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RESEARCH ARTICLE

Detection and Classification of Temporal Changes for Citrus Canker Growth Rate Using Deep Learning

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ABSTRACT Citrus canker is among the major plant diseases caused by Xanthomonas citri which affects the quality and quantity of citrus fruit. This results in the reduction of citrus production which causes a huge financial loss and livelihood of the farming community. Thus, it is critically important to build a robust, accurate, and time-efficient detection method for real-time identification of the disease. Due to their powerful learning capabilities and improved feature extraction, deep learning approaches have made it feasible to carry out a number of tasks related to the identification of citrus canker in citrus leaves. Previous research has primarily focused on detecting citrus canker on fruits, early detection on leaves can facilitate the adoption of preventive measures before the disease reaches a critical stage. This paper proposes a novel deep learning-based approach for determining the growth rate of citrus canker by classifying it into six distinct stages: water soaking, yellow chlorosis/initiation, chlorosis, blister formation, canker development start, canker infection (50% of the inoculated area), and canker infection (100% of the inoculated area). The proposed approach involves image conversion, size reduction, image augmentation, and the utilization of DenseNet-121. Experimental results demonstrate a classification accuracy of 98.97% using the suggested approach. The Accuracy was 98.97% with macro precision 97%, weighted precision 99%, Macro recall 98%, weighted recall 98%, macro F1_Score 97% and weighted F1_Score 98%. This study presents a unique technique for detecting and classifying the growth rate of citrus canker based on six different stages, while also calculating the temporal change in the affected area of the disease in inoculated citrus leaves. Furthermore, a mathematical model is proposed to predict the disease's growth rate at any given time, offering valuable insights for disease management and prevention.

INDEX TERMS Citrus canker, plant diseases, growth rate prediction, deep learning.

I. INTRODUCTION

Citrus production and quality face significant threats from diseases, such as citrus canker, insect pests, water availability, and climate change [1], [2]. Among these issues, citrus diseases have emerged as a primary factor contributing to reduced yield, compromised fruit quality, and shortened tree lifespan worldwide [3]. As a result, citrus exports to key global markets, including the European Union (EU) and American citrus markets, are hindered due to quarantine measures aimed at controlling fruit diseases like citrus canker [4]. The bacterium Xanthomonas citri causes citrus canker

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(hereafter referred to as X. citri), and poses a significant threat to the citrus industry [5]. It is classified as a quarantine disease, prohibiting the movement of citrus fruits across markets and countries, thereby imposing severe limitations on citrus producers. Infected citrus fruits exhibit unsightly appearances, excessive discoloration, reduced quality, and premature maturity, rendering them undesirable in the market [6]. The range of impacts caused by X. citri, ranging from mild symptoms to complete plantation loss, has devastating consequences for citrus production and its contribution to the national economy [5].

Early detection of citrus canker disease at its initial stages of development is very important as it could be helpful for designing a plan for control of the disease before it attains threshold level and severe productivity and financial loss. Early identification of citrus canker during the initial growth phase can prevent disease transmission to other plant parts, particularly fruits, which are a vital economic product, thereby enabling significant cost savings [11]. Accurate estimation of citrus fruit production prior to harvest is highly crucial for the citrus producer community and decision-makers. However, identifying cankers poses a significant challenge for plant pathologists, requiring the adoption of scientific methods, laboratory procedures, and long-term observations [7]. Previously, in situ disease identification was not feasible, and farmers had to send infected leaf and fruit samples to a plant pathology lab, where a pathologist confirmed the disease and assessed its severity. This process is labor-intensive and time-consuming [8]. The delay caused by laboratory procedures impeded timely responses, leading to reduced crop productivity [9]. Therefore, the automation of disease detection systems is crucial for rapid identification and assessment of disease severity [10].

Computer vision has become a novel technology for the detection and diagnosis of image-based diseases in a variety of uses, including medicine, security, and agriculture [12]. It includes image processing, image analysis, and image classification [13]. Modern image processing and pattern recognition tools have been found to help farmers and agricultural specialists in identifying plant diseases. It is possible to automatically assess the quality of agricultural goods using images and different artificial intelligence-based approaches [15]. Images of the various plant parts can be taken in order to develop a system for detecting plant diseases. The leaves of plants are the part where plant diseases are most frequently seen at an initial stage.

Despite the fact that image processing techniques are effective in identifying plant diseases, these systems are prone to errors in leaf images because of differences in form, color, texture, and other factors. These images might be used to train machine learning and deep learning models. The accuracy of the input data representation is a key component of prior machine learning techniques employed in the past [14]. Poor feature extraction from raw data may result in inaccurate data classification being provided by machine learning algorithms [16]. In a previous study [17], authors used different machine learning techniques on their own developed dataset to diagnose and identify the growth rate of citrus canker. In their study, they investigate the efficiency of different classifiers in the classification of different stages of disease development in citrus cankers. The authors found that the efficiency of classifiers (NB, NN, and KNN) was low (below 90%). To achieve high accuracy regarding the classification of different citrus canker stages, they proposed to apply deep learning techniques.

Recently, the agriculture industry has employed a number of deep learning models to tackle a variety of challenges, including insect identification, fruit detection, plant leaf categorization, and fruit and leaf disease detection [18]. Deep learning techniques can pave the way for overcoming difficulties regarding feature extraction, classification, and developing expert systems that could help the agricultural community in improving the quality and production of their fruit plants. DenseNet-121, ResNet-50, and MobileNet are a few popular models that have been used previously for image detection and classification in the diagnosis and identification of various plant diseases [19]. ResNet-50 performs better on large-scale datasets [20]. With its ability to capture deeper and more hierarchical features, ResNet-50 can excel in scenarios where there is an abundance of training data. It can effectively learn complex representations from large datasets and achieve superior classification accuracy. MobileNet models, on the other hand, used in the optimization of efficiency, still maintain a good level of accuracy [21]. However, due to the reduction in parameters and computations, they may not perform well under certain conditions especially when the dataset is not fairly big enough. In contrast, DenseNet-121 tends to perform better than ResNet-50 on smaller datasets [22]. This is due to the fact that DenseNet-121, demonstrates a strong performance in various computer vision tasks and achieves high accuracy [23]. The dense connectivity pattern allows information to flow through the network more effectively, enabling better feature representation [24]. Therefore, DenseNet-121 due to its dense connectivity pattern, parameter efficiency, and feature reuse makes it a powerful choice for image classification tasks, especially when resources are limited [25]. However, the choice between CNNs and DenseNet-121 ultimately depends on the specific task requirements and available resources. For diagnosis and identification of different plant diseases, different image classification models like CNN, ResNet-50, and MobileNet have been extensively used but these techniques have never been employed for the estimation of temporal change in the growth of particular plant disease which is of utmost importance for guidelines and adaptation of precautionary measures to farmer's community based on disease stage/severity. Hence, it is very important to find the different disease growth stages of citrus canker and model them accordingly to identify the crucial stage of disease severity or the level at which minimum economic loss is predicted and indicate the guidelines about adopting measures against the disease. Moreover, most recent studies have shown significant difficulties in improving the classification accuracy rates, especially in the complex background. Images of plant leaves can be analyzed in a fairly complicated way to reveal the majority of disease signs. Even agronomic professionals, citrus growers, and farmers struggle to detect plant diseases because of the complicated nature of phytopathological issues and the wide range of crops. The effectiveness of disease characteristics, their extraction, and the type of classifiers utilized determines the success of plant disease detection systems [26]. Instead of real-field image datasets, the majority of studies used image datasets that have been developed under laboratory conditions, such as the PlantVillage dataset. It has been noted that the type of dataset utilized for training and testing purposes has a significant impact on the performance of the classifiers employed. Researchers should thus first develop a significant number of real-conditioned images for the model's training and testing in order to improve classification on real-conditioned images of diseased plant leaves. Furthermore, previously, citrus canker datasets were developed in fruits, leaves, and twigs under controlled laboratory conditions. However, as described real field conditions are much more diverse and complicated. Keeping in view the above issues and challenges and developing a prediction system for a growth rate of citrus canker with six severity levels in a natural real field environment with high accuracy the present study was planned. The primary goal of the proposed study is to employ the proposed model using DenseNet-121 to identify and categorize citrus canker disease rate at different phases of its growth with several fine-tuning layers for enhanced and precise results. For this purpose, the DenseNet-121 model was used with additional layers, to enhance the classification accuracy of the different stages of citrus canker growth rate for a timely early detection system. For this purpose, the proposed model uses DenseNet-121, to enhance the classification accuracy of the different stages of citrus canker growth rate for a timely early detection system. The proposed model exhibited macro F1 score as 97% and weighted F1 score 98% using DenseNet-121 which was significantly higher than the previously employed DenseNet-121 models in detection of various plant diseases as F1-score 95% [64] macro F1 score as 85% and weighted F1 score 93% [65] F1-score 92.83% [66].

A. RESEARCH CONTRIBUTIONS

- A Real-field dataset is created for Citrus canker growth rate assessment under diverse and complex environmental conditions.
- Implementation of a hybrid deep learning model to enhance the efficiency of classifying different stages of disease development in citrus leaves. Our Dataset is novel in the sense that it captures disease at different growth stages.
- Temporal calculation of the affected area of citrus diseased leaves to determine the growth rate of citrus canker.
- A mathematical model is also proposed to predict the percentage of the affected area over a specified time.

The research paper is structured as follows: Section II provides details on the dataset collection, and Section III presents the proposed methodology for diagnosing citrus canker disease in leaves. Section IV analyzes the results and outcomes discussion obtained from the implemented approach. Finally, Section V summarizes the research work and presents the conclusion.

II. DATASET

This section provides a brief overview of the dataset collection and annotation process carried out by domain experts. A comprehensive procedure and way of collecting datasets can also be found in the author's article [17].

A. SPECIMEN DATASET COLLECTION

Bacterial strains X. citri was obtained from the Crop Diseases Research Institute (CDRI), National Agricultural Research Centre (NARC), Pakistan. By means of a monthly transfer, the culture was kept on yeast- dextrose-calcium carbonate agar (YDC) slants for regular usage [27] and, yellow mucoid colonies were included. Cells were grown in liquid Nutrient Broth Yeast extract NBY and the obtained log phase suspensions were adjusted to have 108 CFU/ml in 0.85% saline [28]. Citrus paradisi (Grapefruit) newly unfolded leaves were infected by gently pushing the aperture of a syringe without a needle on the abaxial leaf surface while being maintained by one finger and 1×108 CFU ml of X. citri strains [29]. Control inoculations were made with 0.85% saline.The progression of canker symptoms was recorded over a period of 21 days until the maximum affected area was observed. Plants were inoculated under natural field conditions with the culture of already prepared X. citri strains. Sample images depicting citrus canker development are presented in Fig. 1. A systematic diagram illustrating different stages of citrus canker development has been presented in Fig. 2. Moreover, a detailed description of various stages of citrus canker development has been presented in Table 1.

B. EVALUATION OF GROWTH STAGES OF CITRUS CANKER

The dataset used in this study exhibited class imbalance, with varying numbers of images for each of the six stages of canker development (Table 2). This imbalance was a result of natural field conditions and the severity of the disease, impacting leaf health and growth. The six different stages of disease development based on lesion appearance or halo zone appearance were as follows: water soaking, yellow (chlorosis)/initiation (pale yellow/pale green), chlorosis, blister formation, canker development start, and canker infection (50% and 100% of the inoculated area) [30]. Water soaking manifests as a moist,

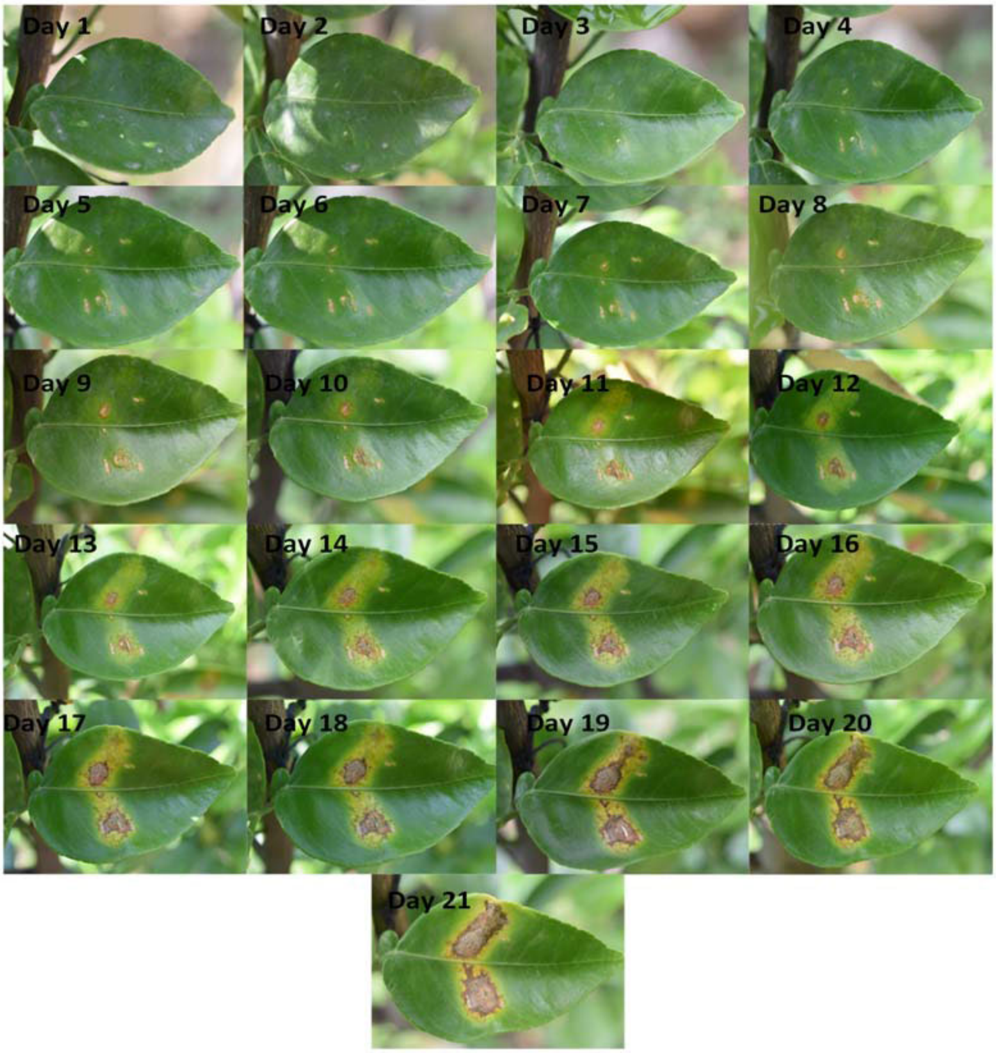

FIGURE 1. Sample images of citrus canker levels/growth rate.

dark, and typically sunken and/or transparent appearance on plants or lesions [31]. The presence of a yellow halo characterizes yellow (chlorosis) symptoms [32]. Chlorosis, which affects chlorophyll, leads to the yellowing of typically green leaves. Severe disease attacks result in the formation of brown elevated areas, often referred to as craters, pustules, or blisters, surrounded by a yellow halo. Within 12 days of inoculation, small, slightly elevated blister-like lesions appear on leaves under optimal conditions [33]. Round to irregular, swollen, flattened, cracked, discolored, or dead patches on the leaves are the early warning indications of canker growth. The training set and validation set had 1004 and 253 images, respectively.

III. METHODOLOGY

The framework for the detection and classification of the Citrus canker growth rate has been shown in Fig. 3. In preprocessing, the first reduction in image size was done and then converted into Grayscale. Image augmentation was employed in the proposed technique to enhance the size of the dataset using various approaches including vertical flip and horizontal flip because deep learning techniques demand a significant quantity of data. DenseNet-121 was later employed for feature extraction and classification of levels and growth rates of citrus canker disease.

A. PROPOSED APPROACH

Preprocessing of input image data with a size (h, w, c) of 250, 250, 3 that had been carried out in a series of procedures was the initial stage. In preprocessing, reduce the size of the image and convert it into greyscale. To avoid the issue of overfitting, deep learning models rely on a large quantity of data. Agriculture is one of several industries where access to massive data is challenging and it was a special case as we were required data to find the growth rate of citrus canker on a daily basis. In the present study, the authors captured images of citrus canker-diseased leaves at various growth phases. Using the Image Data Generator method, the dataset was

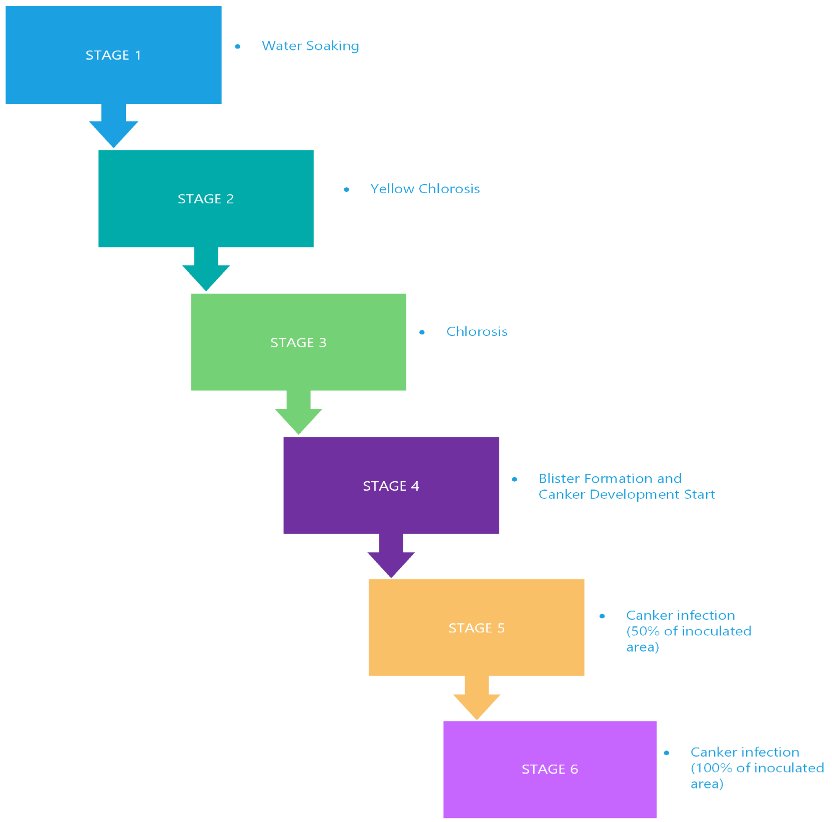

FIGURE 2. Stages of citrus canker development.

TABLE 1. Description of different stages in the growth of citrus canker.

Levels/ Stages	Days Appearance	Description
1	2-3	No significant lesions formed on the leaf surface. The first signs were small, faintly elevated blister-like lesions.
2	4-7	Images of young citrus canker lesions with a yellow halo zone. The lesions developed from tan to brown, and a yellow halo emerged around the water-soaked edge.
3	8-11	The old lesions of citrus canker displaying the shot hole effect.
4	12-14	Raised corky lesions that were dark brown or black in color surroundings by oily or wet margins as signs of blister formation and initial canker development
5	15-18	Images have clear hollow circles and dead cells around them
6	19-21	The lesions start to seem scabby or corky as they become older

TABLE 2. Imbalanced citrus canker training and validation dataset.

Category	Training Data	% of Classes	Validation Data	% of Classes
Water Soaking	24	2.39	06	2.37
Yellow (Chlorosis) / initiation (Pale yellow/ Pale green)	65	6.47	17	6.72
Chlorosis	80	7.96	20	7.91
Blister formation and Canker development start	156	15.53	40	15.81
Canker infection (50% of inoculated area)	416	41.43	104	41.11
Canker infection (100% of inoculated area)	263	26.19	66	26.08
Total	1004		253	

generated which comprised images of diseased citrus leaves. Since deep learning algorithms often require a lot of data, image augmentation was performed to increase the quantity of the dataset. This issue of insufficient data was resolved by image augmentation [34]. In order to provide datasets for deep learning models with enhanced accuracy, a variety of strategies are used in image augmentation [35]. This kind of augmentation can involve both horizontal and vertical axis flipping. Vertical and horizontal flipping has been used as shown in Fig. 4. Among generated images 80% dataset was used for training and 20% for testing/validation. There was a total of 06 classes in the dataset. Feature Extraction was performed by using the DenseNet-121 Model. The generalized systematic architecture of the proposed model using DenseNet-121 is shown in Fig. 5. Hyperparameters, namely optimizer like Adam, batch size like 50, a learning

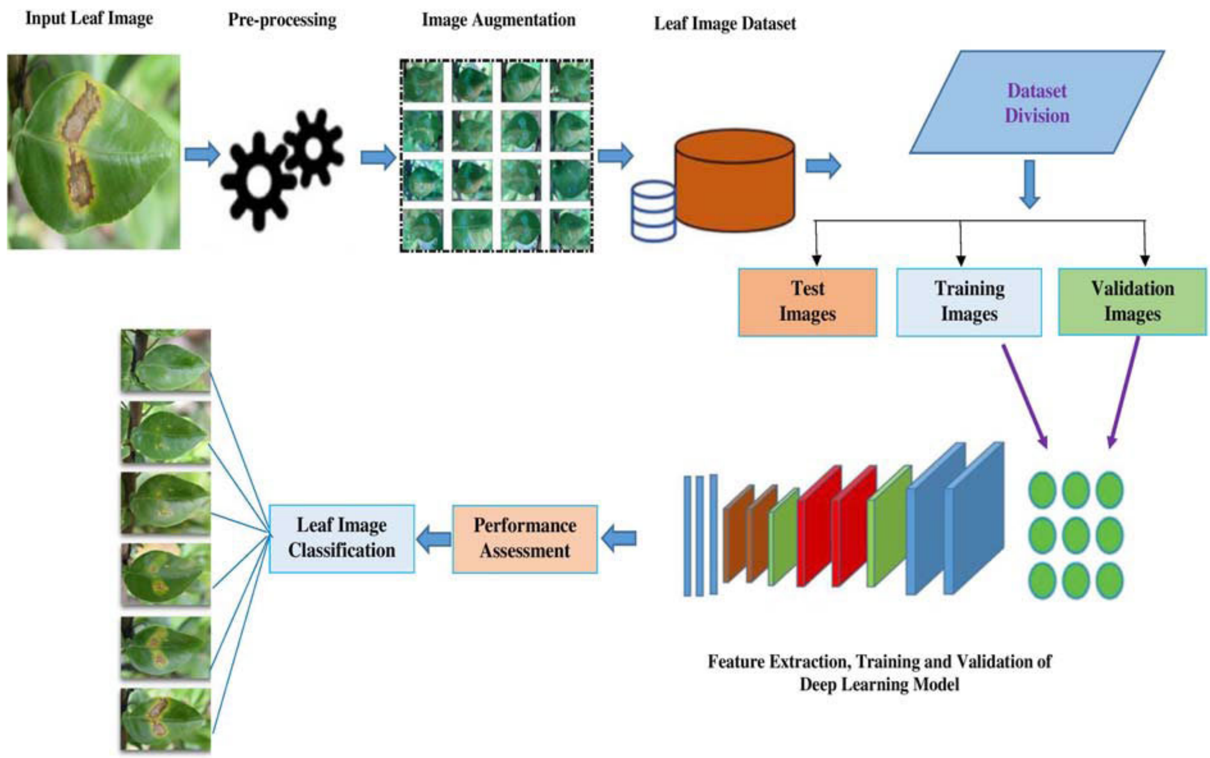

FIGURE 3. Framework for detection and classification of Citrus canker levels/growth rate.

rate of about 0.002, and dropout at 0.5 applied during training the model as shown in Table 3.

DenseNet-121 is a convolutional neural network (CNN) architecture widely used for tasks like image classification [36]. It is based on the concept of densely connected layers, where each layer is connected to every other layer in a block.

First, the input layer receives the input image and passes it to the subsequent layers for processing. DenseNet-121 consists of several convolutional layers that perform feature extraction [37]. These layers use filters to scan the input image and detect various patterns and features. The dense blocks in Dense-121 are a distinctive feature. Dense Block 1 contains multiple densely connected convolutional layers. Each layer receives inputs from all preceding layers within the block, enabling feature reuse and promoting gradient flow. After each dense block, a transition layer is included to down-sample the feature maps. It performs spatial compression by using techniques like average pooling or convolution with stride to reduce the dimensionality of the feature maps. Similar to Dense Block 1, Dense Block 2 continues the pattern of densely connected convolutional layers. These layers further extract features from the down-sampled feature maps. Another transition layer follows Dense Block 2 to further downsample the feature maps. Dense Block 3 continues the densely connected layers and feature extraction process. The last transition layer further reduces the spatial dimensions of the feature maps. After the last transition layer, a global average pooling layer is applied to convert the 2D feature maps into a 1D vector. This operation calculates the average value for each feature map, reducing the spatial information to a fixed-length vector. DenseNet121 ends with a set of fully connected layers. These layers take the global average pooled vector as input and perform classification. Batch normalization helps to speed up the training process, dropout is a regularization approach that prevents overfitting. Softmax is an activation function that is used for a multi-classification model. The output layer using the softmax activation function produces the desired output, such as the predicted class probabilities for image classification into six classes based on lesions appearance/severity of the disease i.e. Water Soaking, Yellow (Chlorosis)/initiation (Pale Yellow/Pale Green), Chlorosis, Blister formation, Canker Development Start, Canker Infection (50% of Inoculated area) and Canker Infection (100% of Inoculated area). The proposed deep learning model using DenseNet121 layers is shown in Table 4.

TABLE 3. Deep learning model parameters.

DL Model	Optimizers	BS	LR	DO
DenseNet121	Adam	50	0.002	0.5

IV. RESULTS AND DISCUSSION

The leaves images after inoculation of X. citri over a specified time interval were taken. The diseased/infected leaves images were categorized into six stages based on the lesions' appearance or hallo zones on the surface of the citrus leaves surface. These levels describe the various stages of disease development. These six different disease development stages

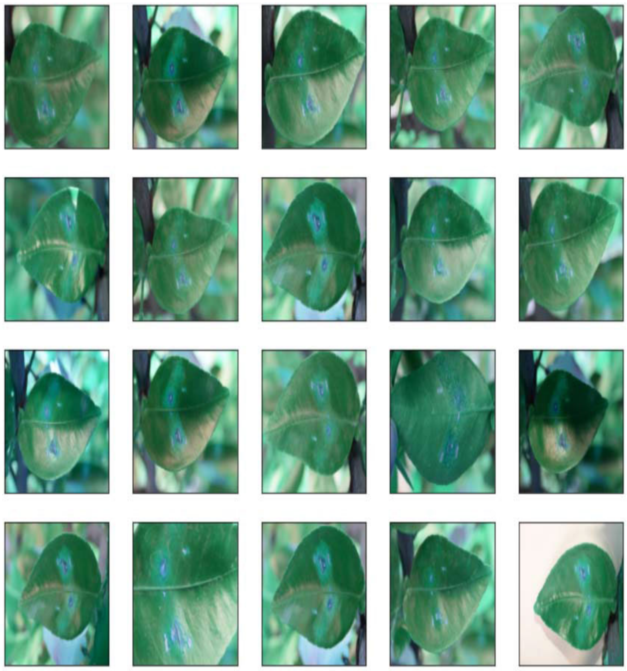

FIGURE 4. Different scenarios of image augmentation.

TABLE 4. Proposed deep learning model using DenseNet-121.

Layer(type)	Output Shape	Param#
Input Layer	[(None,250,250,3)]	0
Conv2	[(None, 250, 250,3)]	84
Densenet121 (Functional)	[(None, None, None, 1024)]	7037504
Global Average Pooling2D	(None, 1024)	0
Batch Normalization	(None,1024)	4096
Dropout	(None,1024)	0
Dense	(None,256)	262400
Batch Normalization	(None,256)	1024
Dropout	(None,256)	0
root (output)	(None,6)	5397

were then modeled and the stage initiation was predicted using the proposed model.

A. PERFORMANCE MEASURE

Accuracy, precision, recall, F1_Score, and Support measures were used to assess the performance of the classification model. A combination of precession Eq.(1) and recall Eq.(2) is the F1 score that is generally applied for imbalanced datasets.

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

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

where
TP = True Positives
FP = False Positives
FN = False Negatives

B. EXPERIMENTAL RESULTS

The Accuracy was 98% with macro precision 97%, weighted precision 99%, Macro recall 98% weighted recall 98%, macro F1_Score 97% and weighted F1_Score 98% at hyper parameters batch size 50, learning rate 0.002, the dropout rate was 0.5 and number of epochs were 100 for getting these optimal results to train the DenseNet-121 model. The classification report of the proposed model using DenseNet-121 is shown in Table 5. The proposed model using DenseNet-121 training accuracy, validation accuracies, and training loss, validation loss, respectively has been also depicted in Figures 6 and 7.

TABLE 5. Classification results of proposed method using validation data.

Levels/Stages	Precision	Recall	F1-score	Support
1	0.92	1.00	0.96	12
2	1.00	0.91	0.95	22
3	0.89	1.00	0.94	17
4	1.00	0.97	0.99	40
5	1.00	1.00	1.00	46
6	1.00	1.00	1.00	56
Accuracy			0.98	193
Macro Avg.	0.97	0.98	0.97	193
Weighted Avg.	0.99	0.98	0.98	193

From Fig. 6, while epochs were increasing, accuracy also increased for training the proposed model using the DenseNet-121 model for 100 epochs and reached a training accuracy of about 100% and validation accuracy of about 98.97%.

From the confusion matrix, as shown in Fig. 8, the water soaking was correctly predicted for 12 samples out of 12 samples. Yellow (Chlorosis) was perfectly predicted for 22 samples out of 22 samples. The Chlorosis was predicted for 16 samples out of 17 samples. The Blister formation and the inoculated area) was correctly predicted for 40 samples out of 40 samples. The Canker infection (50% of the inoculated area) was predicted for 45 samples out of 46 samples. The Canker infection (100% of the inoculated area) was correctly predicted for 56 samples out of 56 samples.

C. CLASSIFICATION ACCURACY

The classification accuracy of different models indicates that the proposed technique achieved the highest accuracy (98.97%) compared to other employed models like N.N, NB, KNN, SVM, ResNet-50, and MobileNet (Table 6). This is due to the fact that DenseNet-121 is more parameter-efficient compared to ResNet-50 [40]. DenseNet achieves parameter efficiency through its dense connectivity pattern, where feature maps from previous layers are directly connected to subsequent layers. This allows for efficient feature reuse, resulting in a smaller number of parameters required compared to ResNet-50. Similar to this, MobileNet is a lightweight network that uses depth-wise separable convolution to deepen the network while minimizing parameters and computation [41]. The lightweight model MobileNets strives to strike a compromise between model accuracy and compression [42]. Similar to this, Support Vector Machine (SVM) classifications the data by employing hyperplanes that serve as decision boundaries between various classes [43]. According to Mammone et al. [44], SVM seeks for

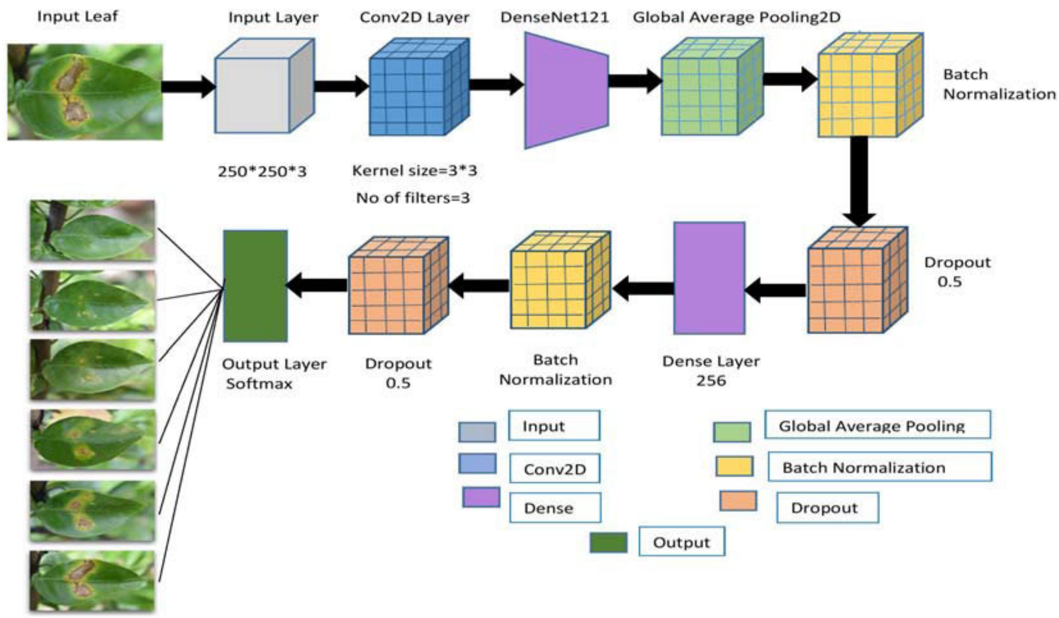

FIGURE 5. Proposed approach using DenseNet-121 architecture.

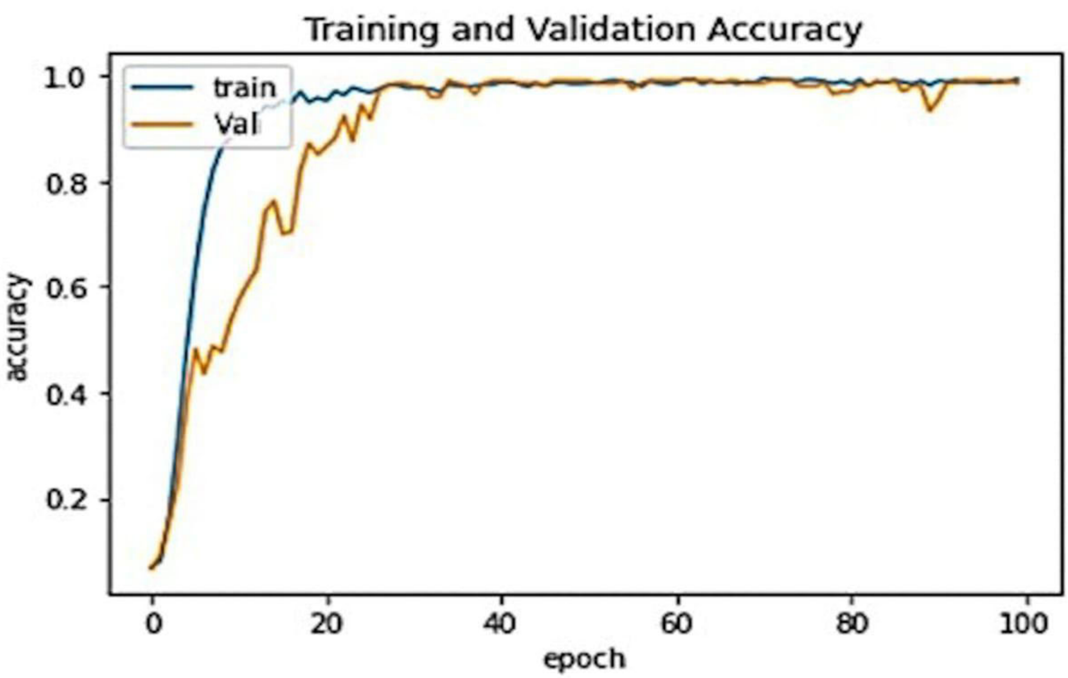

FIGURE 6. Training and validation accuracy.

TABLE 6. Classification accuracy achieved by employed various classifiers.

Classifiers	Accuracy achieved
NN	82%
NB	84%
KNN	90%
SVM	96.77%
ResNet-50	94%
MobileNet	92%
Proposed Approach	98.97%

the best and most ideal hyperplane that maximizes the margin from each Support Vector. However, SVM has a number of drawbacks, including the difficulty in selecting the right Kernel function (to handle the non-linear data)

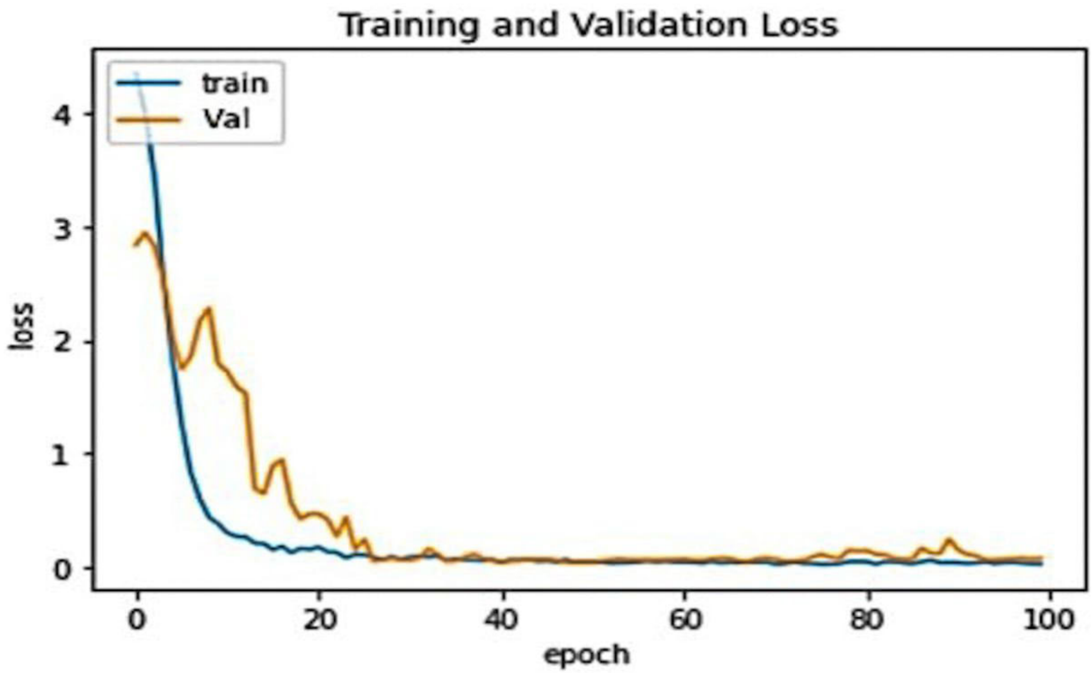

FIGURE 7. Training and validation loss.

TABLE 7. Comparative analysis of proposed technique with previously employed approaches in detecting citrus canker.

Reference	Year	Technique used	Accuracy
Sharif et al. [40]	2018	SVM	90.4%
Meen.[49]	2019	CNN	96.5%
Shireesha and Reddy. [50]	2022	DenseNet-121	96%
Syed-Ab-Rahman et al.[1]	2022	CNN	94.37%
Pal.[51]	2022	MobileNet V2	93.28%.
Rahman et al. [52]	2022	VGG19 model	97.54%
Thilagavathi et al. [67]	2023	CNN	90%
Behera et al.[54]	2018	SVM	90%
Kukreja et al.[55]	2023	Hybrid model(CNN and SVM)	94.03%
Sharma and Kukreja.[39]	2022	CLTN model	94.2%
Khattak et al.[56]	2021	CNN	94.55%
Chen et al.[57]	2021	Enhanced ANN and CNN	93.75%
Almola et al.[58]	2022	CNN	88%
Proposed	-	Proposed technique using DenseNet-121	98.97%

[45]. The accuracy of other employed classifier KNN was also observed low (90%) compared to the proposed approach. This is due to the nature of the KNN as the KNN algorithm is one of the simplest classification algorithms [46]. A supervised machine learning method called Naive Bayes was utilized for classification tasks [47] which also exhibited low efficiency (84%) while the Neural network only showed 82% classification accuracy. The proposed model accuracy was also compared with the previous studies and findings are summarized in Table 7.

The higher accuracy is due to the technique proposed using DenseNet-121. The higher efficiency of DenseNet-121 has been reported in several previous studies. Shireesha and Reddy [50], proposed a DenseNet-121 model, for comparison of detection and classification of healthy leaves with those infected with citrus canker. The results demonstrated that the model does well on a number of different metrics. Using the ImageNet pre-trained DenseNet-121 model, they achieved 96% accuracy in 50 epochs and five classes. Kukreja et al. [55], who used deep learning technology for effective and precise detection of citrus canker disease, obtained some similar outcomes. On a dataset of six citrus canker severity levels, ranging from healthy to seriously diseased, their suggested model was trained. The proposed model's total accuracy on the testing set was 94.03%.

D. MEASUREMENT OF CITRUS CANKER AFFECTED AREA

Citrus canker is harder to identify from images taken in real field conditions than it is from images taken in labs for a number of reasons, one of which is that the background can occasionally resemble a particular area of a canker lesion [4]. To deal with this problem, the proposed approach was used which includes image conversion, size reduction, image augmentation, and DenseNet-121. In the present study, the affected area with each passing day was also calculated and

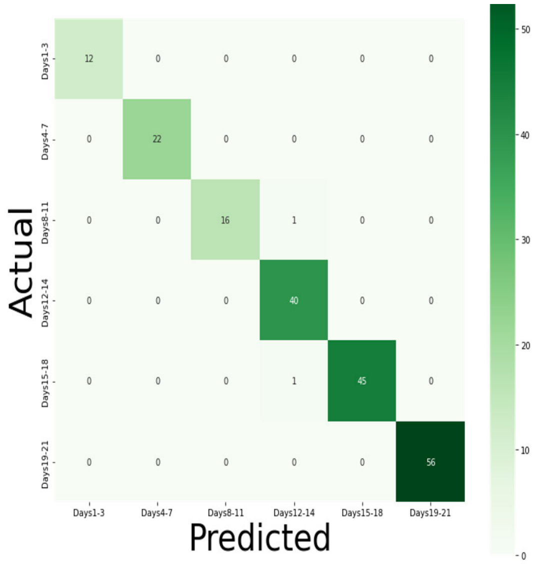

FIGURE 8. Confusion matrix of DenseNet121 on validation data.

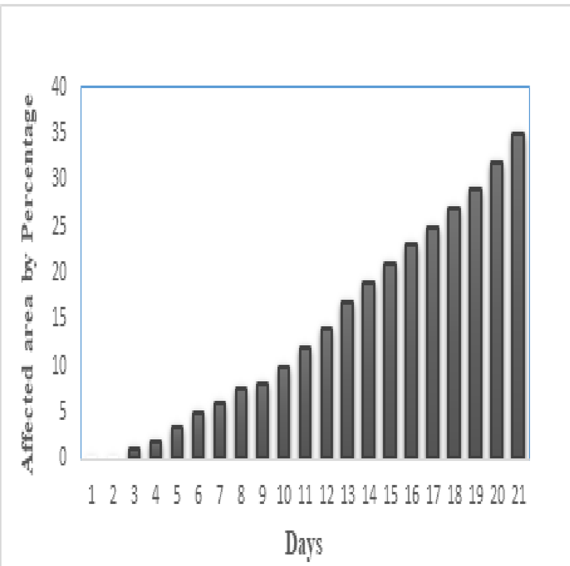

FIGURE 9. Temporal change in diseased affected area of citrus leaves.

is shown in Fig. 9 which indicates that in the first two days, the affected area was 0%. This could be due to the fact that the disease in the initial days started to proliferate and its symptoms appeared after a few days. A similar observation was also made by Lins et al. [59] who described that on the initial day, canker development under natural field conditions was not visible significantly. From day 3, the disease symptoms started to appear and the affected leaf area recorded was 1%. Gottig et al. [60] also illustrated a similar phenomenon and visible symptoms in the development of citrus canker by Xanthomonas axonopodis pv. citri. From day 3 onward, the affected area continuously increased with each passing day and reached its maximum value at 21 days (35%). Thus it was observed that the minimum affected area appeared on day 3 while the maximum affected area was

TABLE 8. Comparison of mathematical model with observed data.

Duration Days	Affected Area observed %	Affected Area Predicted %	Error%
1	0	0.669	0.669
2	0	0.196	0.196
3	1	1.161	0.161
4	2	2.225	0.225
5	3.5	3.389	0.110
6	5	4.651	0.348
7	6	6.012	0.012
8	7.5	7.472	0.027
9	8	9.032	1.032
10	10	10.690	0.690
11	12	12.448	0.448
12	14	14.304	0.304
13	17	16.260	0.739
14	19	18.315	0.684
15	21	20.469	0.530
16	23	22.721	0.278
17	25	25.073	0.073
18	27	27.524	0.524
18	29	27.524	1.475
20	32	32.723	0.723
21	35	35.472	0.472

TABLE 9. Percentage of affected area as predicted by the mathematical model.

Number of days	Percentage of affected area
25	47.455 %
30	64.663 %
35	84.347 %
38.5	100 %

observed on day 21. Thus we can observe that 35% area was affected by the disease in 21 days.

However, from the proposed model it was calculated that complete damage of the leaf (100%) would have occurred at 39 days. The affected area was calculated daily by the given formula as described by Zainab et al. [17].

$$AffectedArea = \frac{A1}{A2} \times 100 \tag{3}$$

A1 = Diseased Area
A2 = Healthy Area

E. PROPOSED MATHEMATICAL MODEL

A mathematical model of second order polynomial is proposed to predict the percentage of affected area (A) as Eq.(4):

$$A = -1.43626 + 0.71741\ T + 0.04953\ T^2 \tag{4}$$

A = % affected area
T = number of days

The error in the percentage of affected area observed and predicted by the mathematical model is shown in Table 9. Maximum error was less than 1.5%. A comparison of proposed mathematical model with observed data of affected area by citrus canker has been presented in Fig. 10.

Using this mathematical model, the affected area is also tabulated up to 100% effect, as shown in Table 9.

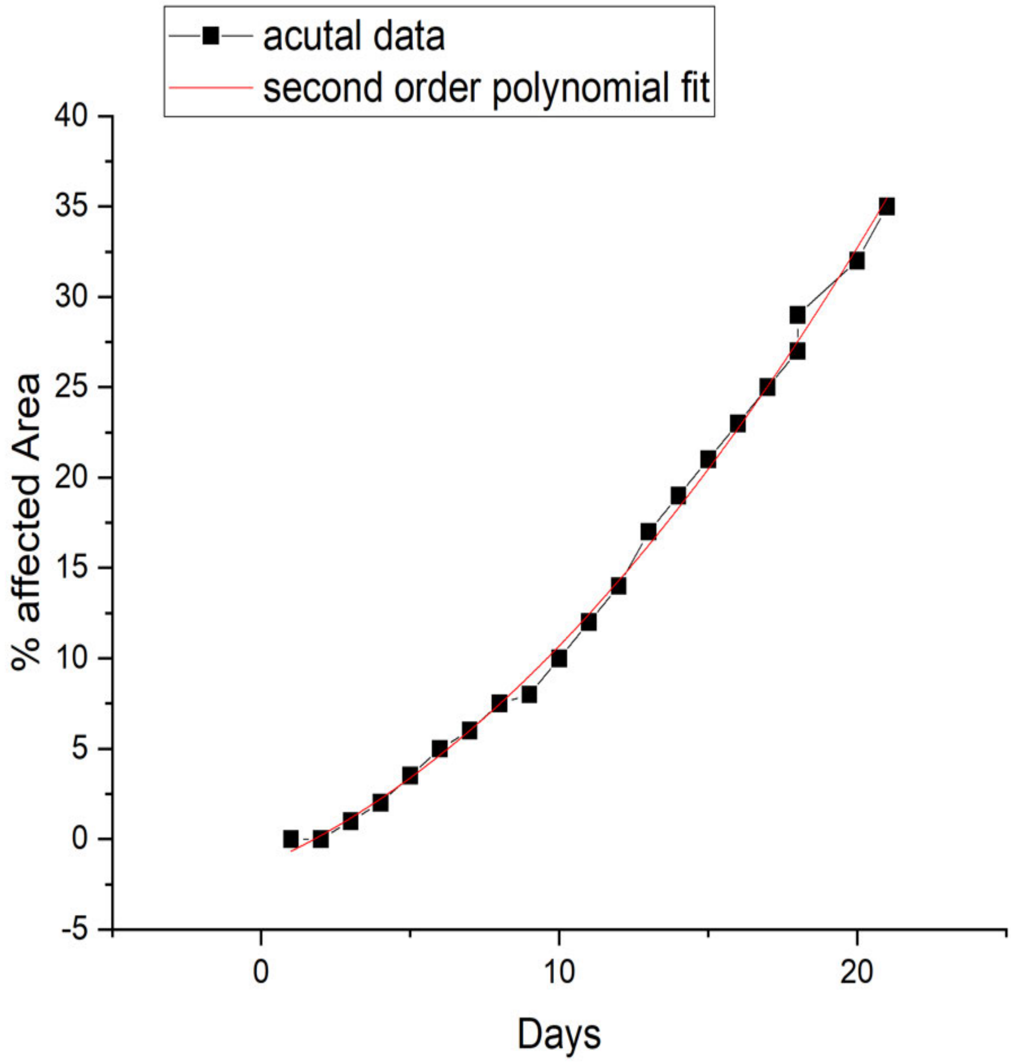

FIGURE 10. Comparison of proposed mathematical model and observed data of affected area.

Based on the prediction of the model, a similar generalized mathematical model can be developed Eq. (5) for any other study of disease effects by collecting three days' data and simultaneously solving the following mathematical model to evaluate the unknown constants (C1, C2, C3).

$$A = C_1 + C_2T + C_3T^2 \tag{5}$$

Early plant disease detection has been a field of interest in many aspects as it provides an early sign of controlling disease and minimizing economic loss. Several studies illustrate the importance of the reorganization model. By using the Involution Bottleneck module in the network topologies of YOLOv5, Wu et al. [61] developed a new YOLOv5-B model. According to their findings, the YOLOv5- model outperformed the YOLOv5 and PP-YOLOv2 models for multi-target identification of bananas, with a mean average position (mAP) of 93.2% overall. Wu et al. [62] used a deep learning-based edge detection technique to identify the overall cluster of banana fruits. According to their findings, the final bunch detection accuracy rate was 86%, the mean pixel precision was 0.936, and the target segmentation MIoU was 0.878 during the debudding phase. A bunch counting accuracy rate of 93.2% and a bunch detection accuracy rate of 76% were also attained. In-depth illustrations of the techniques for enhancing fruit detection in complicated contexts were also provided by Tang et al. [63].

V. CONCLUSION

Deep learning-based approaches have shown promising results in plant disease detection. The detection of citrus canker can be determined by observing the structure deformation of citrus leaf images. A deep learning-based approach was suggested in this paper to detect and classify the different stages of citrus canker disease development, and to find the temporal change in citrus canker growth rate. As our classes in the Dataset were imbalanced, we used different pre-processing methods and data augmentation for image generation because of this, the performance of the model increased significantly and achieved 98.97% accuracy for identifying six different levels of Citrus canker as the growth rate of disease. The proposed method accurately detects six citrus canker stages: water soaking, yellow chlorosis/initiation, chlorosis, blister formation, canker development start, canker infection (50% of the inoculated area), and canker infection (100% of the inoculated area). with an overall classification accuracy of 98.97%. The proposed approach involves image conversion, size reduction, image augmentation, and the utilization of DenseNet-121. The Accuracy was 98.97% with macro precision 97%, weighted precision 99%, Macro recall 98%, weighted recall 98%, macro F1_Score 97% and weighted F1_Score 98%. A maximum disease-affected area was observed from day 1 to day 21 which was later mathematical modeled and predicted as 100% damage at 35 days. It finds disease severity from low to high. Previously, mostly image processing, computer vision, and machine learning techniques have been extensively applied for the identification and classification of different plant diseases on fruits and stem surfaces rather than leaf surfaces that in fact delayed the time process for adaptation of precautionary measures. The present study is novel in the sense that it proposes a deep learning technique for the early detection and classification of different levels of citrus canker to find the growth rate of disease through leaves and also calculate the affected area of the leaf with each passing day. A mathematical model of second-order polynomials is also proposed to predict the percentage of the affected area. Additionally, the findings of our experiment demonstrate that the proposed strategy is superior to the already used methods. The present approach findings will be helpful in the early detection and classification level of citrus canker disease identification and adaptation of preventive measures to control the disease before approaching the threshold level.

DECLARATION OF INTERESTS

The authors affirm that they have no known financial or interpersonal conflicts that would have seemed to have an impact on the research presented in this study.

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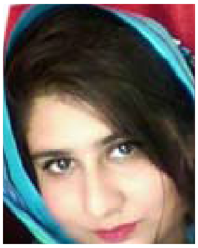

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