IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 21 February 2024, accepted 21 March 2024, date of publication 1 April 2024, date of current version 10 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3383154

RESEARCH ARTICLE

Precision Agriculture Through Deep Learning: Tomato Plant Multiple Diseases Recognition With CNN and Improved YOLOv7

MUHAMMAD UMAR[1], SAUD ALTAF[2], SHAFIQ AHMAD[3], HAITHAM MAHMOUD[3], ADAMALI SHAH NOOR MOHAMED[4], AND RASHID AYUB[5]

[1]University Institute of Information Technology, Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi 46300, Pakistan
[2]Department of Information Engineering Technology, National Skills University, Islamabad 44000, Pakistan
[3]Industrial Engineering Department, College of Engineering, King Saud University, Riyadh 11421, Saudi Arabia
[4]Electrical Engineering Department, College of Engineering, King Saud University, Riyadh 11421, Saudi Arabia
[5]Science Technology and Innovation Department, College of Computer Sciences, King Saud University, Riyadh 11451, Saudi Arabia

Corresponding author: Saud Altaf (saud@nsu.edu.pk)

This work was supported by King Saud University through Researchers Supporting Project, King Saud University, Riyadh, Saudi Arabia, under Grant RSP2024R387.

ABSTRACT The ability to accurately identify tomato leaves in a field setting is crucial for achieving early yield estimation, particularly with the growing importance of Precision Agriculture. It may be difficult to determine exactly what diseases are affecting tomato plants due to the overlap in symptoms between different diseases. These are the earliest signs of disease that we found in the leaves of tomato plants. Yellow leaf curl virus, leaf mold, light blight, early blight, Mosaic virus, Septoria leaf spot, and bacterial spot are just some of the seven types of plant leaf diseases that were taken into account in this paper. For the development of a testbed environment for data acquisition, the greenhouse at the university was utilized for data on the leaves of tomato plants. This study proposes a target detection model based on the improved YOLOv7 to accurately detect and categorize tomato leaves in the field. To improve the model's feature extraction capabilities, we first incorporate the detection mechanisms SimAM and DAiAM into the framework of the baseline YOLOv7 network. To reduce the amount of information lost during the down sampling process, the max-pooling convolution (MPConv) structure is then improved. After that, this model arrived at a satisfactory outcome. Then, the image is segmented using the SIFT technique for classification, and the key regions are extracted for use in calculating feature values. After that, these data points are sent to a CNN classifier, which has a 98.8% accuracy rate and a 1.2% error rate. Finally, we compare our study to previous research to show how useful the proposed work is and to provide backing for the concept.

INDEX TERMS Tomato leaf diseases detection, YOLOv7, image classification, convolutional neural network, SIFT, feature extraction.

I. INTRODUCTION

The tomato is cultivated in many different countries and regions. The United Nations Food and Agriculture Organization (FAO) estimates that in 2021, the world produced 370.750 kilotons of tomatoes [1]. In 2021, Turkey produced 32,600 kilotons of tomatoes, ac-cording to the Turkish Statistical Institute. Damage from pests and diseases has an effect on the yields of tomatoes. In order to protect crops from diseases and pests, the agricultural industry uses a wide range of pesticides and expensive methods. Using these chemical methods on a large scale has negative effects on biodiversity, human health, and agricultural productivity. The cost of production increases as a result of these methods as well.

Scientists have devoted a lot of time and energy to studying plant diseases, primarily examining their biological characteristics. Studies conducted with tomato and potato varieties provide an example of how disease-prone plants can be. The

The associate editor coordinating the review of this manuscript and approving it for publication was Siddhartha Bhattacharyya.

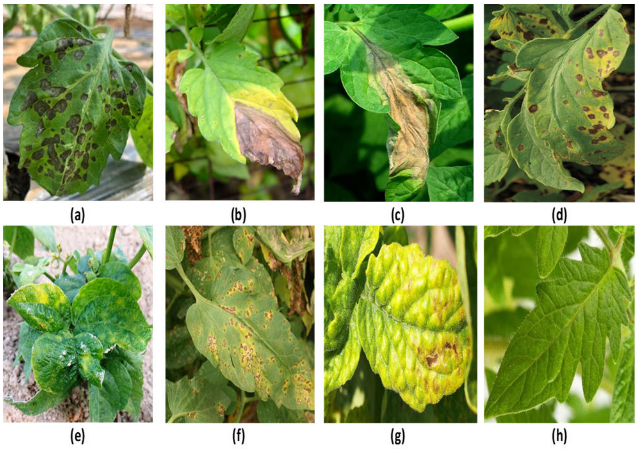

FIGURE 1. **Some sample images from tomato diseases and healthy leaves. (a) Bacterial spot (b) Early blight (c) Late blight (d) Leaf mold (e) Mosaic virus (f) Septoria leaf spot (g) Yellow curl virus (h) Healthy leaf.**

problem of plant dis-eases has global repercussions because of its effect on food security. Plant diseases have a significant negative effect on farmers regardless of location, media, or technology. Early disease detection in the modern era can be challenging and requires careful planning [2]. Image processing is commonly used today. For use in agriculture as evidenced by photo-graphs taken via remote sensing or other field cameras. Image processing is used in a wide variety of plant-related tasks, including species identification, fruit grading, disease diagnosis, severity measurement, and symptom description. Recently, researchers have tried using deep learning for detection. Using deep learning, Mohanty [3] were able to determine which plant diseases were present by analyzing the leaves.

Tomatoes are used in a wide variety of cuisines for their flavor and nutritional value. The thin skins, tender meat, substantial sugar content, and high calories all contribute to their popularity as one of the most commonly produced fruits in the world. Black tomatoes, Momotaro tomatoes, golden tomatoes, and cherry tomatoes are some of the most widely grown types of tomatoes in Taiwan. About fifty different kinds of tomatoes are produced there. Tomatoes are widely grown in Taiwan. The primary growing regions for tomatoes in Taiwan are located in the counties of Chiayi, Kaohsiung, Tainan, Yunlin, and Nantou, covering a total area of more than 5,000 acres of land. The average value of tomatoes produced is close to TWD 30 billion, and it continues to rise [4].

Recognizing plant diseases is crucial in agriculture because it is the fundamental step in preventing the spread of infection and the final step in ensuring the quality of a harvested crop. Tomatoes are grown in many parts of the world because they are both a nutritious food source and a lucrative crop for farmers. Diseases that manifest themselves on tomato plants' leaves reduce both quality and yield. Figure 1 shows that mosaic virus, yellow leaf curl virus, leaf mold, late blight, early blight, bacterial Spot, Septoria, and healthy leaf virus can damage tomato plants and their leaves.

Different diseases require different image-processing techniques and feature sets, and it is up to the researcher to determine which ones will be used in their investigation [5]. Disease in plants occurs when a pathogen (a virus, bacteria, or fungus) infects a plant and renders it unable to grow. There is a risk that the plant's leaves will die or turn color as a result. Viruses, nematodes, fungi, and bacteria are all represented in Figure 1 as potential disease culprits.

- Bacterial Spot: Capsicum leaves are mostly destroyed by bacterial spot. Tomato plants often die from bacterial spot infection. Seeds, agricultural waste, and host plants could spread the bacteria. Bacteria can spread during times of heavy precipitation and wind power, or when water is poured from on high, as in irrigation. In-sects, animals, and machinery that pass through the crop could also spread it.
- Early blight: Pakistan has early blight year-round, one of among the most common tomato diseases. The plant may begin to yellow at the roots, and the brown, spherical spots may be as large as half an inch in diameter. It wreaks havoc on the plant, reducing yields by damaging the leaves, fruit, and stems
- Late blight: Tomato leaves, stems, fruit, and tubers are susceptible to late blight. In damp, cold conditions, fungus blooms spread the disease quickly.
- Leaf mold: Tomato leaves are susceptible to leaf mold, especially in greenhouses. It's easy to confuse the signs of this disease with those of something else, like grey mold or tomato blight, when leaves are affected. High humidity (over 85%) exacerbates disease symptoms.
- Tomato mosaic virus: Weeds, infected seeds, and insects can spread this plant pathogenic virus. Plants, on average, develop a fuller, lighter form. Leaves can curl. Mosaic symptoms can cause fruit deformities [5].
- Septoria leaf Spot: Septoria leaf spot is caused by Septoria lycopersici fungus. Symptoms of this fungus usually appear when tomatoes develop into fruit on maturer, lower stems, and leaves. Petioles stems, and calyx can also show signs, but leaves usually don't.
- Tomato Yellow Leaf Curl Virus: Tomato Yellow Leaf Curl Virus is transmitted by whiteflies in early transplants. Plants with the illness take up to three weeks to show symptoms. When symptoms appear, you'll see changes in leaves, and flower buds, and growth.

It's important to develop a system for quickly and cheaply diagnosing plant diseases. Leaf diseases, detectable with image processing tools, are evident on its leaves. This work developed a MATLAB-based program to automatically, cheaply, and accurately detect and classify leaf diseases. Web images of damaged tomato leaves can be assessed using an ANN-based clustering technique. Because of the advancement of Matlab based computer software, farmers may be able to boost output while saving time and money com-pared to conventional methods of disease diagnosis. This study's practical application can boost tomato production while saving farmers time and money [6].

The techniques described in provide workable and reliable solutions for tomato detection. More effort is needed to improve their performance in tough greenhouse conditions. The current group proposed a CNN-based strawberry disease classification method [7]. The current study builds on by classifying tomatoes on the vine into three categories: ripe, immature, and damaged using the Yolov5 medium and four different CNN classification models (Yolo5m, ResNet50, ResNet-101, and EfficientNet-B0).

There is a lot going on in the background of a picture of a plant leaf, so it's not surprising that a single color component can only tell you so much about the leaf's hues. Be-cause of this, the results of the feature extraction process are less reliable. More is better than less when it comes to the number of color elements used. Using the PlantVilliage dataset's tomato leaf images as inputs, the aforementioned study trained a CNN model on their RGB components [8]. As a classifier, we decided to go with the Learning Vector Quantization (LVQ) method due to the topology of it and the adaptable model it uses. Knowledge of pests and diseases, the need for specific environmental conditions during the growing season, and corrective measures during tomato planting are all largely determined by the closeness of peasant communities and the experience gained from previous tomato plantings. Commercial tomato cultivation suffers from these logistical issues.

Precision agriculture is a farming method that maximizes agricultural yield while minimizing waste through the utilization of technology. It involves collecting and analyzing data on soil conditions, weather patterns, and crop growth using various technologies, including drones, sensors, and machine learning algorithms. Farmers can make informed decisions about planting, irrigation, fertilization, and harvesting by leveraging this data. Precision agriculture increasingly employs deep learning algorithms to detect and classify plant diseases, such as those affecting tomato plants. These algorithms categorize plant leaves based on the presence of diseases by analyzing images using convolutional neural networks (CNNs). This capability allows farmers to detect illnesses early, enabling them to take necessary precautions to prevent disease spread and enhance crop yield [9]. AI technology and deep learning play pivotal roles in advancing precision agriculture, revolutionizing how we manage crops and optimize yields. One significant aspect is predictive analytics, where AI algorithms analyze vast datasets to forecast crop growth, disease outbreaks, and optimal harvest times with remarkable accuracy. By leveraging historical and real-time data, farmers can make informed decisions, reducing resource wastage and increasing productivity.

Previously published investigations have several limitations that hinder their full applicability to the task of diagnosing diseases in tomato leaves. These limitations include the following:

- It may be difficult for small-scale Pakistani tomato producers to identify and track diseases without ready possession of resources like technological advances and specialized knowledge.
- It can be difficult for algorithms using computer vision to tell the difference between healthy and diseased tomato leaves because some leaf diseases cause symptoms that are otherwise indistinguishable.
- One issue is that existing datasets do not contain enough photographs of real-world settings that have been meticulously annotated for machine learning purposes. Therefore, training is performed with images captured in a stable setting.
- Existing proposed algorithms are limited in their ability to recognize multiple dis-eases within a single image or multiple occurrences of the same disease within a single image.

The following is a brief overview of the major findings and contributions from this study:

- A robust framework is proposed for recognizing multiple diseases on tomato plant leaves, which can be used as a preliminary indicator of plant health.
- Leaf samples dataset from tomato plants were collected from university greenhouses.
- Cropping, sorting and labelling the images into categories facilitates analysis and yields more accurate results for training process.
- This study proposed a target detection model based on the improved YOLOv7 to accurately detect and categorize tomato leaves in the field.
- To improve the model's feature extraction capabilities, we first incorporate the detection mechanisms SimAM and DAiAM into the framework of the baseline YOLOv7 network.
- To reduce the amount of information lost during the down-sampling process, the max-pooling convolution (MPConv) structure is then improved.
- Then, the image is segmented using the SIFT technique for classification, and the key regions are extracted for use in calculating feature values.
- Finally, we compare our study to previous research to show how useful the proposed work is and to provide backing for the concept.

This paper's organizational structure sets it apart. Section II's literature review suggests topics for the study of tomato pathogen detection. Section III describes the analysis and proposes an approach for disease identification, including a mathematical model. The experiments and results are discussed in Section IV. The conclusion is presented in Section V, along with some recommendations for future directions.

II. LITERATURE REVIEW

The use and testing of fruit recognition algorithms based on machine learning, especially deep learning, has increased in recent years. When compared to conventional methods, machine learning provides a more dependable and accurate alternative, offering a superior solution to problems such as obstruction and green tomato detection. Since green tomatoes and backgrounds are so visually similar, little research has been done on the is-sue of green tomato recognition. This is shown by the research of Siddiquee et al. [10]. They tried out a system that uses the cascaded object detector, a machine learning technique, in conjunction with more traditional image processing methods like "color transformation," "color segmentation," and "circular Hough transformation" to identify ripe tomatoes. Re-search shows that compared to conventional methods, machine learning techniques im-prove accuracy by 95%.

A ripe tomato identification algorithm was proposed by Malik et al. [11], and it makes use of watershed segmentation and the HSV (Hue, Saturation, Value) color space. Excluding the background and detecting only ripe tomatoes required the use of the HSV color space, and thresholding allowed for the modification of the discovered fruits. The watershed segmentation method "separated" the clumped fruit. When combined, these two methods resulted in a precision of 81.6%.

Researchers Xiang et al. [12] evaluated a cluster tomato ripeness recognition algorithm. There were four main phases to the algorithm: Segmenting a tomato image using a normalized color difference; identifying the clustered region using the length of the greatest edge of the smallest circle enclosing the rectangular shape of the tomato region; processing the clustered region as a binary image using iterative damage obviously to separate each tomato within the clustered region; and restoring each seed region within the grouped region obtained by the iterative erosion using a circulatory dilation operation. They were able to detect at a rate of 87.5% within 500 mm, but this dropped to 58.4% be-tween 300 mm and 700 mm.

In most cases, authors use the plant canopies as their region of interest (RoI) and Yolov5 to detect and segment tomatoes within plants. Due to the presence of competing structures in this RoI, it may be challenging to identify the fruits and pinpoint their precise location [13]. These challenges are exacerbated because of the high degree of color related to leaves and tomato products during the initial phases of ripening. However, most of the relevant research on tomatoes that have been published looks at the time of year when the tomatoes are already red, so color is a feature often utilized in identifying the items that need to be recognized [14]. When analyzing the situation of fruit detection and segmentation, the authors try to distinguish fruit from any external and environmental factors, which at the plant level may be quite complex. Besides using machine learning and statistical methods, mathematical morphological approaches [15] have been used for fruit recognition in obstruction and overlap scenarios.

A faster and more accurate method for locating ripe tomatoes was developed by Xu et al. [16], which builds on the YOLOv3-tiny approach. The accuracy of the model was enhanced by tweaks to the primary network, and detection was bolstered by the addition of pictures in more difficult scenarios. Based on the numbers, the presented model per-formed better than the YOLOv3-small technique by 12% (F1-score = 91.92%).

Green tomatoes can be difficult to locate in greenhouses, but Mu et al. [17] created an algorithm for detection that can do so. The model, which is based on the Common Objects in Context (COCO) dataset, uses a deep convolutional neural network and a pre-trained Faster R-CNN architecture with ResNet-101 and Yolov4 to achieve an accuracy of 87.83% when recognizing tomatoes. To track the maturation of tomato plants and ensure the production of fruit and flowers, Luna et al. [18] created a computer visualization system. Both the R-CNN and the SSD deep learning models were used. When comparing the SSD and R-CNN models, we find that the SSD model is significantly more effective at identifying objects, with a 95.99% identification rate compared to just 19.48% for the R-CNN model.

Using YOLOv3 detection, Liu et al. [19] created the YOLO-Tomato model. In order to accomplish this, we used a dense framework for feature extraction and substituted the proposed C-box for the more common R-box. The model improved its detection accuracy by 4% in moderate occlusions compared to severe occlusions, reaching an overall accuracy of 94.58%.

The AdaBoost classifier was used to retrieve and categorize grey-scale images and characteristics for the framework proposed by Zhao et al. [20] for identifying ripe tomatoes. The resulting false negatives (APV) were eliminated so that the mean-based pixel value color analysis technique could be used. The results showed that a 96% identification rate was achievable when AdaBoost categorization and color assessment were utilized together, despite the presence of 10% false negatives and the absence of detection for 3.5%.

In [21], the authors use conditional generative adversarial networks (C-GAN) to construct synthetic images of tomato plant leaves in order to train a deep learning (DL) model for disease detection in tomato plants. Next, we use TL to teach a DenseNet-121 CNN to divide images of tomato leaves into five, seven, and ten different disease categories. The authors achieved an accuracy of 97.11% when classifying images of tomato leaves into 6 categories, 8 categories, and 10 categories, respectively.

In order to extract the most important features, the authors of [22] devised a novel method based on attention-based dilated CNN and Yolov5. Both Otsu segmentation and bilateral filtering were used in the preliminary processing of the images. After the photos have been preprocessed, the CGAN model is applied to them to generate synthetic images. In order to classify previously examined attributes, a logistic regression (LR) classifier was used, which achieved an accuracy of 96.6%.

To distinguish between a disease-free tomato variety and six others, Rangarajan et al. [23] trained a neural network

TABLE 1. Comparative analysis of related works.

Ref	Targeted Leaf Disease	Method	Dataset	Limitation	Accuracy (%)
[19]	Green, intermediate, and Ripe tomato	YOLOv3	Self dataset	less accuracy achiev	94.58%
[22]	Target Spot, Mosaic virus, Bacterial spot, Late blight, Leaf Mold, Yellow Leaf Curl Virus, Early blight, Septoria leaf spot, Mosaic virus,	attention-based dilated CNN logistic regression (ADCLR)	PlantVillage	This process may take time and space complexity.	96.6%
[27]	Bacterial Spots, Mosaic Virus, Septoria Spots, Yellow Curl	Handcrafted and DT	Self-dataset	Less feature extract and small dataset	94.00
[28]	Bacterial spot, Early blight, Late blight, Leaf mold, mosaic virus, Septoria leaf spot, spider mites, yellow leaf curl	CNN and KNN	Taiwan dataset	Used only six classes for feature extraction	96.50
[29]	Early blight, late blight, leaf mold, Bacterial Spots and Citrinitas leaf curl	YOLOv3 detection model based on ABCK, BWTR, and B-ARNet	Self-dataset	Less accuracy has been achieved	89
[30]	Healthy,Late blight,Leaf mold,Two-spotted Spider mite attack,Target spot,Tomato mosaic virus disease,Tomato yellow leaf curl virus disease	AlexNet VGG 16	PlantVillage	They used only 373 images	97.49%

composed of VGG 16 and AlexNet. Performance was measured by varying training parameters like the number of photos used, the batch size, the bi-as, and the weighted learning rate. AlexNet was found to be superior to VGG 16 in terms of accuracy and performance speed. Given that the goal of this work is to categorize the diseases that affect tomato plants, it is important to note that the construction of the suggested approach is based on the results obtained from this comparison, providing support for the separation of the task and choosing the architectures to deploy. VGG 16's implementation has flaws compared to AlexNet, especially when it comes to computational cost, so it can be ignored.

To classify apple tree damage and nutrient deficiencies, Nachtigall et al. [24] used convolutional neural networks. They compared CNN's AlexNet architecture to that of the MLP and then analyzed the results with the help of seven human experts. A total of 97.3% accuracy was achieved by CNN, 96% by deep learning, and 77.3% by MLPs.

Using an EfficientNetB7 model, Kaur et al. [25] investigated leaf diseases in the PlantVillage dataset for grape plants. The fully linked layer was designed with the intention of extracting the most vital characteristics. The feature extractor vector was then cleaned up using the variance method to get rid of any extraneous elements. Logistic regression was used to reduce the influence of the features with a 98.7% accuracy in classification.

One method proposed by Liu et al. [26] for distinguishing between field-ripened and greenhouse-matured tomatoes is to use the Histogram of Oriented Gradients (HOG) at-tribute to train a support vector machine (SVM) classifier. Scratchy scanning was used to find the fruit, and the Color Removal (FCR) method was proposed to eliminate any false positives. Non-Maximum Suppression (NMS) was ultimately used to combine the previously separate results. The algorithm had a 94.41% success rate in identifying fruits. Several recent studies are summarized in detail in

Table 1 presents a comprehensive summary of recent studies, outlining their contributions, methodologies, results, limitations, and accuracy rates.

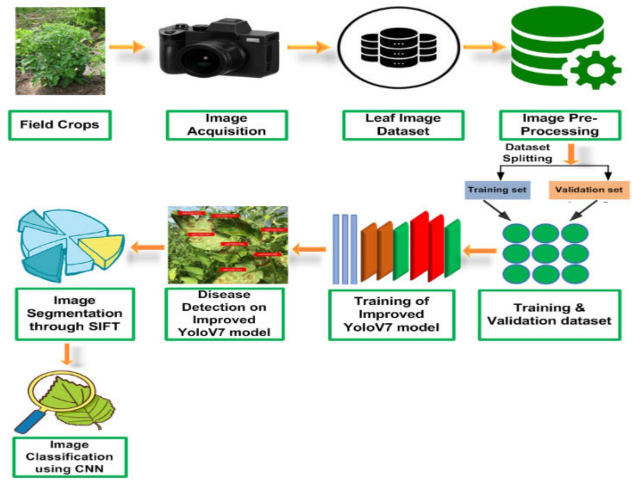

FIGURE 2. Proposed framework to recognition of the disease and health of tomato leaves.

III. MATERIALS AND METHODS

The proposed tomato leaf disease detection system should be explained in this section. Tomato leaf images are used in the proposed framework to produce a set of labels that each represent one of three distinct concepts. A healthy leaf can be identified by first checking the input image for any indications of a known disease. Second, when it comes to categorizing things, segmentation comes first, followed by dollar figures and rough estimates of percentages. Third, in Figure 2, you can see the entire procedure by which we used an efficient algorithm to identify and classify diseases in tomato leaf

A. IMAGE ACQUISITION

A digital camera is used to capture images of the tomato plant's leaves, which are then uploaded to a computer for further study. The image of the leaf is first transformed into a format that can be read by a computer, then its RGB colour structure is transformed into one that is independent of the user's screen resolution

B. IMAGE PRE-PROCESSING

Images can be improved through the use of pre-processing techniques such as noise reduction, rotation, and skewing. Cropping, or clipping, an image involves selecting the unwanted parts of a picture, particularly of leaves. When an image needs to be smoothed out, a filter specifically designed for that purpose is applied. Image enhancement is carried out with the intention of increasing the contrast of the image.

C. DATASET SPLITTING

A text file with the same name as the image can be generated by gathering all the images and using labeling to manually label each one with its category and leaf. Following the establishment of the training and validation directories, 80 percent of the images and their corresponding text files should be transferred to the training directory, while the remaining 20 percent should be transferred to the validation directory. The remaining 20% of the images, along with their associated label files, are then transferred to a validation folder.

D. DISEASE DETECTION

Object detection algorithms typically take large sample sizes from the input image before deciding whether or not those sections contain any relevant features. The system then adjusts the region's border in order to better foresee the actual boundary region box of the diseased portion of the leaf. Direct analysis of complex field scenes is not possible with the generic depth learning algorithm YOLOv7. In order to achieve the desired Tomato dis-ease leaf detection, we optimize and select the model parameters. The loss function curve seen in this research shows a clear downward and then upward trend when applied to the obtained validation set. After tweaking and fine-tuning various parameters, a target initialization rate for learning is established.

E. IMAGE SEGMENTATION

To segment an image means to divide it into subsets sharing common characteristics. Segmentation can be accomplished using a wide variety of techniques, one of which is translating the colors of the RGB spectrum into the HIS model. After the RGB image has been transformed into a HIS representation, the segmentation is carried out using an edge and spot recognition technique. Both boundary detection and spot detection can be used to pinpoint the exact location of damage on a leaf, and we employ these techniques to pin-point the damaged area.

Segmentation, the next step to be discussed, makes use of the SIFT method. Important landmarks can be identified in images annotated with the HIS model with the help of the SIFT method, which extracts relevant features from the photos. Algorithm 1 below demonstrates the SIFT algorithm

This SIFT method utilizes a combination of hue and grain to impart a unique character upon an image. For this purpose, we first create an HSI image from the original RGB image. Hue, saturation, and intensity (I) are the three components of RGB (1)-(4), and their respective variables H, S, and I are used in the following equations.

Algorithm 1 Production of Keypoints Using Scale-Invariant Feature Transform (SIFT)

calculating the Gaussian scale-space
Information of input: *e for* image
Information about Output: *p is use for* scale-space
difference Of gaussians (dOg)
Information of input: *p* scale-space
Information about Output: *o* dOg
Finding a vital intersection (extrema of dOg)
Information of input: *o* dOg
Information about Output: $\{(fo, do, \alpha o)\}$ assembling of various extremes (position and scale)
Keypoints for localization with sub-pixel accuracy
Information of input: *o* dOg and $\{(fo, do, \alpha o)\}$ individual extremes
Information about Output: $\{(r, c, \alpha)\}$ severe instances
Eliminate unstable extremes
Information of input: *o* dOg and $\{(f, d, \alpha)\}$
Information about Output: $\{(f, d, \alpha)\}$ refined keypoints
Filter edges with localised keypoints
Information of input: *o* dOg and $\{(f, d, \alpha)\}$
Information about Output: $\{(f, d, \alpha)\}$ filtered keypoints
Each point should have a reference orientation.
Information of input: $(\partial mv, \partial nv)$ scale-space gradient and $\{(f, d, \alpha)\}$ list of keypoints
Information about Output: $\{(u, j, \alpha, \theta)\}$ list of oriented keypoints
Feature descriptor generator for SIFT
Information of input: $(\partial mv, \partial nv)$ scale-space gradient and $\{(u, j, \alpha, \theta)\}$ list of keypoints
Information about Output: $\{(r, c, 1 : \alpha, \theta, f)\}$ list of the most important points

$$H = \cos^{-1} \times \frac{R_a - 0.5\,(G_b) - 0.5\,(B_c)}{\sqrt{R_a^2 + G_b^2 + B_c^2 - (R_a G_b) - (R_a B_c) - (G_b B_c)}} \quad \text{if } G_b > B_c \text{ OR} \tag{1}$$

$$H = 360 - \cos^{-1} \times \frac{R_a - 0.5\,(G_b) - 0.5\,(B_c)}{\sqrt{R_a^2 + G_b^2 + B_c^2 - (R_a G_b) - (R_a B_c) - (G_b B_c)}} \quad \text{if } G_b < B_c \tag{2}$$

$$S = 1 - \frac{2}{(R_a + G_b + B_c)} * [\min(R_a, G_b, B_c)] \tag{3}$$

$$I = \frac{1}{3}(R_a + G_b + B_c) \tag{4}$$

where T represents the probability that a given c and u value are located in neighbor-ing pixels of the actual image within the given window. where u denotes the row and c the column, where c is the DN value of the pixel of interest and u denotes its nearest neighbors. The GLCM quantization level is denoted by the letter L. Power can also be referred to as the "angular second instant" or as homogeneity. It provides the total square of the GLCM matrix's components. It's common practice to use homogeneous regions as a gate-way to less uniform ones

$$Energy = \sum_{c,u=0}^{L=-1} (T_{c,u})^2 \tag{5}$$

Contrast is the degree to which two neighboring pixels are related to one another while examining a picture. To aid in the process of determining contrast, the following equation is provided.

$$\text{Contrast} = \sum_{\text{c,u}=0}^{L=-1} (\text{C} - \text{U})^2 \tag{6}$$

An image's degree of randomness is quantified by its entropy. Therefore, the entropy of a uniform image will be smaller. The following equation can be used to determine a system's entropy.

$$Entropy = \sum_{c,u=0}^{L=-1} \ln (T_{cu}) T_{cu} \tag{7}$$

The method of assessing the linear connections between the various grey tones in a picture is referred to as "correlation." It shows how the individual pixels are connected. There is a link that has been shown. The mean, represented by, is used as an input in the GLCM calculation.

$$Correlation = \sum_{c,u=0}^{L=-1} T_{cu} \frac{(c-\mu)(u-\mu)}{\sigma^2} \tag{8}$$

The degree of uniformity in the appearance of a picture's pixels is referred to as homogeneity. When the GLCM matrix value is 1, we know the image is perfectly smooth. If just slight changes to the texture are needed, the cost is rather minimal. Here, the homogeneity of the data is assessed using the formula below.

$$Homogeneity = \sum_{c,u=0}^{L=-1} T_{cu} \frac{T_{cu}}{1+(c-u)^2} \tag{9}$$

The statistical technique known as mean in GLCM may be used to determine how frequently two pixels in a picture have the same value and orientation. Often quantized grayscale is represented as a matrix with an equal number of columns and rows.

$$\mu_c = \sum_{c,u=0}^{L=-1} C(T_{cu}) \tag{10}$$

$$\mu_u = \sum_{c,u=0}^{L=-1} U(T_{cu}) \tag{11}$$

$$\mu = \frac{(\mu_c + \mu_u)}{2} \tag{12}$$

Variance measures the range of the GLCM frequency values by calculating the statistical variance of the matrix in respect to the GLCM mean. The GLCM Mean and GLCM Var formulas are used to compute the mean and standard deviation, respectively, in the GLCM equation.

$$\sigma_c^2 = \sum_{c,u=0}^{L=-1} T_{cu}(c-\mu_c)^2 \tag{13}$$

FIGURE 3. Tomato leaf images acquisition from plant nursery (a) Image acquisition, (b) Sample of tomato leaf.

$$\sigma_u^2 = \sum_{c,u=0}^{L=-1} T_{cu}(U-\mu_u)^2 \sigma_c = \sqrt{\sigma_c^2} \sigma_u = \sqrt{\sigma_u^2} \tag{14}$$

It assesses the distribution's stability in relation to the normal distribution.

$$\text{Kurtosis} = \sum_{\text{c,u}=0}^{\text{L}=-1} \frac{((\text{c, u}) - \text{L})^2}{(\text{L})\sigma^2} \tag{15}$$

A distribution's skewness can be measured to see how asymmetrical it is. When the left and right sides of a distribution do not mirror images one another, such distribution is asymmetrical.

$$\text{skewness} = \frac{\sum_{\text{c,u}=0}^{\text{L}=-11} (\mu_{\text{cu}} - \mu)^3}{(\text{L}-1)\sigma^3} \tag{16}$$

RMS(Root mean square error) RMS values gradually raise the value as the mistake progresses Yet, the inability to offer information on the early stages of a defect while The value steadily rises as the mistake manifests, as defined in Equation 17.N is non missing data points, $\boldsymbol{x_i}$ actual observations time series and $\hat{\boldsymbol{x}}_i$ estimated time series

$$\text{RMS} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}} \tag{17}$$

F. CLASSIFICATION

A CNN consists of at least one convolutional layer and at most one maximum pool-ing layer. To process the input, a convolutional layer uses a set of filters that are repeated across the entire input space. A max-pooling layer is produced by using the highest possible filter activation from different points within a defined window to generate a lower-resolution variation on the layer of convolution activation. This provides additional translation in-variance and allows for more lenient placement tolerances of object components. In order to process the increasingly complex elements of the input, higher layers' employ filters with a lower resolution and a wider range of inputs. The highest fully connected layers combine data from everywhere into a single dataset before classifying it. The results are effective because of the hierarchical structure.

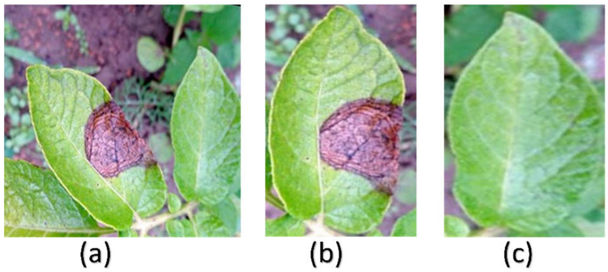

FIGURE 4. Cropped image (a) Original Image (b) Early blight (c) Healthy Leaf.

TABLE 2. Transformations applied to the dataset with these values.

Transformation	Value
Rotation	$-60° \, to \, 60°$
Scaling	$50\,\% - 150\,\%$
Translation	$0\,\% \, to \, 30\,\% \, left \, or \, right$
Flip	$Image \, mirroring$
Blur (Gaussian Filter)	$N\,(0, 1 \, to \, 3)$

IV. EXPERIMENTAL SETUP AND RESULTS

In Figure 3, we observe how a digital camera with sufficient resolution can be utilized to capture sharp images of the tomato leaves available at the University Plant Nursery. The photos were saved in JPEG format, ensuring that their quality would remain high even after being archived. The changing of seasons and the general upheaval of the environment have reduced the prevalence of diseases that are genetically identical to one another. Collection of the afflicted leaves has been accomplished in various ways.

A. IMAGE ACQUISITION

In order to obtain a clearer depiction of the tomato leaves, we applied filters to the photos we took later. The steps involved in this process are illustrated graphically in Figure 4. The approach for merging an image with the dataset is contingent upon its intended purpose. The proposed method and classifier heavily depend on the optimal relationship between image quality and the dataset, as well as the image acquisition process.

The dataset includes images of healthy leaves as well as leaves affected by a variety of diseases. Bacterial sport disease, for instance, is depicted with the help of 1060 photographs of bacterial leaf spots and 1093 photographs of Septoria leaf spots. The Mosaic Virus is represented on the leaf by 950 photographs, the Yellow Leaf Curl Virus by 1226, the leaf mold disease by 1009 photographs, the early blight disease by 2000, and the late blight disease by 2000, with 999 photographs depicting healthy leaves.

B. IMAGE PRE-PROCESSING

The images of the diseased and healthy leaves of the tomato were obtained. Figure 5 depicts the effects of applying augmentation techniques to the original photographs, which

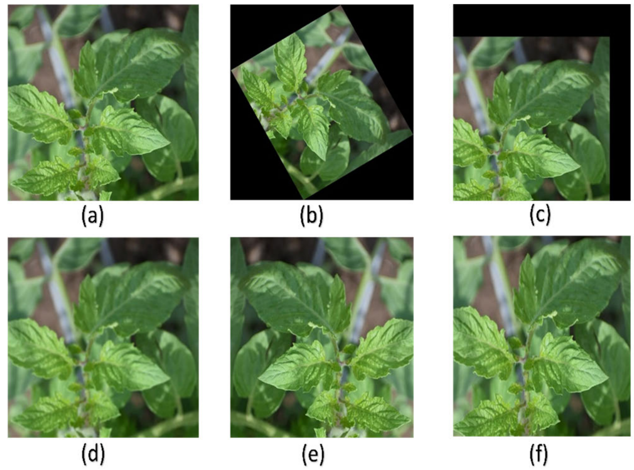

FIGURE 5. Pre-processing (a) Original image (b) Rotation, (c) Translation (d) Blur,(e) Flip Horizontal (f) Scaling.

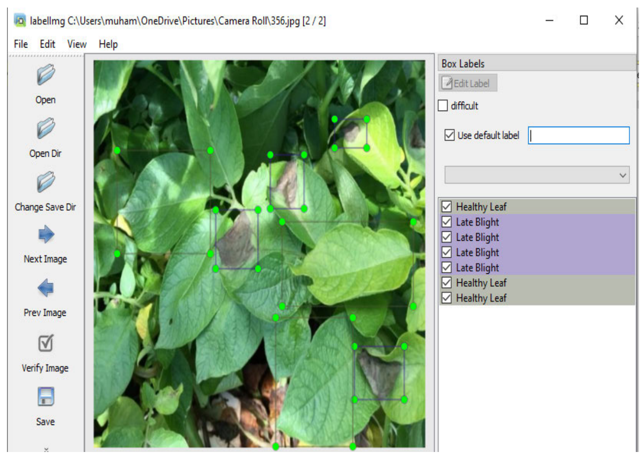

FIGURE 6. Leaf category labeling.

allowed for an increase in variability and the addition of new data before the photographs were subjected to transformations such as rotation, translation, scaling, horizontal flipping, and blurring. The diagram outlining the entire process, from determining which category each leaf belongs to finally labeling it, is shown below. By following the steps in Figure 6 to acquire the entire image, you can classify each leaf into the appropriate category. Their new values are shown in Table 2.

C. DISEASE DETECTION

The YOLOv7 model stands out from other recent object detectors due to its faster speed and better precision, and as a result, it has attracted a lot of attention. The system was made available for testing on user-supplied data in the hopes of improving its performance. The YOLOv7 consists of a backbone, neck, and head. The backbone layer acts as the central node and also as part of the other layers that make up the whole network architecture. convolution, batch normalization, and SiLU activation (CBS), Max-Poling (MP), Extended efficient layer aggregation networks (ELAN), and

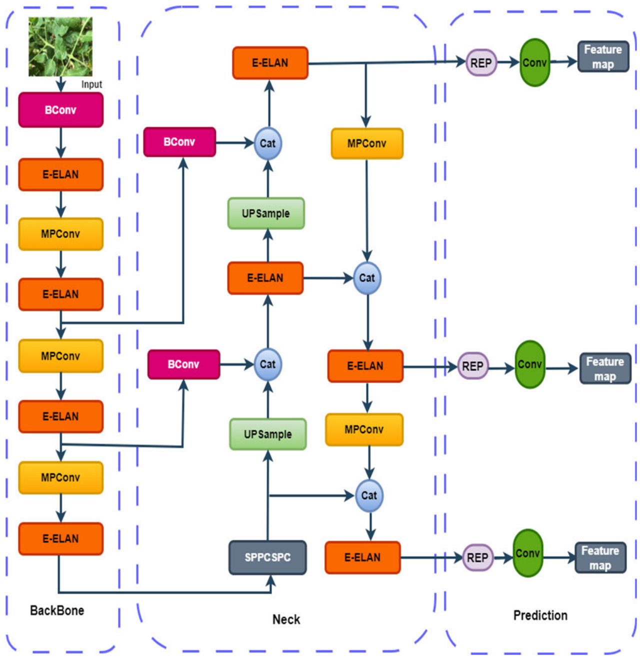

FIGURE 7. Yolov7 network architecture.

Spatial Pyramid Pooling Cross-Stage Partial Connections SPP-CSPC are just a few of its many modules. Fig. 7 shows the hierarchy of the network model. It improves performance while reducing parameters and is faster and more accurate than other real-time object detectors. The detection speed of our proposed yolov7 model was within an acceptable range, and it outperformed competing models in terms of accuracy. Therefore, it is more effective than the competing models to recognize tomato leaf disease when applied in a complex field environment. Figure 8 depicts the identification of tomato leaves in accordance their category.

D. IMPROVEMENT ON YOLOv7

To recognize tomato leaves in a complicated field setting, several elements must be taken into consideration. For instance, many diseases are comparable modest variations in it due to the varying sunlight and rain circumstances. The model has to be able to recognize tomato leaves for this investigation [30]. According to the illness present on a tomato leaf, there are eight distinct categories that may be used to detect the disease. Consequently, it is to get better detection results, it is not acceptable to employ YOLOv7 as the detection model directly. Instead, enhancement strategies are required. We enhanced the YOLOv7 model to make it more suited for field tomato leaf recognition

E. IMPROVEMENT VERSION OF YOLOv7 NETWORK STRUCTURE

The network architecture of YOLOv7 incorporates the Dual Attention in Attention Model (DAiAM) as well as a large number of attention mechanism modules from SimAM [30]. The model's ability to extract features from

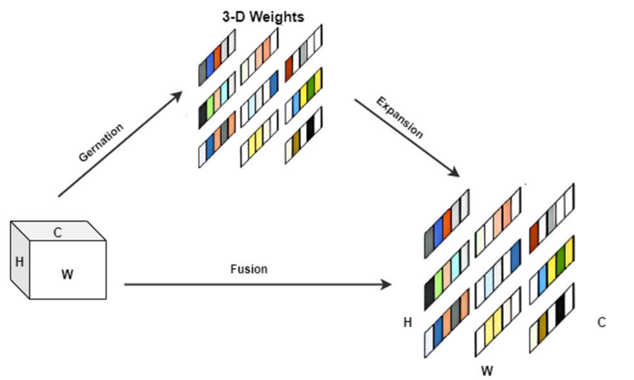

FIGURE 8. The basic idea behind a parameter-free attention module.

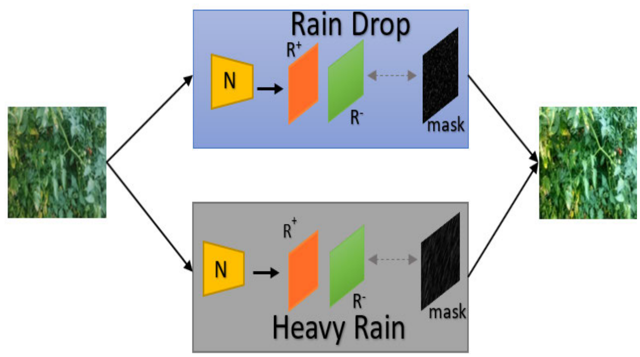

FIGURE 9. DAiAM's architecture for removing raindrops and rain streaks together.

complex backgrounds is significantly improved by adjusting the weights assigned to the network input portion. The attention mechanism's SimAM module can only support a small number of configuration settings for the underlying network. It is capable of easy connect functionality and can be installed in any location throughout the model. The basic concept is depicted in Fig. 8. The attention weights that make up the system are computed using the SimAM energy function. Tomato leaf detection is hindered by a busy background, but SimAM helps by highlighting the most important features of the detected leaf against a simplified back-ground. The method of calculation is detailed below

$$\hat{C} = \mathrm{sigmoid}\left(\frac{1}{R}\right) \otimes C \tag{18}$$

$$U = \frac{4\left(\sigma^2 + \lambda\right)}{(u-\mu)^2 + 2\sigma^2 + 2\lambda} \tag{19}$$

$$\mu = \frac{1}{W}\sum_{p=1}^{w} c_p \tag{20}$$

$$\sigma^2 = \frac{1}{W}\sum_{p=1}^{w} \left(c_p - \mu\right)^2 \tag{21}$$

where $\hat{C}$ is the tomato leaf's improved feature map. U is every channel's energy function. The divergence between the tomato disease leaf is larger the lower the energy. The value of U was constrained using the sigmoid function to avoid having

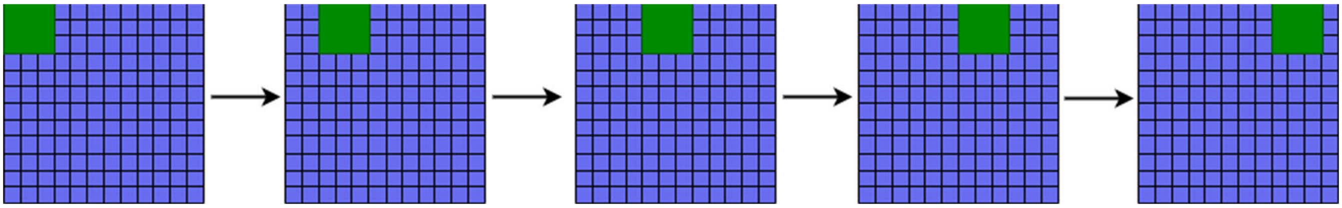

FIGURE 10. Using a two-step convolution method to update the 3 × 3 convolution kernel.

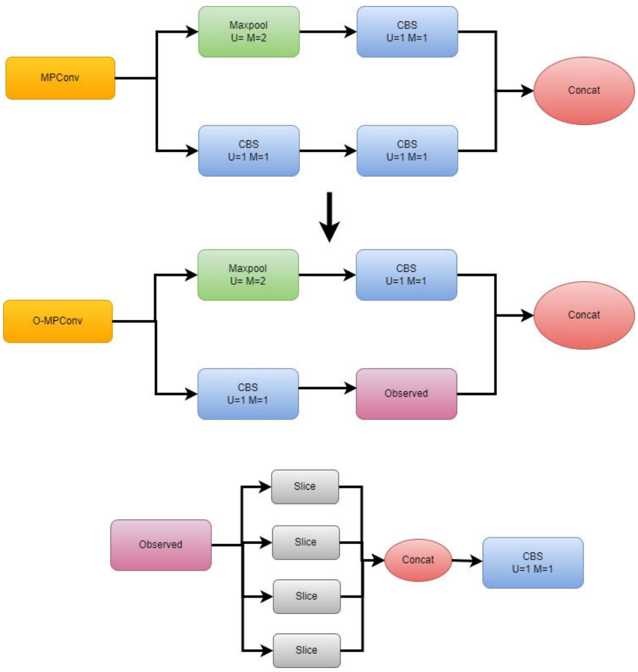

FIGURE 11. A graphical representation of improved mpconv method.

an excessively high value. ⊗ is the dot product operation. C is the input tomato feature map's leaf, and m is the mean value of each channel's input tomato leaf characteristic map's channel. $\boldsymbol{\sigma^2}$ is each channel's variation in the tomato leaf feature map's input. λ is a super-parameter and u is the target disease leaf.

It becomes increasingly challenging to eliminate rain drops from leaf images captured in the field. DAiAM is used to remove both heavy raindrops and rain streaks at the same time. Both the first and second attention-in-attention models contribute to the occurrence of raindrops and rain streaks, but the former is responsible for the heavier variety. The first attention model causes torrential downpours, while the second model is responsible for more moderate precipitation such as light rain or rain streaks. Figure 9 depicts the central concept of DAiAM. the optimized DAM uses rainy photos as its input to extract features J from the first-step encoder N. Following that, two attention sub-networks are supplied with the feature maps to produce heavy-rain-aware and light-rain-aware maps, respectively. The definitions of the light-rain-aware attention map R^{-} and the heavy-rain-aware attention map R^{+} are

$$R^{+} = h(Q * J + v) \tag{22}$$

where $*$, Q and v denote respectively convolution, convolution filters and biases h is the sigmoid function

The image of the raindrops and the rain streaks is supplied into our suggested DAiAM, which contains two branches to focus on the removal of the relevant elements [32]. The primary distinction is that the attention loss function R_attis computed using the mask of raindrops rather than rain streaks. So, the DAiAM first concentrates on two types of rain variations before concentrating on two types of rain intensity in various branches. This is a description of the DAiAM's ultimate loss function

$$R_{DAIAM} = R_{streak} + R_{drop} \tag{23}$$

where R_{drop} and R_{streak} are two loss functions that may be used to eliminate raindrops and streaks, respectively. They're loss functions are

$$R_{streak} = \alpha.R_{att}^{streak}(\beta_1.R_{heavy}^{streak} + \beta_2.R_{light}^{streak}) \tag{24}$$

$$R_{drop} = \alpha.R_{att}^{drop}(\beta_1.R_{heavy}^{drop} + \beta_2.R_{light}^{drop}) \tag{25}$$

where the α, β_1 *and* β_2 parameters are used to balance various loss terms. Based on the masks of raindrops and rain streaks, the attention loss R_{heavy}^{drop} *and* R_{light}^{drop} function is derived, respectively

The MPConv is primarily used to downscale data, which could lead to some loss of features while simultaneously decreasing feature size. It's important to note that the 3 × 3 convolution kernel matrix is used for convolution operation in the YOLOv7 bottom branch of the MPConv module. Figure 10 shows that when the step size is set to 2, the network may learn features inefficiently due to the loss of some feature information. In order to up-date the 3 × 3 convolution kernel, which was itself inspired by the focus module in YOLOv7, we introduced the focus module in the branch below the MPConv. Figure 7 shows that by cutting the feature map in half, we were able to reduce feature loss, boost the learning efficiency of the features, and improve the effectiveness of tomato leaf recognition against a complex background.

The validation graph shown in Figure 14 after training a YOLOv7 model on a custom dataset typically shows the model's performance on a separate validation set. These graph can provide insights into the model's accuracy and loss

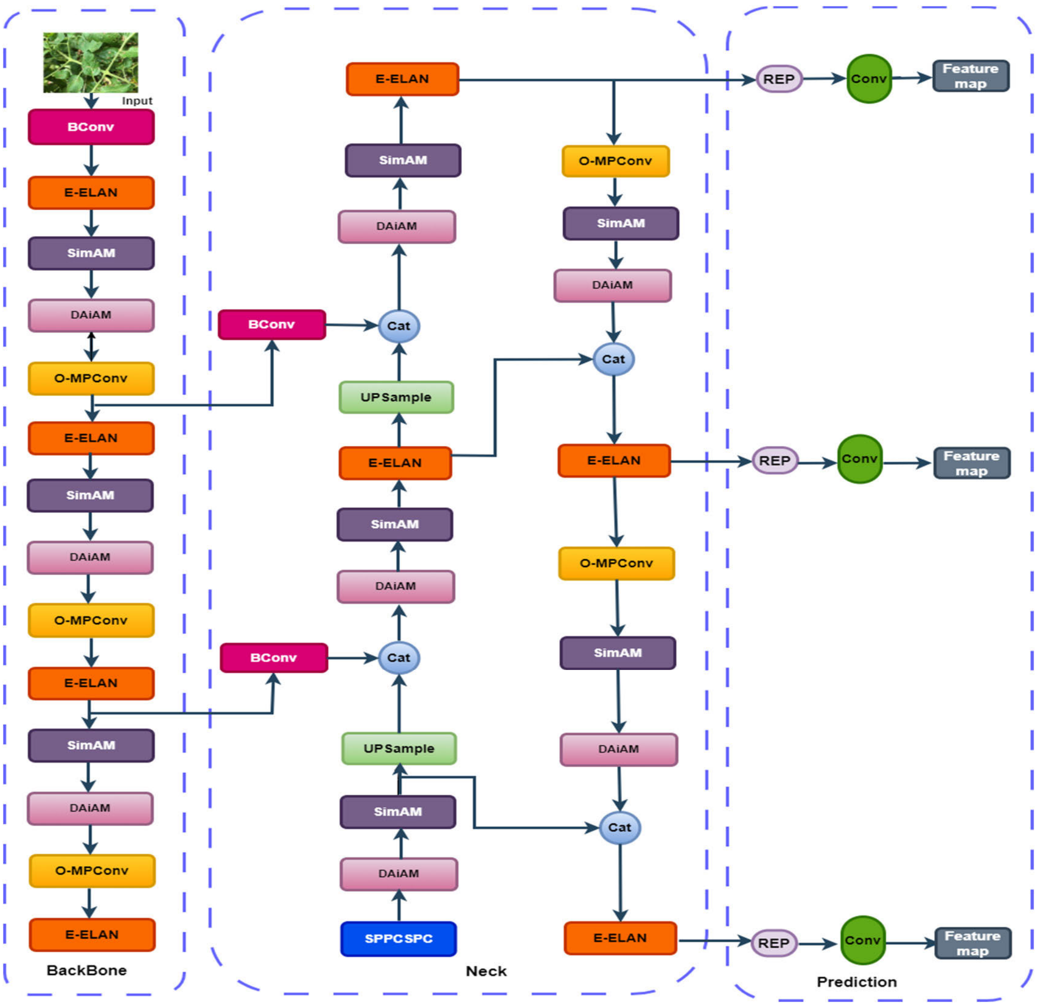

FIGURE 12. Improved YOLOv7 network structure.

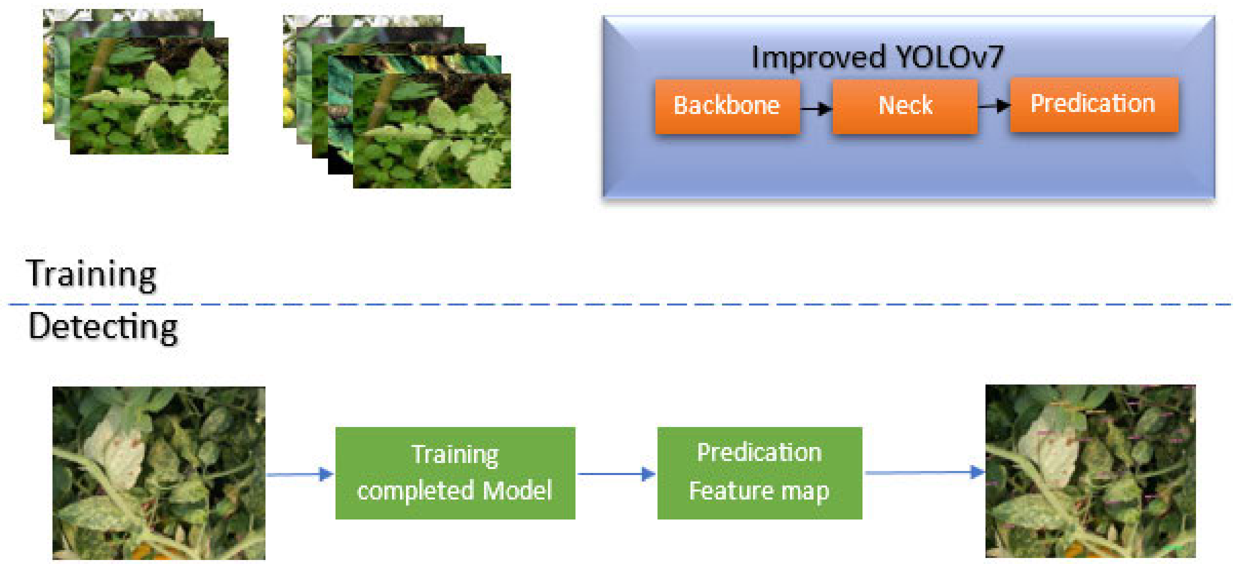

FIGURE 13. Flow diagram of tomato leaf disease detection in field.

during training. Unfortunately, the provided search results do not contain specific information or examples of the validation graph after training a YOLOv7 model. However, based on general knowledge, the validation graph usually displays

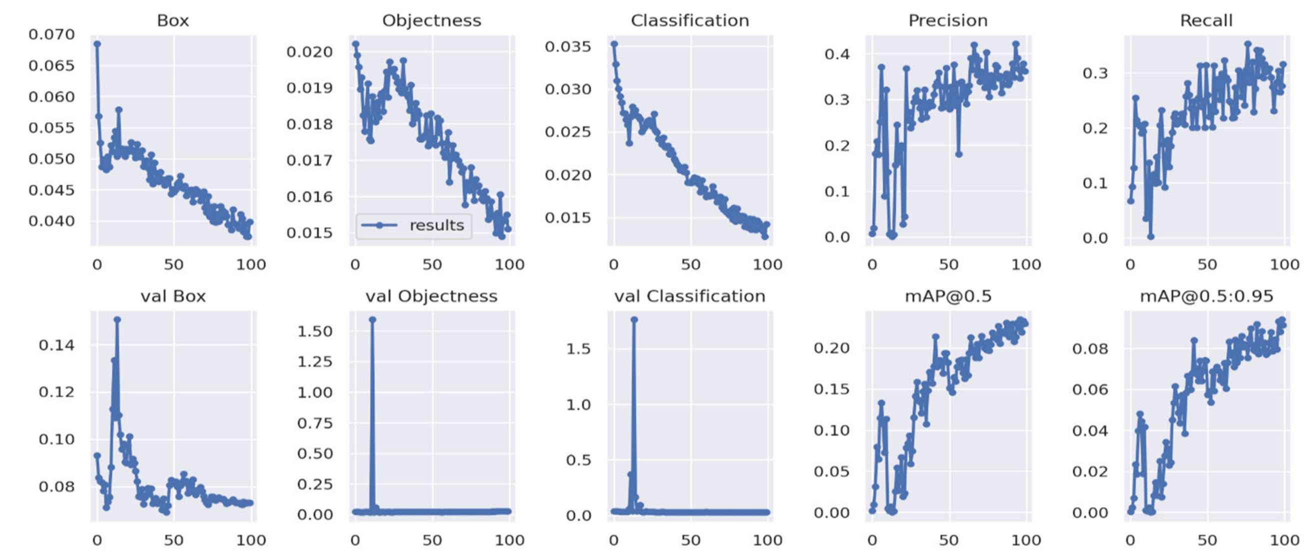

FIGURE 14. Valdition graph from improved yolov7 model.

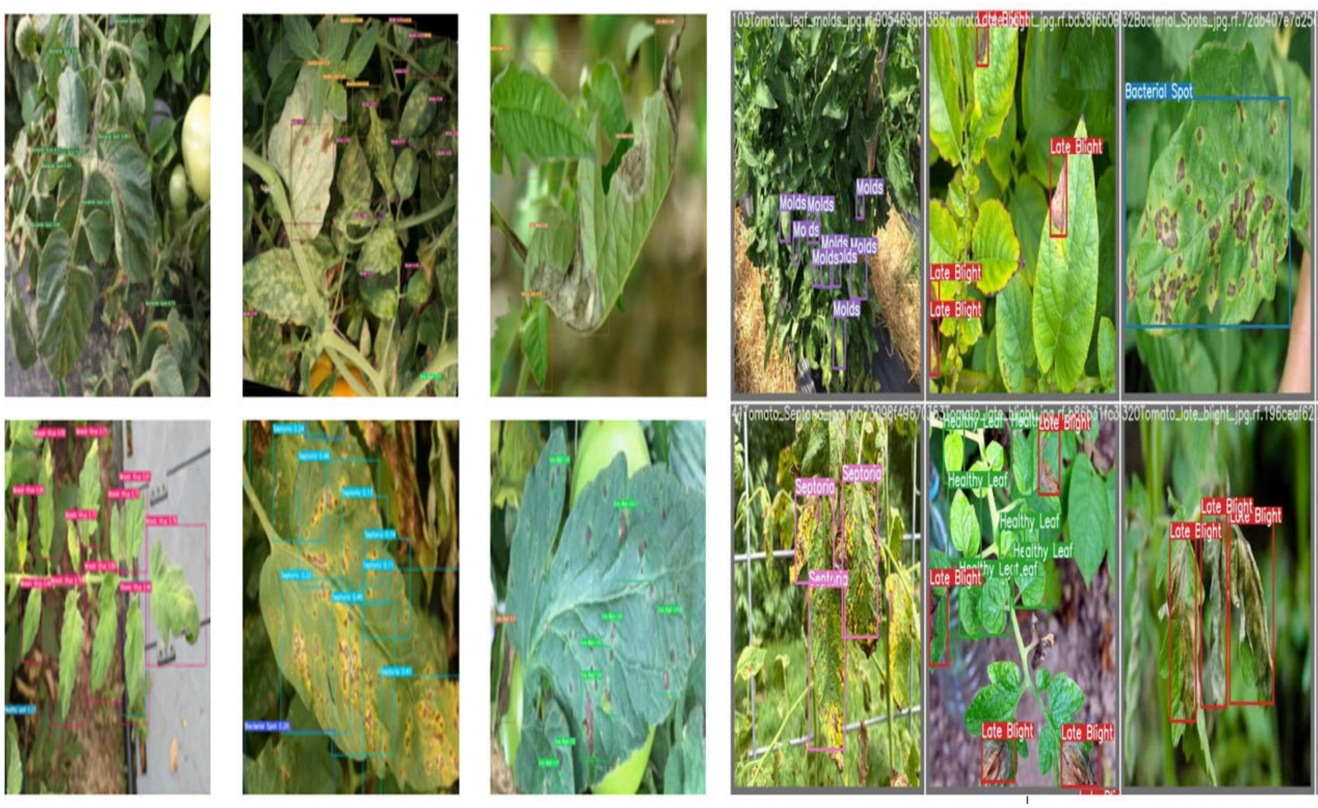

FIGURE 15. Detecting tomato leaf with their category utilizing Improved yolov7 model.

metrics such as mean average precision (mAP) and loss over the training epochs, allowing users to assess the model's performance and potential overfitting.

F. IMAGE SEGMENTATION

The segmentation results are shown in Figure 16 below, and they were generated us-ing the SIFT Image Algorithm to locate the diseased area of the leaf. This method employs a combination of multiple feature extracts, as mentioned above, to locate the diseased area of the leaf and then calculate its area: Plant disease detection using image processing involves the extraction of features from plant images to identify the presence of disease. The features used for plant disease detection include Kurtosis, Mean, Entropy, Variance, Contrast,

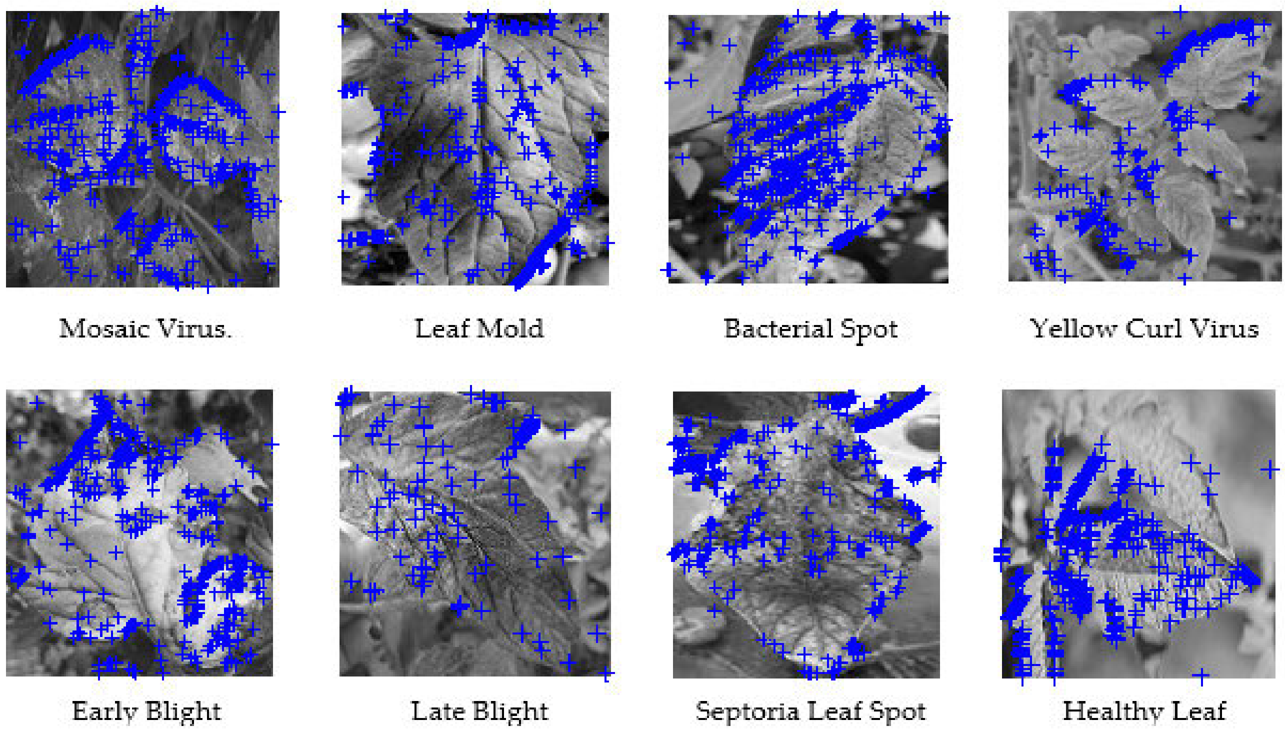

FIGURE 16. Significant points on leaf to extract feature using SIFT.

TABLE 3. Feature extraction from segmented leaf images significant points.

Sr#	Kurtosis	Mean	Entropy	Variance	Contrast	Energy	RMS	Correlation	Homogeneity	Skewness
D1	1.118	114.78	2.1326	1038.57	0.2414	0.7413	9.957	0.9271	0.9875	0.3778
D2	0.987	91.227	2.3865	2078.11	0.1934	0.4662	5.361	0.4359	0.9685	0.1231
D3	2.304	20.645	1.9876	1908.23	0.2601	0.8930	7.361	0.8631	0.7645	0.4234
D4	1.781	183.03	2.2317	5818.35	0.1415	0.6519	9.453	0.9103	0.6724	0.5341
D5	2.001	60.132	2.1031	4218.37	0.2413	0.5856	6.924	0.9012	0.9641	0.8031
D6	1.976	178.13	2.7581	9741.49	0.3503	0.4514	8.763	0.9789	0.9517	0.2369
D7	0.782	21.977	2.1473	2590.14	0.5841	0.413	9.234	0.9.781	0.9188	0.6270
D8	1.089	145.012	4.2717	131740	0.3989	0.3103	7.759	0.9495	0.9783	0.3981

Energy, RMS, Correlation, Homogeneity, and Skewness. These features are used because they provide information about the texture, shape, and color of the plant images, which can be used to differentiate between healthy and diseased plants. Feature selection is an important step in plant disease detection, and various feature selection strategies have been proposed to identify the most relevant features for accurate disease detection.

The use of these features in combination with machine learning algorithms has been shown to produce high classification and detection accuracy, precision, recall, and F-measure performance, with a low false rate [33].

G. CLASSIFICATION PROCESS

In order to classify data, we've implemented a Convolutional Neural Network (CNN) architecture, and we've used it to predict the accuracy of our classifications. Features with a high mean entropy, variance, correlation, homogeneity, RMS, kurtosis, skewness, and contrast are used in the computation of feature values. The main reason put forward in support

TABLE 4. Performance comparison with other plant disease recognition research.

Ref	Dataset	Number of images	Number of Images After Preprocessing	Method	Accuracy	Error rate
[34]	Self-dataset	3100	3800	YOLOv3	94.58%	5.42%
[35]	Collected dataset	15,000	18000	Improved Yolo V3 algorithm	92.39%	7.61%
[36]	PlantVillage	1,500	3800	DCGAN and CNN	94.3%	5.7%
[37]	PlantVillage	18,345	18,345	CNN and SVM	96.1%	3.9%
[38]	PlantVillage	12,742	12,742	Neuro-fuzzy neural network	94.19%	5.81%
[39]	Self-dataset	1600	2000	CNN	97.85%	2.15%
Our work	Self-dataset	8,337	37,685	Improved Yolo V7 and CNN	98.8%	1.2%

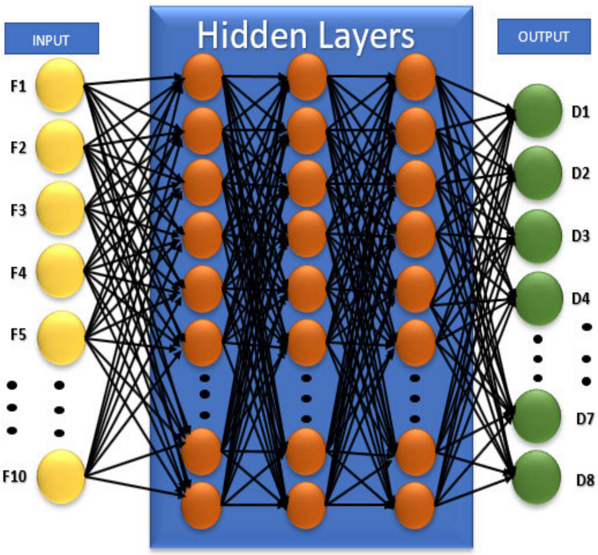

FIGURE 17. Proposed CNN architecture between features and leaf categories.

of the selection of these characteristics is that they have some connection to the version of Plant leaf that is currently in use. Diseased leaves, healthy leaves, and the emergence of uncertainty in the recognition of phytopathogens are all excellent indicators of the efficacy of the entire process and reaction time. The transform signals' peculiar sights are now easily identifiable by the CNN, thanks to its inherent capacity for classification and generalization [34]. Figure 17 shows the proposed CNN architecture for disease detection in plant leaves

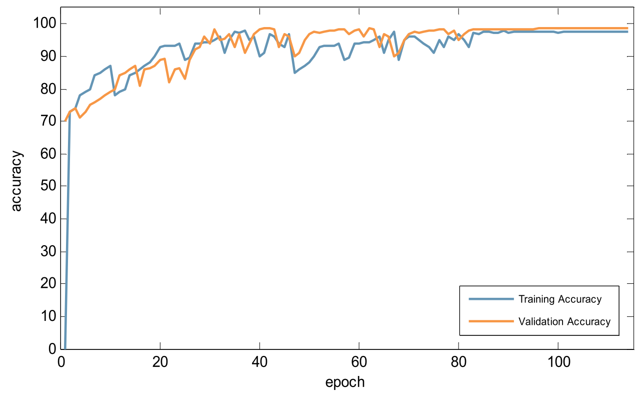

FIGURE 18. Performance graphs samples using Convolutional neural network architecture.

The next step in validating the data is to determine whether or not the retrieved characteristics are accurate. In Figure 13, we can see the results of the testing conducted on the neural network thanks to the training performance graph for the CNN design. Figure 13 below displays the training and validation results for the proposed CNN network model. There are a total of seven diseases that need to be taken meticulously: Diseases that can strike plants include bacterial spot, early blight, late blight, leaf mold, mosaic virus, Septoria leaf spot, yellow curl virus, and healthy leaf that were under consideration in this re-search. By multiplying the confusion matrices together, we can estimate the test-target training error. Confusion matrix networks are constructed utilizing the system depicted in Figure 15 and a database of test highlight data. Training data for comparing predicted and actual classes can be found in a graph's confusion grid. Eight distinct types

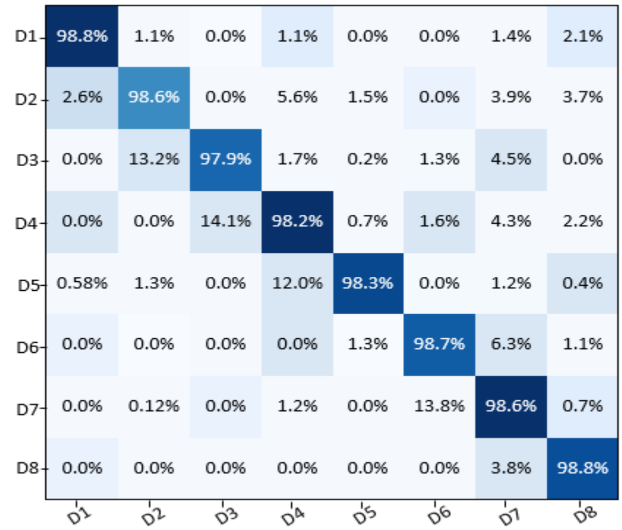

FIGURE 19. **Confusion matrices of disease & healthy samples using targeted and output classes (D1) Bacterial Spot, (D2)Early Blight, (D3)Late Blight, (D4)Leaf Mold, (D5)Mosaic Virus,(D6)Septoria leaf spot,(D7) Yellow Curl Virus,(D8)Healthy Leaf.**

of tomato leaf are represented in the con-fusion matrices shown in Figure 18. Confusion matrices are two-dimensional arrays in which each row represents a class instance and each column represents a prediction. Prediction accuracy is represented by values that fall on the diagonal of the matrix, while off-diagonal ones indicate an error. A 98.8 percent accuracy was found in these tests

V. CONCLUSION AND FUTURE DIRECTIONS

Identification of plant diseases is a significant and practical agricultural issue because it is the initial step in disease prevention and the final step in product preservation. Tomatoes are cultivated globally due to their status as both a healthy food source and a financially rewarding crop for farmers. Diseases that develop on tomato plants' leaves re-duce both quality and yield. Several common diseases can severely impact tomato plants and their leaves. These include the mosaic virus, the yellow leaf curl virus, leaf spot, leaf mold, late blight, early blight, and bacterial spot. This research established a re-liable framework for recognizing leaf symptoms of disease in tomato plants. To back up the concept presented in this paper, the authors developed a target detection algorithm based on an improved version of YOLOv7 and described how it performed admirably under harsh field conditions when identifying tomato leaves. Tomato leaf samples were collected in a wide range of conditions, and pathogens such as mosaic virus, yellow leaf curl virus, leaf spot, leaf mold, late blight, early blight, Mosaic Virus, Septoria leaf spot, and bacterial spot were taken into account in this study. By incorporating a mechanism for focus, improving the original network module, and altering the post-processing mode, we were able to improve the model's detection speed and accuracy. The university green-house served as the source for a data sample gathered from the leaves of tomato plants. The cropped images can then be pre-processed using a variety of techniques, such as rotation, translation, blur-ring, flipping horizontally, and scaling, to achieve the best possible results. After that, these pictures spread throughout the training and the validation process. The YOLOv7 model has been greatly enhanced and can now detect disease. The SIFT method of image segmentation is used to extract and select crucial features for determining the health of the leaves on a tomato plant. There are seven diseases that require special care: In this study, we looked at a number of plant diseases, including bacterial spot, early blight, late blight, leaf mold, mosaic virus, Septoria leaf spot, yellow curl virus, and healthy leaf. As an approximation of the test-target training error, we can multiply the confusion matrices together. The system depicted along with a collection of test-highlight data is used to build confusion matrix networks. The confusion matrix of a graph can be used to train models through comparisons between predicted and actual classes. The conflation matrices include eight distinct tomato leaf types. CNN architectures are then fed these feature points to verify the data even further. The experimental results show that the proposed model can accurately identify the state of a plant's health at an early stage 98.8 percent of the time. Finally, a comparison is drawn between the proposed research and existing studies. We looked at the various disease classifications, feature selection classifiers, extracted features, and accuracy rates.

Tomato plant multi-disease recognition using CNN and YOLOv7 has great potential to advance agricultural productivity in the future. Here are some suggestions for the future to consider.

- Pre-training the CNN with massive datasets of plant diseases across related plant species is a great way to explore the possible benefits of transfer learning. In order to improve generalization and convergence speed, fi-ne-tuning the machine-learning model on tomato-related data sets may help.
- Advanced data augmentation techniques like rotation, flipping, and color jittering can be used to add to the training dataset. This can improve the model's disease detection accuracy in a wide range of settings and lighting conditions.
- Explore the benefits of ensemble learning, where different CNN and YOLOv7 frame-works with different architectures are used to make predictions. The reliability and precision of predictions may be improved as a result.
- Research unsupervised anomaly detection methods to spot diseases that haven't been seen before in tomato plants. Additionally, look into unlabeled data's potential for boosting the model's disease detection accuracy.
- Create online methods of learning to consistently improve the model with new in-formation as more samples of the disease are gathered. Because of this,

the model can easily accommodate shifting disease trends.

- Investigate techniques for cross-domain adaptation, in which the model is trained using information gathered from a variety of environments (such as farms in different regions) to better handle variations in environmental conditions.
- To facilitate instantaneous disease detection in off-the-grid agricultural areas, the model's framework and computational needs must be optimized for placement in environments with limited resources, such as those con-strained by resource-edge mobile devices.

REFERENCES

[1] H. Durmus, E. O. Günes, and M. Kirci, "Disease detection on the leaves of the tomato plants by using deep learning," in *Proc. 6th Int. Conf. Agro-Geoinformatics*, Aug. 2017, pp. 1–5.

[2] A. Fuentes, S. Yoon, H. Youngki, Y. Lee, and D. S. Park, "Characteristics of tomato plant diseases—A study for tomato plant disease identification," in *Proc. Int. Symp. Inf. Technol. Converg*, vol. 1, 2016, pp. 226–231.

[3] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers Plant Sci.*, vol. 7, Sep. 2016, Art. no. 215232.

[4] H. T. Lin, *Cherry Tomato 'TSS ASVEG No. 22'. Taiwan Seed Improvement and Propagation Station*. Taichung, Taiwan: COA, 2017.

[5] E. Özbilge, M. K. Ulukök, Ö. Toygar, and E. Ozbilge, "Tomato disease recognition using a compact convolutional neural network," *IEEE Access*, vol. 10, pp. 77213–77224, 2022.

[6] A. H. T. Rusli, B. C. C. Meng, N. S. Damanhuri, N. A. Othman, M. H. Othman, and W. F. A. W. Zaidi, "Potato leaf disease classification using image processing and artificial neural network," in *Proc. IEEE 12th Int. Conf. Control Syst., Comput. Eng. (ICCSCE)*, Oct. 2022, pp. 107–112.

[7] Q.-H. Phan, V.-T. Nguyen, C.-H. Lien, T.-P. Duong, M. T.-K. Hou, and N.-B. Le, "Classification of tomato fruit using YOLOv5 and convolutional neural network models," *Plants*, vol. 12, no. 4, p. 790, Feb. 2023.

[8] P. Tm, A. Pranathi, K. SaiAshritha, N. B. Chittaragi, and S. G. Koolagudi, "Tomato leaf disease detection using convolutional neural networks," in *Proc. 11th Int. Conf. Contemp. Comput. (IC3)*, Aug. 2018, pp. 1–5.

[9] A. Dwivedi, A. Goel, M. Raju, D. Bhardwaj, A. Sharma, F. Kidwai, N. Gupta, Y. Sharma, and S. Tayal, "Precision agriculture: Using deep learning to detect tomato crop diseases," in *Proc. Int. Conf. Innov. Comput. Commun.* Singapore: Springer, 2024, pp. 857–865.

[10] K. N. E A. Siddiquee, M. S. Islam, M. Y. U. Dowla, K. M. Rezaul, and V. Grout, "Detection, quantification and classification of ripened tomatoes: A comparative analysis of image processing and machine learning," *IET Image Process.*, vol. 41, pp. 2442–2456, Sep. 2020.

[11] M. H. Malik, T. Zhang, H. Li, M. Zhang, S. Shabbir, and A. Saeed, "Mature tomato fruit detection algorithm based on improved HSV and watershed algorithm," *IFAC-PapersOnLine*, vol. 51, no. 17, pp. 431–436, 2018.

[12] R. Xiang, Y. Ying, and H. Jiang, "Tests of a recognition algorithm for clustered tomatoes based on mathematical morphology," in *Proc. 6th Int. Congr. Image Signal Process. (CISP)*, vol. 1, Dec. 2013, pp. 464–468.

[13] Q. Feng, X. Wang, G. Wang, and Z. Li, "Design and test of tomatoes harvesting robot," in *Proc. IEEE Int. Conf. Inf. Autom.*, Aug. 2015, pp. 949–952.

[14] E. R. Dougherty, "Optimal binary morphological bandpass filters induced by granulometric spectral repre-sentation," *J. Math. Imag. Vis.*, vol. 7, pp. 175–192, Jan. 1997.

[15] K. Yamamoto, W. Guo, Y. Yoshioka, and S. Ninomiya, "On plant detection of intact tomato fruits using image analysis and machine learning methods," *Sensors*, vol. 14, no. 7, pp. 12191–12206, Jul. 2014.

[16] Z.-F. Xu, R.-S. Jia, Y.-B. Liu, C.-Y. Zhao, and H.-M. Sun, "Fast method of detecting tomatoes in a complex scene for picking robots," *IEEE Access*, vol. 8, pp. 55289–55299, 2020.

[17] Y. Mu, T.-S. Chen, S. Ninomiya, and W. Guo, "Intact detection of highly occluded immature tomatoes on plants using deep learning techniques," *Sensors*, vol. 20, no. 10, p. 2984, May 2020.

[18] R. G. de Luna, E. P. Dadios, A. A. Bandala, and R. R. P. Vicerra, "Tomato growth stage monitoring for smart farm using deep transfer learning with machine learning-based maturity grading," *AGRIVITA J. Agricult. Sci.*, vol. 42, no. 1, pp. 24–36, Feb. 2020.

[19] G. Liu, J. C. Nouaze, P. L. Touko Mbouembe, and J. H. Kim, "YOLO-tomato: A robust algorithm for tomato detection based on YOLOv3," *Sensors*, vol. 20, no. 7, p. 2145, Apr. 2020.

[20] Y. Zhao, L. Gong, B. Zhou, Y. Huang, and C. Liu, "Detecting tomatoes in greenhouse scenes by combining AdaBoost classifier and colour analysis," *Biosystems Eng.*, vol. 148, pp. 127–137, Aug. 2016.

[21] A. Abbas, S. Jain, M. Gour, and S. Vankudothu, "Tomato plant disease detection using transfer learning with C-GAN synthetic images," *Comput. Electron. Agricult.*, vol. 187, Aug. 2021, Art. no. 106279.

[22] M. S. Islam, S. Sultana, F. A. Farid, M. N. Islam, M. Rashid, B. S. Bari, N. Hashim, and M. N. Husen, "Multimodal hybrid deep learning approach to detect tomato leaf disease using attention based dilated convolution feature extractor with logistic regression classification," *Sensors*, vol. 22, no. 16, p. 6079, Aug. 2022.

[23] A. K. Rangarajan, R. Purushothaman, and A. Ramesh, "Tomato crop disease classification using pre-trained deep learning algorithm," *Proc. Comput. Sci.*, vol. 133, pp. 1040–1047, Jan. 2018.

[24] L. G. Nachtigall, R. M. Araujo, and G. R. Nachtigall, "Classification of apple tree disorders using convolutional neural networks," in *Proc. IEEE 28th Int. Conf. Tools Artif. Intell. (ICTAI)*, Nov. 2016, pp. 472–476.

[25] P. Kaur, S. Harnal, R. Tiwari, S. Upadhyay, S. Bhatia, A. Mashat, and A. M. Alabdali, "Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction," *Sensors*, vol. 22, no. 2, p. 575, Jan. 2022.

[26] G. Liu, S. Mao, H. Jin, and J. H. Kim, "A robust mature tomato detection in greenhouse scenes using machine learning and color analysis," in *Proc. 11th Int. Conf. Mach. Learn. Comput.*, Feb. 2019, pp. 17–21.

[27] J. Basavaiah and A. Arlene Anthony, "Tomato leaf disease classification using multiple feature extraction techniques," *Wireless Pers. Commun.*, vol. 115, no. 1, pp. 633–651, Nov. 2020.

[28] E. Cengil and A. Çinar, "Hybrid convolutional neural network based classification of bacterial, viral, and fungal diseases on tomato leaf images," *Concurrency Comput., Pract. Exper.*, vol. 34, no. 4, p. e6617, Feb. 2022.

[29] X. Chen, G. Zhou, A. Chen, J. Yi, W. Zhang, and Y. Hu, "Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105730.

[30] T.-H. Nguyen, T.-N. Nguyen, and B.-V. Ngo, "A VGG-19 model with transfer learning and image segmentation for classification of tomato leaf disease," *AgriEngineering*, vol. 4, no. 4, pp. 871–887, Oct. 2022.

[31] Y. Lai, R. Ma, Y. Chen, T. Wan, R. Jiao, and H. He, "A pineapple target detection method in a field environment based on improved YOLOv7," *Appl. Sci.*, vol. 13, no. 4, p. 2691, Feb. 2023.

[32] K. Zhang, D. Li, W. Luo, and W. Ren, "Dual attention-in-attention model for joint rain streak and raindrop removal," *IEEE Trans. Image Process.*, vol. 30, pp. 7608–7619, 2021.

[33] X. Xie, F. Xia, Y. Wu, S. Liu, K. Yan, H. Xu, and Z. Ji, "A novel feature selection strategy based on salp swarm algorithm for plant disease detection," *Plant Phenomics*, vol. 5, p. 39, Jan. 2023.

[34] M. Hasan, B. Tanawala, and K. J. Patel, "Deep learning precision farming: Tomato leaf disease detection by transfer learning," in *Proc. 2nd Int. Conf. Adv. Comput. Softw. Eng. (ICACSE)*, 2019.

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

[36] Q. Wu, Y. Chen, and J. Meng, "DCGAN-based data augmentation for tomato leaf disease identification," *IEEE Access*, vol. 8, pp. 98716–98728, 2020.

[37] A. K. Singh, S. Sreenivasu, U. S. B. K. Mahalaxmi, H. Sharma, D. D. Patil, and E. Asenso, "Hybrid feature-based disease detection in plant leaf using convolutional neural network, Bayesian optimized SVM, and random forest classifier," *J. Food Qual.*, vol. 2022, pp. 1–16, Feb. 2022.

[38] X. Tian, X. Meng, Q. Wu, Y. Chen, and J. Pan, "Identification of tomato leaf diseases based on a deep neuro-fuzzy network," *J. Inst. Eng. (India), Ser. A*, vol. 103, no. 2, pp. 695–706, Jun. 2022.

[39] L. Tan, J. Lu, and H. Jiang, "Tomato leaf diseases classification based on leaf images: A comparison between classical machine learning and deep learning methods," *AgriEngineering*, vol. 3, no. 3, pp. 542–558, Jul. 2021.

MUHAMMAD UMAR received the Graduate degree in computer science from BIMS, in 2019. He is currently pursuing the master's degree with the University Institute of Information Technology (UIIT), Pir Mehr Ali Shah Arid Agriculture University (PMAS–AAR), Rawalpindi, Pakistan. His major research interests include wireless sensor networks and image processing, involve human–machine interaction, leafdisease recognition, the Internet of Things (IoT), and artificial intelligence.

SAUD ALTAF received the master's degree in computer science from Iqra University, Islamabad, Pakistan, in 2007, and the Ph.D. degree in computer science from Auckland University of Technology (AUT), New Zealand, in 2015. He is a Professor with the National Skills University, Islamabad. He is the author of a number of research publications in international impact factor journals and conference proceedings. His research interests span several fields of wireless sensor networks, biomedical signal and image processing, security of cyber-physical systems (CPSs), gesture recognition, through-the-wall radar imaging and sensing, visible light communication, the Internet of Things (IoT), artificial intelligence, and data mining.

SHAFIQ AHMAD received the Ph.D. degree from RMIT University, Melbourne, Australia. He is currently an Professor with the Industrial Engineering Department, College of Engineering, King Saud University, Riyadh, Saudi Arabia. He has more than two decades of working experience both in industry and academia in Australia, Europe, and Asia. He has published a research book and several research articles in international journals and refereed conferences. His research interests include smart manufacturing, the IIoT, data analytics, multivariate statistical quality control, process monitoring and performance analysis, operations research models, and bibliometric network analysis. He is a certified practitioner in the Six Sigma business improvement model.

HAITHAM MAHMOUD received the Ph.D. degree in industrial engineering from Helwan University, Egypt, in 2012. He is currently an Assistant Professor with the Department of Industrial Engineering, College of Engineering, King Saud University, Riyadh, Saudi Arabia, and the Mechanical Engineering Department, Faculty of Engineering, Helwan University. He is a certified Six Sigma Green Belt (CSSGB) from ASQE. He has more than 15 years of experience in the industrial and academic organizations in Egypt and Arab Gulf countries. He has trained many engineers on the quality management and maintenance management. His current research interests include optimization modeling, theory, and algorithm design, with the applications in waste management and energy management, financial engineering, and big data.

ADAMALI SHAH NOOR MOHAMED received the M.E. degree in power electronics and industrial drives from Sathyabama University, Chennai, India. He is currently a Researcher with the Electrical Engineering Department. He has more than ten years of teaching experience and excellent research potential and an ability to actively contribute to the research project goals and a proven publication track record. He has published several research articles in international journals and refereed conferences. His research interests are related to industrial control process, discrete averaging of dc–dc converters and also developing converter models using MATLAB package.

RASHID AYUB received the double master's degree in computer applications and in mathematics and the Ph.D. degree in computer science and applications from Sunrise University, Alwar, Rajasthan, India. His Ph.D. thesis entitled ''Extension of Bounded Rationality in Artificial Intelligence to Sensing Activity Through Limited Resource Sensing Problem.'' He is currently a Researcher with the Science Technology and Innovation Department, National Plan for Science and Technology (NPST) Setup, College of Computer Science, King Saud University, Riyadh, Saudi Arabia. He has more than two decades of working experience both in industry and academia in India and abroad. He was also a Trainer by United Nations Training Program on ''Integrated Management Information System (iMIS) Based on ERP'' conducted by RAOP-CAP Team, United Nations (UNEP) Office, Bangkok, Thailand. He was a MIS Officer/a Coordinator with the Ministry of Environment and Forest, New Delhi, India, and produced ''MIS Vision Document for Compliance Era of 2004–2007,'' covering aspects such as e-based mechanism for dissemination of information, knowledge management, and reporting requirement. He also involved in ''Development of Centralized MIS System for Cohesive Data Compilation of ODS-III and ODS-IV'' with the help of MIS vision document. He has published a few research articles in international journals and refereed conferences. His research interests are related to the Internet of Things (IoT), deep learning, artificial intelligence (AI), machine learning, cloud computing, and neural network/fuzzy logic and their applications in the areas of e-healthcare, smart city, and bio-informatics.