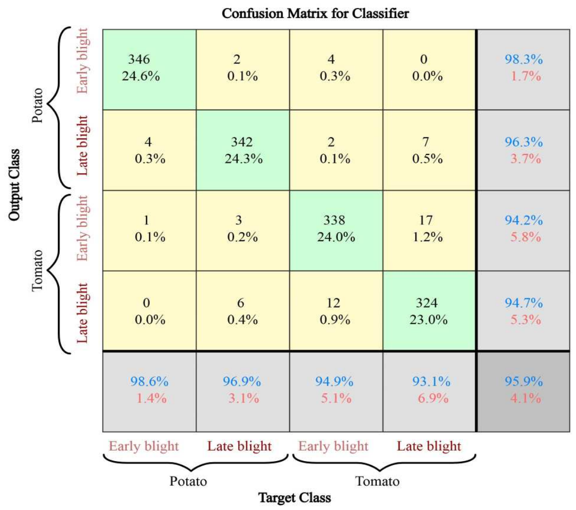

Fig. 8 Confusion Matrix used in leaf diseases engaging for AlexNet

TABLE V
PERFORMANCE MEASUREMENT IN LEAF DISEASES ENGAGING ALEXNET MODEL

Status label	Number of leaf images	Correctly classified images	OC_{Acc}	TC_{Acc}
P_{BE}	352	346	98.3%	98.6%
P_{BL}	355	342	96.3%	96.9%
T_{BE}	359	338	94.2%	94.9%
T_{BL}	342	324	94.7%	93.1%

In this context, the confusion matrix illustrates the accomplishment of the model classifiers for unhealthy leaf image categories to identify the disease families of tomato and potato plants. This confusion matrix assesses the performance of the target class and output class relating to distinct category labels based on tomato late and early blight and potato late and early blight leaves through AlexNet and ResNet-50 models. After exploring the consequences, it can be shown that the confusion matrix indicates a fairly better accuracy in detecting leaf diseases through correctly classified diagonal line cells. Regardless, there were some instances where the model incorrectly predicted the status of a few leaves, as indicated by the remaining cells. In particular, Fig. 8 represents the consequences of the standard metrics for distinct leaf disease families from unhealthy leaves of tomato and potato plants, employing the AlexNet model. The performance of this model based on the target class and output class is recorded in TABLE V, as measured by evaluation metrics. Based on the findings of this model, the classification accuracy for the disease cases in plant leaves is relatively better at 95.9%. However, misdiagnosis occurs in some cases, accounting for 4.1% of the total samples.

As a further matter, based on the classification analysis applying ResNet-50, the disease diagnosis from unhealthy leaves is illustrated in Fig. 9 by a confusion matrix. Measured performance by evaluation metrics according to the target class and output class is recorded in TABLE VI. In accordance with the consequences of the model, the accuracy of classifying leaf disease cases is quite impressive at 97.3%. Nonetheless, there are some samples where misidentification happens, which comprise 2.7% of the total leaf samples.

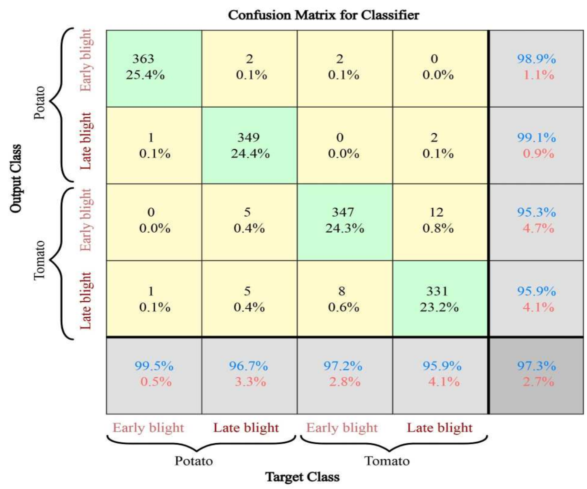

Fig. 9 Confusion Matrix used in leaf diseases engaging ResNet-50

TABLE VI
PERFORMANCE MEASUREMENT IN LEAF DISEASES ENGAGING RESNET-50 MODEL

Status label	Number of leaf images	Correctly classified images	OC_{Acc}	TC_{Acc}
P_{BE}	367	363	98.9%	99.5%
P_{BL}	352	349	99.1%	96.7%
T_{BE}	364	347	95.3%	97.2%
T_{BL}	345	331	95.9%	95.9%

In addition, based on the precision and recall values for the performance of the AlexNet and Resnet-50 models, F1 Scores are measured and recorded in TABLE VII. The ResNet-50 model has higher F1 Scores for all leaf status labels than the AlexNet model. This indicates that ResNet-50 is more reliable and effective in classifying healthy and unhealthy leaves and detecting various leaf diseases in tomato and potato plants.

TABLE VII
F1-SCORE ENGAGING ALEXNET AND RESNET-50 MODEL

Status label	F1-Score	
	AlexNet	Resnet-50
P_H	97.1%	99.1%
P_{UH}	95.1%	96.8%
T_H	97%	98%
T_{UH}	95.7%	96.4%
P_{BE}	98.3%	99.2%
P_{BL}	96.3%	97.%9
T_{BE}	94.2%	96.2%
T_{BL}	93.9%	95.9%

Hence, the proposed work adopts the plant care management system using the CNN models for leaf data processing. The classification analysis has been conducted to detect disease by comparing the determining accuracy values of two classified deep learning models using a dataset of leaf images under varying conditions. An evaluation setting has been organized to illustrate the performance analysis between AlexNet and ResNet-50. For the observation of the health status of plant leaf images, the analysis exploration has been conducted on potato healthy, potato unhealthy, tomato healthy, and tomato unhealthy, which are denoted by P(H), P(UH), T(H), and T(UH), respectively. Fig. 10(a) shows the correctly classified images of leaves where plant health status is plotted as healthy-unhealthy leaves. In this case, the number of correctly classified images based on leaf health data varies significantly, and ResNet-50 supports better performance than the AlexNet model. Correspondingly, evaluation results have been performed between AlexNet and ResNet-50 models to illustrate the performance of accuracy of the target class regarding the health status of leaves for tomato and potato plants, which has been presented in Fig. 10(b). In this case, the results achieved a high accuracy of 99.7% through the Resnet-50 model. According to the experiment results demonstrated in Fig. 10(c), both AlexNet and ResNet-50 models have been employed to exhibit the visual performance of accuracy for the output class about the leaf health status of the plant. Among these two models, ResNet-50 has attained a high accuracy of 98.6%.

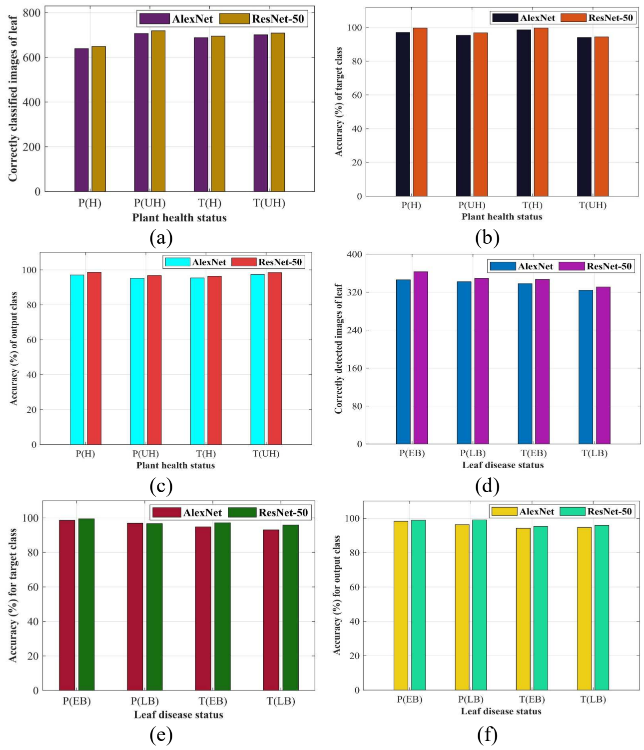

Fig. 10 Comparative performance results between ResNet-50 and AlexNet for (a) correctly classified H and UH leaf samples, (b) accuracy of the target class in terms of leaf health status, (c) accuracy of the output class on leaf health status, (d) correctly detecting the disease of leaves, (e) accuracy of the target class for leaf disease status, and (f) accuracy of the output class for leaf disease status

Furthermore, the evaluation setting for the leaf disease detection has been accomplished based on the leaf image samples of tomato early blight, tomato late blight, potato early blight, and potato late blight, remarked by T(EB), T(LB), P(EB), and P(LB), respectively. Fig. 10(d) demonstrates the correctly detected leaf images from the unhealthy leaves where leaf disease status is introduced as early and late blights for potato and tomato leaves. In this state, the number of correctly detected leaf images varies notably based on leaf disease, whereas ResNet-50 performs relatively better than the AlexNet model. According to the analysis results presented in Fig. 10(e), both ResNet-50 and AlexNet models have been utilized to demonstrate the visual performance of accuracy for the target class regarding leaf disease status. Among these models, ResNet-50 has performed with the highest accuracy of 99.5%. In addition, experimental results have been accomplished between ResNet-50 and AlexNet models to assess the accuracy of the output class about distinct leaf disease families, as demonstrated in Fig. 10(f). The results specify that the ResNet-50 model has shown higher performance with an accuracy of 99.1%.

According to the study, ResNet-50 has been depicted to be more accurate and performant than AlexNet in classifying healthy and unhealthy leaves and detecting leaf disease families. Specifically, ResNet-50 attained an overall accuracy rate of 97.5% in classifying healthy and unhealthy leaves, while AlexNet achieved 96.2%. Also, for detecting leaf disease families, ResNet-50 outperformed AlexNet with an overall accuracy of 97.3% compared to 95.9% for AlexNet. Based on the analysis, ResNet-50 outperformed AlexNet regarding accuracy and performance. The ResNet-50 model performs better than AlexNet because its deeper architecture with residual connections enhances its ability to accurately classify healthy and unhealthy leaves and detect various leaf diseases with higher precision and recall.

IV. Conclusion

This study aims to explore the application of deep-learning architectures for detecting and identifying leaf disease in potato and tomato plants. The analysis provides a viable solution for disease detection in the leaves of grains and vegetables, a major concern for farmers in the agricultural industry. The study supports a diagnostic approach that utilizes AlexNet and ResNet-50 convolutional neural network architectures to diagnose and classify leaf disease families accurately. The developed interface can identify specific leaf disease families from a collection of leaf images and provides farmers with detailed instructions on mitigating further damage. The study involves image processing procedures on Kaggle datasets containing images of leaves from tomatoes and potatoes. Pre-processing, augmentation, and data extraction methods have been used to prepare leaf image data for quality enhancement. The processed images are classified into healthy and unhealthy leaves using AlexNet and ResNet-50 architectures. The work is then used to detect early and late blight in potatoes and tomatoes using the same architecture. The equipped design has produced encouraging results in terms of implementation and effectiveness. Furthermore, the paper decides the classification accuracy for leaf disease diagnosis, and the ResNet-50 model has been found to perform better than the AlexNet model with higher accuracy. This approach has a graphical interface that identifies the disease family from leaf images and provides prevention instructions. It promotes effective disease management and enhances plant health awareness among farmers. The research outcomes in this paper are limited by the dataset size and diversity, including data augmentation techniques. To further improve model performance, incorporating advanced data augmentation techniques and experimenting with other deep learning architectures like DenseNet could enhance the model's ability to generalize and capture finer details. This approach will also be extended to an IoT-enabled leaf disease detection system for smart plant care management.

Acknowledgment

This research is funded by the research grant PGRS220338 at Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) in Malaysia. Bangabandhu Sheikh Mujibur Rahman Science and Technology University in Bangladesh and Universitas Malikussaleh in Indonesia support this study.

References

[1] E. A. Rosyidah, A. F. Hadi, and Y. S. Dewi, "The classification of tea leaf disease using CNN image classifier," in *Proc. Atlantis Press Int. Conf.*, 2023, pp. 89–112, doi: 10.2991/978-94-6463-174-6_10.

[2] P. Singla, V. Kalavakonda, and R. Senthil, "Detection of plant leaf diseases using deep convolutional neural network models," *Multimed. Tools Appl.*, pp. 64533–64549, 2024, doi: 10.1007/s11042-023-18099-3.

[3] M. Nawaz et al., "A robust deep learning approach for tomato plant leaf disease localization and classification," *Sci. Rep.*, vol. 12, no. 1, pp. 1–18, 2022, doi: 10.1038/s41598-022-21498-5.

[4] A. Petchiammal, D. Murugan, and K. S. Briskline, "PaddyNet: An improved deep convolutional neural network for automated disease identification on visual paddy leaf images," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 6, pp. 1141–1149, 2023, doi:10.14569/ijacsa.2023.01406122.

[5] H. Waheed et al., "A mobile-based system for detecting ginger leaf disorders using deep learning," *Future Internet*, vol. 15, no. 3, pp. 1–23, 2023, doi: 10.3390/fi15030086.

[6] M. V. Sanida et al., "An efficient hybrid CNN classification model for tomato crop disease," *Technologies*, vol. 11, no. 1, pp. 1–17, 2023, doi:10.3390/technologies11010010.

[7] Ü. Atila et al., "Plant leaf disease classification using EfficientNet deep learning model," *Ecol. Inform.*, vol. 61, p. 101182, 2021, doi:10.1016/j.ecoinf.2020.101182.

[8] H. Ulutaş and V. Aslantaş, "Design of efficient methods for the detection of tomato leaf disease utilizing proposed ensemble CNN model," *Electronics*, vol. 12, no. 4, pp. 1–21, 2023, doi:10.3390/electronics12040827.

[9] A. A. Gomaa and Y. M. A. El-Latif, "Early prediction of plant diseases using CNN and GANs," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 5, pp. 514–519, 2021, doi: 10.14569/IJACSA.2021.0120563.

[10] H. Ulutaş and M. E. Sahin, "Classification of cucumber leaf diseases on images using innovative ensembles of deep neural networks," *J. Electron. Imaging*, vol. 32, no. 5, p. 053040, 2023.

[11] V. K. Vishnoi, K. Kumar, and B. Kumar, "A comprehensive study of feature extraction techniques for plant leaf disease detection," *Multimed. Tools Appl.*, vol. 81, no. 1, pp. 367–419, 2022, doi: 10.1007/s11042-021-11375-0.

[12] S. M. Kiran and D. N. Chandrappa, "Plant leaf disease detection using efficient image processing and machine learning algorithms," *J. Robot. Control*, vol. 4, no. 6, pp. 840–848, 2023, doi:10.18196/jrc.v4i6.20342.

[13] N. Hasan, S. Ibrahim, and A. Azlan, "Fish diseases detection using convolutional neural network (CNN)," *Int. J. Nonlinear Anal. Appl.*, vol. 13, no. 1, pp. 1977–1984, 2022, doi: 10.22075/ijnaa.2022.5839.

[14] K. Adem, M. M. Ozguven, and Z. Altas, "A sugar beet leaf disease classification method based on image processing and deep learning," *Multimed. Tools Appl.*, vol. 82, no. 8, pp. 12577–12594, 2023, doi: 10.1007/s11042-022-13925-6.

[15] 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, doi: 10.3390/s21237987.

[16] H. Sun et al., "MEAN-SSD: A novel real-time detector for apple leaf diseases using improved light-weight convolutional neural networks," *Comput. Electron. Agric.*, vol. 189, p. 106379, 2021, doi:10.1016/j.compag.2021.106379.

[17] A. Elaraby, W. Hamdy, and M. Alruwaili, "Optimization of deep learning model for plant disease detection using particle swarm optimizer," *Comput. Mater. Contin.*, vol. 71, no. 2, pp. 4019–4031, 2022, doi: 10.32604/cmc.2022.022161.

[18] A. Abbas et al., "Tomato plant disease detection using transfer learning with C-GAN synthetic images," *Comput. Electron. Agric.*, vol. 187, p. 106279, 2021, doi: 10.1016/j.compag.2021.106279.

[19] S. Uğuz and N. Uysal, "Classification of olive leaf diseases using deep convolutional neural networks," *Neural Comput. Appl.*, vol. 33, no. 9, pp. 4133–4149, 2021, doi: 10.1007/s00521-020-05235-5.

[20] C. Xu et al., "Multi-scale convolution-capsule network for crop insect pest recognition," *Electronics*, vol. 11, no. 10, p. 1630, 2022, doi:10.3390/electronics11101630.

[21] G. Sakkarvarthi et al., "Detection and classification of tomato crop disease using convolutional neural network," *Electronics*, vol. 11, no. 21, p. 3618, 2022, doi: 10.3390/electronics11213618.

[22] S. F. Syed-Ab-Rahman, M. H. Hesamian, and M. Prasad, "Citrus disease detection and classification using end-to-end anchor-based deep learning model," *Appl. Intell.*, vol. 52, no. 1, pp. 927–938, 2022, doi: 10.1007/s10489-021-02452-w.

[23] C. Sun et al., "SE-VisionTransformer: Hybrid network for diagnosing sugarcane leaf diseases based on attention mechanism," *Sensors*, vol. 23, no. 20, p. 8529, 2023, doi: 10.3390/s23208529.

[24] A. Fazari et al., "Application of deep convolutional neural networks for the detection of anthracnose in olives using VIS/NIR hyperspectral images," *Comput. Electron. Agric.*, vol. 187, p. 106252, 2021, doi:10.1016/j.compag.2021.106252.

[25] J. Zhang et al., "Identification of cucumber leaf diseases using deep learning and small sample size for agricultural Internet of Things," *Int. J. Distrib. Sens. Netw.*, vol. 17, no. 4, pp. 1–13, 2021, doi:10.1177/15501477211007407.

[26] A. R. Luaibi, T. M. Salman, and A. H. Miry, "Detection of citrus leaf diseases using a deep learning technique," *Int. J. Electr. Comput. Eng.*, vol. 11, no. 2, pp. 1719–1727, 2021, doi:10.11591/ijece.v11i2.pp1719-1727.

[27] P. Deepalakshmi et al., "Plant leaf disease detection using CNN algorithm," *Int. J. Inf. Syst. Model. Des.*, vol. 12, no. 1, pp. 1–21, 2021, doi: 10.4018/IJISMD.2021010101.

[28] S. M. Rallapalli and M. A. Saleem Durai, "A contemporary approach for disease identification in rice leaf," *Int. J. Syst. Assur. Eng. Manag.*, pp. 1–11, 2021, doi: 10.1007/s13198-021-01159-y.

[29] J. A. Pandian et al., "A five convolutional layer deep convolutional neural network for plant leaf disease detection," *Electronics*, vol. 11, no. 8, p. 1266, 2022, doi: 10.3390/electronics11081266.

[30] Y. Wang, Y. Chen, and D. Wang, "Convolution network enlightened transformer for regional crop disease classification," *Electronics*, vol. 11, no. 19, p. 3174, 2022, doi: 10.3390/electronics11193174.

[31] B. Min et al., "Data augmentation method for plant leaf disease recognition," *Appl. Sci.*, vol. 13, no. 3, pp. 1–17, 2023, doi:10.3390/app13031465.

[32] J. Lu, L. Tan, and H. Jiang, "Review on convolutional neural network (CNN) applied to plant leaf disease classification," *Agriculture*, vol. 11, no. 8, pp. 1–18, 2021, doi: 10.3390/agriculture11080707.

[33] J. Fu, Y. Zhao, and G. Wu, "Potato leaf disease segmentation method based on improved UNet," *Appl. Sci.*, vol. 13, no. 20, p. 11179, 2023, doi: 10.3390/app132011179.

[34] V. Tiwari, R. C. Joshi, and M. K. Dutta, "Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images," *Ecol. Inform.*, vol. 63, p. 101289, 2021, doi:10.1016/j.ecoinf.2021.101289.