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LeafSpotNet: A deep learning framework for detecting leaf spot disease in jasmine plants

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ABSTRACT

Leaf blight spot disease, caused by bacteria and fungi, poses a threat to plant health, leading to leaf discoloration and diminished agricultural yield. In response, we present a MobileNetV3 based classifier designed for the Jasmine plant, leveraging lightweight Convolutional Neural Networks (CNNs) to accurately identify disease stages. The model integrates depth wise convolution layers and max pool layers for enhanced feature extraction, focusing on crucial low level features indicative of the disease. Through preprocessing techniques, including data augmentation with Conditional GAN and Particle Swarm Optimization for feature selection, the classifier achieves robust performance. Evaluation on curated datasets demonstrates an outstanding 97% training accuracy, highlighting its efficacy. Real world testing with diverse conditions, such as extreme camera angles and varied lighting, attests to the model's resilience, yielding test accuracies between 94% and 96%. The dataset's tailored design for CNN based classification ensures result reliability. Importantly, the model's lightweight classification, marked by fast computation time and reduced size, positions it as an efficient solution for real time applications. This comprehensive approach underscores the proposed classifier's significance in addressing leaf blight spot disease challenges in commercial crops.

1. Introduction

The global agricultural landscape is under constant threat from the increasing incidence of plant diseases caused by bacteria, fungi, and viruses. These infections not only jeopardize various stages of agricultural production but also lead to a substantial reduction in plant yields, impacting food security worldwide (Nazarov et al., 2020; Rathi et al., 2012; Bodenhausen et al., 2013). The consequences of these diseases extend beyond agriculture, affecting human reliance on plants for essential resources such as food, shelter, and clothing, especially in economically challenged regions (El-Ramady et al., 2022; Calicioglu et al., 2019). Numerous studies have documented the damaging effects of bacterial and fungal infections on diverse plant species, including tomatoes, cassava, strawberries, tobacco, and the widely cultivated jasmine plants in Southeast Asia (Lu et al., 2018; Lilhore et al., 2022; Abo Zaid et al., 2020; Wikee et al., 2011). Among the numerous afflictions, jasmine plants face the menace of Alternaria leaf blight spot, showcasing early signs of yellow patches with dark brown stains surrounded by yellow circles (Kamenova et al., 2006). As this disease progresses, the spots grow larger, covering substantial portions of the leaves, eventually leading to blight with concentric rings within the lesions. The impact extends to affecting the stem, petiole, and flowers, demanding timely and accurate detection for effective disease management (Nivedha et al., 2019; Sanoubar and Barbanti, 2017). Early detection of leaf spots in blight spot disease is crucial to maximize productivity. CNN-based models have been employed for plant disease detection using leaf images. For instance, a CNN model based on the Inception-v1 module and Inception ResNet-v2 was used for grape leaf disease detection (Xie et al., 2020). Another study focused on tomato leaf disease identification and classification using a CNN model and Learning Vector Quantization (LVQ) technique, utilizing 500 images of tomato leaves with four disease symptoms (Sardogan et al., 2018). Contextual information from leaf characteristics was extracted using a hybrid approach (Lee et al., 2017). CNN based approaches for detecting plant leaf diseases on various datasets, including cassava, tomato, cotton, and tobacco, have also been reported (Durmuş et al., 2017; Atabay, 2017; Zhang et al., 2019; Agarwal et al., 2020; Guo et al., 2017). Moreover, recent research (Abayomi-Alli et al., 2021) (Atila et al., 2021), (Mahum et al., 2023), and (Khan et al., 2022) have underscored the imperative for enhanced models tested in diverse conditions, highlighting a common concern primarily attributed to the utilization of smaller datasets. This limitation not only restrains the generalization capability of developed models but also compromises their effectiveness in accurately capturing

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the varied manifestations of plant diseases under different circumstances. The reliance on limited datasets undermines the robustness and adaptability of models, restricting their applicability to real world scenarios and diverse agricultural environments. In response to this drawback, our proposed methodology strives to overcome these limitations by incorporating advanced techniques, such as Conditional Generative Adversarial Networks (CGANs), to generate a comprehensive and diverse dataset for jasmine plant leaf spot disease detection. This approach aims to augment the generalization and performance of the classification model, contributing to more reliable and practical solutions in agricultural settings. This study introduces a novel approach by employing Conditional GAN to generate a jasmine plant leaf dataset that accurately simulates blight spot disease.

Additionally, a CNN based classifier algorithm is developed to effectively detect various stages of leaf disease, further enhancing the innovation of this research. The contributions of this work are as follows:

1. This paper presents a novel image based classification model specifically designed to accurately classify the different stages of leaf blight spot disease in jasmine plants.
2. This study introduces a data augmentation preprocessing technique utilizing Conditional GAN. By employing this technique, 10,000 synthetic Jasmine plant images were generated to enhance the diversity and quantity of the training data.
3. The feature selection process for classifying blight spot disease in Jasmine plants is enhanced through the utilization of the Swarm Particle Optimization method. By applying this optimization technique, the classification accuracy significantly improves to 97%.
4. The effectiveness of the proposed methodology is demonstrated by comparing it with existing CNN classifiers used in the literature. Furthermore, its performance is evaluated on leaf image datasets, including those related to leaf spot diseases in other plants such as cassava and tomato.

The structure of the paper is as follows. Section 2 presents the recent works proposed for leaf disease detection in the literature. Sections 3 and 4 present the proposed model and the results of the experimentation. Section 5 presents the conclusion of the study.

2. Related works

In recent years, various approaches have been developed for classifying disease leaf images. These approaches can be categorized into two main groups: traditional methods and deep learning-based methods.

2.1. Traditional methods

Leaf recognition systems have been developed using the fusion of Bag of Features (BOF) and Local Binary Pattern (LBP) texture features (Ali et al., 2018). These features serve as inputs for decision making. The classification was performed using a multiclass classifier based on a support vector machine (SVM). In the work (Reddy et al., 2021) explored machine learning approaches, such as SVM and Random Forest (RF), for leaf based disease detection to enhance agricultural productivity at a lower cost . Performance was evaluated using metrics such as Root Mean Square Error (RMSE), Peak Signal Noise Ratio (PSNR), and the disease affected area of the leaf, measured using Euclidean Distance Methods. The study (Geetha et al., 2020) proposed four preprocessing steps to reduce noise in the leaf image dataset. Additionally, the study (Annabel et al., 2019) utilized traditional classification techniques, including the K Nearest Neighbors (KNN) algorithm, to classify plant leaves based on morphological features such as color, intensity, and size. Various machine learning algorithms such as Naive Bayes (NB), Decision Tree (DT), KNN, and RF were explored, with the RF algorithm achieving the highest accuracy of 79.23% for maize classification (Panigrahi et al., 2020). However, most machine learning approaches struggled to achieve high classification accuracy due to challenges in identifying discriminative features. To address this, hybrid approaches combining a CNN based feature extractor and SVM classifier have been proposed to improve the classification process (Varshney et al., 2022), achieving a classification accuracy of 88.77%.

2.2. Deep learning based methods

Several studies have proposed CNN based approaches for leaf disease detection, as mentioned in the works such as (Falaschetti et al., 2022), (Nawaz et al., 2022), and (Eunice et al., 2022). However, these approaches were limited to specific types of leaf dataset images. In order to address overfitting issues in classifier models, data augmentation methods have been employed (Yadav et al., 2022; Li et al., 2022). The study (Kumar et al., 2016) utilized the Skew Divergence method for feature selection in Cotton Leaf Spot Diseases, while another study (Chuanlei et al., 2017) employed correlation based feature selection methods using a Genetic algorithm for apple leaf disease identification. Previous studies have demonstrated that data augmentation and feature selection processes in leaf image analysis can enhance classification performance and mitigate overfitting issues.

Various studies have addressed plant disease detection using diverse datasets and methodologies. The study (Almadhor et al., 2021) employed color difference image segmentation and machine learning classifiers on the Guava leaf dataset, achieving detection accuracy. In contrast, the research (Rehman et al., 2021) focused on Apple disease detection, utilizing MASK RCNN for infected region identification and SVM classifiers reported an ensemble classification accuracy of 98.12%. The study by (Oyewola et al., 2021) focused on detecting diseases in Cassava, utilizing intricate block processing and a Deep Residual Convolutional Neural Network (DRNN). Notably, DRNN demonstrated a superior performance of 9.25% compared to the plain convolutional neural network (PCNN) when evaluated on the Cassava Disease Dataset. This highlights the importance of employing a robust classifier for effective disease detection. In the investigation of cucumber disease detection,(Kianat et al., 2021) applied feature fusion and selection in conjunction with machine learning classifiers. This approach demonstrated an accuracy of around 93.5%, emphasizing the limited presence of deep learning focused strategies within the field. The study (Singh et al., 2022) adopted Histogram Equalization and Automatic Feature Extraction for Apple disease detection using KNN. They did not utilize deep learning techniques, suggesting potential exploration of data augmentation and the need for lightweight yet robust classifiers to address specific challenges. The work (Abayomi Alli et al., 2023) introduced a fruit dataset for freshness evaluation, employing a ResNet18 classifier. (Pham et al., 2020) focused on Mango disease detection, using binary segmentation with textural and statistical features and an artificial neural network (ANN). The study (Sambasivam and Opiyo, 2021) explored predictive models for the Cassava Mosaic dataset, incorporating Contrast Limited Adaptive Histogram (CLAHE) Equalization with a CNN. The smaller dataset resulted in an accuracy of 93%, indicating the importance of dataset augmentation and classifier robustness. (Sangbamrung et al., 2020) worked on Cassava disease detection with a 15 layer custom CNN, achieving a notable F1 score of 0.96 despite a smaller dataset. The study (Abayomi-Alli et al., 2021) addressed Cassava disease detection using a Gaussian blurring method and a MobileNetV2 classifier. The model achieved 97.7% accuracy on high quality images, but its performance notably dropped on low quality images. (Atila et al., 2021) used the Plant Village dataset with EfficientNet B5 and B4, planning to test their adopted method in varied conditions. (Mahum

Table 1
Summary of the existing methods used in the plant disease detection.

Literature	Dataset	Preprocessing	Classification	Result and Remark
Almadhor et al. (2021)	Guava leaf and fruit	Color difference image segmentation with RGB, HSV histogram integration	Machine learning classifiers	Machine learning classifiers tested on the Guava leaf dataset detection
Rehman et al. (2021)	Apple	MASK RCNN for identifying infected regions	SVM classifier	Ensemble classification reported with accuracy of 98.12%
Oyewola et al. (2021)	Cassava	Incorporating detailed block processing	Deep Residual Convolutional Neural Network (DRNN)	DRNN surpasses plain convolutional neural network (PCNN) by 9.25% on Cassava Disease Dataset
Kianat et al. (2021)	Cucumber plant	Fusing and selecting features for cucumber disease detection	Machine learning classifiers	Accuracy achieved around 93.5% on the selected dataset and lack of deep learning focused approaches
Singh et al. (2022)	Apple	Histogram Equivalization and Automatic Feature Extraction	KNN	Deep learning techniques are not used
Abayomi Alli et al. (2023)	Fruit		ResNet-18 classifier	Fruit dataset is proposed images for freshness evaluation
Pham et al. (2020)	Mango	Utilizing Binary Segmentation with textural and Statistical features	ANN	Binary Segmentation method is employed
Sambasivam and Opiyo (2021)	Casava Mosaic dataset	Contrast Limited Adaptive Histogram Equivalization	CNN	Small dataset resulted in the accuracy of 93%
Sangbamrung et al. (2020)	Casava		15-layer custom CNN	Small dataset scored an F1 score 0.96 accuracy
Abayomi-Alli et al. (2021)	Casava	Guassian blurring method	MobileNetV2 classifier	Achieving 97.7% accuracy on high quality images, the dataset's performance notably drops on low quality images
Atila et al. (2021)	PlantVillage dataset		EfficientNet B5 and B4	Testing the adopted method in varied conditions
Mahum et al. (2023)	Potato leaves		DenseNet-201	Smaller dataset
Khan et al. (2022)	Apple		Faster RCNN	Detection model achieved mAP of 42

et al., 2023) focused on potato leaves with DenseNet-201, working with a smaller dataset. (Khan et al., 2022) applied Faster RCNN for Apple disease detection, achieving a detection model with a mean Average Precision (mAP) of 42%. These diverse approaches contribute to the field's continuous development, emphasizing the importance of robust classifiers and the exploration of data augmentation techniques. The overall comparison of the existing method is given in Table 1.

3. Methodology

The present study introduces a classification model based on MobileNetV3 to detect the different stages of Jasmine plant leaf disease. MobileNetV3 was specifically designed to optimize performance on mobile phone CPUs using hardware aware Network Architecture Search (NAS) (Howard et al., 2019). It is a lightweight neural network with superior classification accuracy compared to larger networks such as AlexNet, InceptionV3, and ShuffleNetV2 in image classification tasks (Qian et al., 2021). Fig. 1 illustrates the proposed methodology, which comprises several key components: a Data augmentation block, a depthwise separable convolution block, an inverted Residual block, a feature extraction block, a feature selection block, and a classification block.

3.1. Dataset

Fig. 2 showcases image samples of diseased leaf stages used in the study. To develop the dataset for diseased leaf images, collaboration was established with experts from Krishi Vigyan Kendra, Karnataka, India. Digital cameras were employed to capture a total of 2000 images. These images represent four stages of Alternaria leaf blight spot disease, with 450 images for stage-1, 550 images for stage-2, 500 images for stage-3, and 500 images for stage-4. To enhance the dataset, Conditional GAN based augmentation techniques were employed, as further discussed in the following section. To assess the robustness of the proposed approach, two additional datasets with similar leaf spot diseases were utilized. The first dataset, referred to as the “cassava dataset,” consisted of images of cassava leaf diseases (Ramcharan et al., 2017). The second dataset, referred to as the “tomato dataset,” included images of tomato leaf diseases (Huang and Chang, 2020). To achieve data reliability the following steps were taken.

1. Collaboration with Experts: Working with experts in plant pathology from Krishi Vigyan Kendra ensures that the captured images are correctly identified and categorized based on the disease stages.
2. Structured Dataset: The dataset is well organized with a specific number of images allocated to each disease stage, providing a systematic representation of the disease's progression.
3. Image Capture with Digital Cameras: The use of digital cameras for image capture contributes to the accuracy of the dataset by ensuring high quality images that faithfully represent the visual characteristics of the disease.
4. Augmentation Techniques: The application of Conditional GAN based augmentation techniques enhances the dataset's diversity, introducing additional variations in disease manifestation. This step is crucial for training a robust model that can handle different scenarios.
5. Incorporation of Additional Datasets: The inclusion of two additional datasets featuring similar leaf spot diseases (cassava and tomato datasets) serves to evaluate the proposed methodology's performance across different plant species. This further strengthens the dataset's reliability by testing the model's generalization capabilities.

3.2. Data augmentation using Conditional GAN

A Conditional Generative Adversarial Network (CGAN) utilizes a conditional argument to generate new samples that belong to a specific category (Wickramaratne and Mahmud, 2021). This conditional input enables the Generator in the CGAN to generate synthetic samples based on the given condition. In the context of GANs, Convolutional Neural Networks (CNNs) are widely used, especially for processing image data. CNNs have shown impressive performance across various computer vision tasks, consistently achieving state of the art results. In the case of GANs, the Generator takes a compressed representation of the training image set as input and produces new images as output. A total of 2000 images were employed for augmentation purposes. The images were partitioned into different sets for training purposes. The training set consisted of 450 healthy images per class, serving as input images. In addition, the template set included images representing different stages of leaf disease, which were incorporated into the training process. Moreover, a 100 dimensional vector was employed, composed of randomly generated numbers drawn from a uniform distribution ranging between 0 and 1. The input image is resolution of 256×256

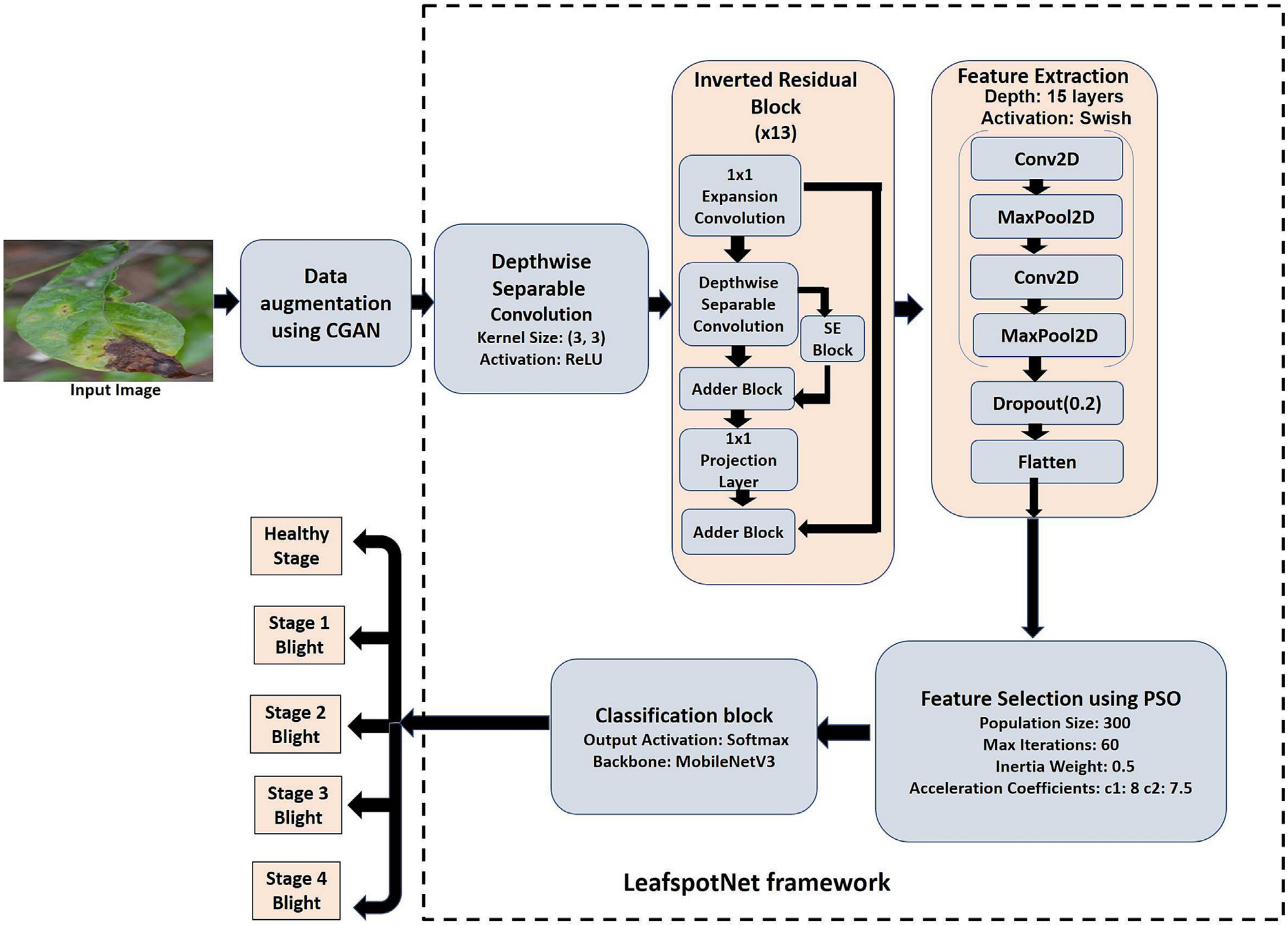

Fig. 1. Overall proposed CNN classification algorithm for Jasmine plant leaf disease detection.

pixels. To achieve a final resolution of 256 × 256 pixels in RGB format for the generated images, a generator was utilized, consisting of Convolutional Transpose layers. In contrast, the discriminator network employed two convolutional layers with 128 neurons each, using a (3,3) kernel size and a (2,2) stride to down sample the input and reduce its resolution. The activation function applied in each layer was LeakyReLU, and the output was scaled using hyperbolic tangent activation. The training process involved the use of the ADAM optimizer. The training of the generator is specifically aimed at preventing the discriminator from accurately identifying fake images. The GAN model is trained to minimize the Ladv loss, which is fine tuned during the training process.

The iterative optimization process focuses on achieving a Frechet Inception Distance (FID) score below 3, a parameter for evaluating the model's performance. The GAN model undergoes 100 training epochs with a batch size of 64. To determine the similarity between the generated results and the template images, parameters such as Structural Similarity Index (SSIM) and Signal to Noise Ratio (SNR) are used as measurement metrics. The overall methodology is shown in Fig. 3.

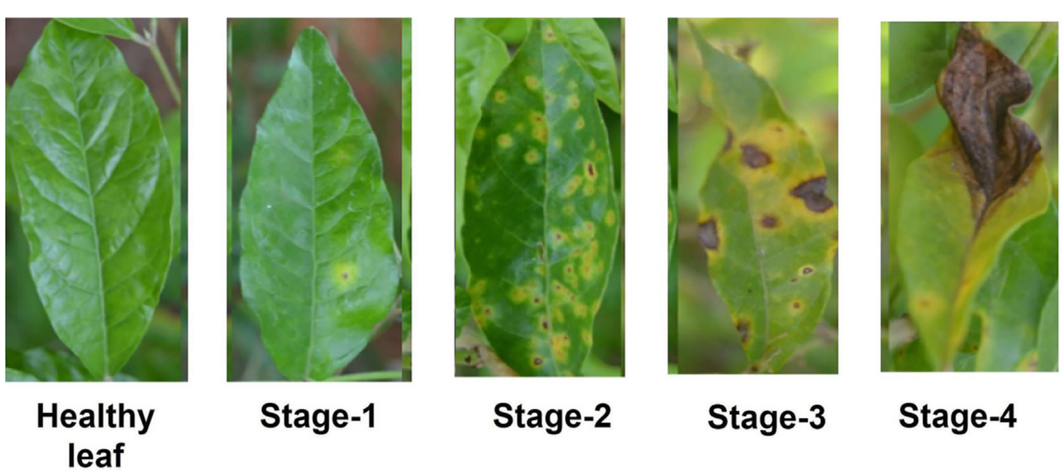

Fig. 2. Jasmine plant leaf spot disease dataset.

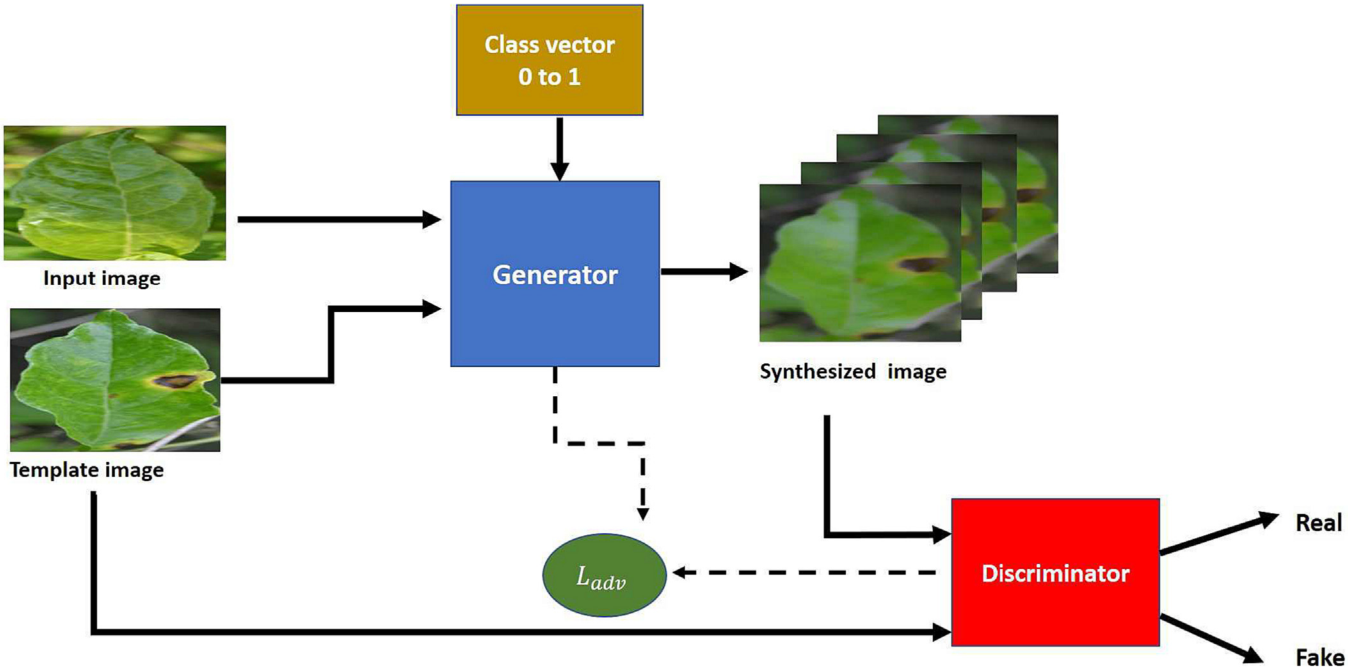

Fig. 3. Data agumentation using CondtionalGAN approach.

By utilizing the template of stage-1, stage-2, and stage- 3 Jasmine plants, along with various healthy leaves as input, the GAN model could generate images representing different stages. The model incorporated a class vector of 100, ranging between 0 and 1, to facilitate the generation of 100 images per iteration. This iterative process enabled the generation of a total of 10,000 images, encompassing various classes. The augmented images were subsequently passed through the classification model for further analysis, detailed in the next section.

3.3. Jasmine Leaf Plant detection classification model

The jasmine leaf plant disease detection is performed using a CNN classifier based on MobileNetV3, as explained in the following section.

3.4. Depthwise separable convolution

MobileNetV3 employs a novel computing technique called depthwise separable convolution. This technique shares similarities with traditional convolution but introduces a two-stage calculation process. Unlike traditional convolution, which performs a single convolutional calculation per layer, depthwise separable convolution splits the calculation into two phases. In the first stage, each input channel undergoes a separate convolutional operation with a 3 × 3 kernel, followed by batch normalization and activation. This step is known as depthwise convolution. In the second stage, the output channels from the depthwise convolution are further processed with a 1 × 1 pointwise convolution. This pointwise convolution is applied to all depthwise convolution output channels. Overall, the use of depthwise separable convolution significantly enhances computational efficiency by reducing the amount of computation required. Table 1 provides a detailed description of the classification framework, including information about Convolution layers 1 and 2. In this study, the depthwise convolution layer is denoted as conv_dw, while the pointwise convolution layer is denoted as conv_pw. The same process is repeated for layers 3 to 12, with the final convolutional layer labeled as layer 13. The parameter reduction at each sequential layer can be observed in Table 2.

3.4.1. Inverted residual block

The inverted residual block found in bottleneck block networks (He et al., 2016) serves as the inspiration for the design of MobileNetV3. To enhance the learning of complex representations while simplifying model computations, MobileNetV3 incorporates 1 × 1 expansion and projection convolution layers alongside depthwise convolutions with a kernel size of 1 × 1. This structure includes a depthwise separable convolution layer along with a residual connection. Additionally, MobileNetV3 integrates a channel wise Squeeze & Excite block (SE) (Mabrouk et al., 2022; Tan et al., 2019) to select channel wise features from the leaf dataset. To improve accuracy, the ReLU function in the

Table 2
Overview of the LeafSpotNet classification network framework, featuring MobileNetV3 large as the backbone architecture.

Name	Layer	Feature Para maps	Meter
Input_1	InputLayer	3	0
conv1	Conv2D	32	864
conv1_bn	BatchNormalization	32	128
conv1_relu	ReLU	32	0
conv_dw_1	DepthwiseConv2D	32	288
conv_dw_1_bn	BatchNormalization	32	128
conv_dw_1_relu	ReLU	32	0
conv_pw_1	Conv2D	64	2048
conv_pw_1_bn	BatchNormalization	64	256
conv_pw_1_relu	ReLU	64	0
conv_pad_2	ZeroPadding2D	64	0
conv_dw_2_bn	BatchNormalization	64	256
conv_dw_2_relu	ReLU	64	0
conv_pw_2	Conv2D	128	8192
conv_pw_2_bn	BatchNormalization	128	512
conv_pw_2_relu	ReLU)	128	0
conv_dw_3	DepthwiseConv2D	128	1152
conv_dw_3_bn	BatchNormalization	128	512
conv_dw_3_relu	ReLU	128	0
conv_pw_3	Conv2D	128	16,384
conv_pw_3_bn	BatchNormalization	128	512
conv_dw_13	DepthwiseConv2D	1024	9216
conv_dw_13_bn	BatchNormalization	1024	4096
conv_dw_13_relu	ReLU	1024	0
conv_pw_13	Conv2D	1024	1,048,576
sequential_1	Sequential	128	17,928
dense_1	Dense	5	645

layer is replaced with a novel activation function called Swish, which is defined by eq. 1.

$$\boldsymbol{swish}(\boldsymbol{x}) = \boldsymbol{x}.\boldsymbol{\sigma}(\boldsymbol{x}) \tag{1}$$

Where $\sigma(x) = \frac{1}{1+\exp(-x)}$ is the sigmoid function. The sigmoid function in the swish formula could use much computational power. In the MobileNetV3 use of the ReLU6 function to approximate the sigmoid function in swish creates an approximation of the swish function, also known as the hard version of swish, which is denoted by $h - swish(x)$ (He et al., 2016) given by the eq. 2.

$$h - swish(x) = x.\frac{ReLU6(x+3)}{6} \tag{2}$$

3.4.2. Feature extraction block

To extract more features related to leaf spots, depthwise 1×1 convolution layers are introduced. The dimensionality of the extracted features is subsequently reduced using a max pooling layer. The classifier is trained using the ImageNet- 21 k dataset (Ridnik et al., 2021), employing a Transfer Learning (TL) approach with the leaf dataset. The input images are standardized to a resolution of 224×224 pixels. The pre-trained model is fine-tuned using the leaf dataset, allowing it to adapt to the specific characteristics of the leaf spots. The output of the pointwise 1×1 convolutional layer, which serves as a pre-classification layer, is flattened to create a feature vector. Each feature vector, with 128 pixels, is utilized in the subsequent feature selection process.

3.4.3. Feature selection using swarm particle optimization

To extract low level features from the leaf dataset images, additional convolutional layers are incorporated. However, this leads to an increase in the feature size. To address this, the feature selection block introduces the Swarm Particle Optimization algorithm. This algorithm aids in the elimination of irrelevant features before the classification process. Particle Swarm Optimization (PSO), also known as the Birds Swarm algorithm was initially developed by Kenny et al. in 1995 (Banks et al., 2008). PSO is employed as a random optimization procedure for feature selection and classification purposes (Hafiz et al., 2018). The goal is to continuously select the most relevant and useful set of features to enhance the classification performance of the leaf spot detection framework. Initially, all particles are assigned initial values, and fitness values are estimated for each particle. The current fitness value is then evaluated, and if it is superior to the previous value, it is updated accordingly. Conversely, if the previous fitness value is higher, it is retained (Shi et al., 2001). This process continues until the best solution is obtained. The PSO algorithm is mathematically represented by an equation (Ahmed et al., 2021). In the context of feature selection for image classification tasks, especially in the domain of plant disease detection, the goal is to identify a subset of relevant features that contribute most to the classification accuracy. PSO is favored for its ability to handle the combinatorial nature of feature selection problems effectively.

$$\begin{aligned} P_i^d(t+1) = {} & wv_i^d(t) + c_1 r_1 \left(Pbest_i^d(t) - x_i^d(t)\right) \\ & + c_2 r_2 \left(Gbest^2(t) - x_i^d(t)\right) \end{aligned} \tag{3}$$

In our approach, the velocity of each particle, denoted as P, is bounded within the range of $wmax$ and $wmin$, where w represents the inertia weight. The time interval t corresponds to the number of iterations i for the population, which defines our feature domain. The dimension of the search area is represented by d. Acceleration factors are denoted as $c1$ and $c2$, while $r1$ and $r2$ represent independent random numbers. The personal best solution is recorded as $P\,best$, and the global solution is recorded as $Gbest$ by the swarm optimizer (Ahmed et al., 2021; Shi et al., 2001).

3.4.4. Classification block

Following the feature selection step, an optimized feature selection process is performed to eliminate unwanted features. The classification block utilizes a softmax activation function to categorize the leaf images into four stages of blight spot disease.

3.4.5. Parameter tuning details

To achieve the optimal classification performance, the model undergoes fine tuning for 50 epochs with a batch size of 32. The Adam optimizer is employed with a learning rate of 0.001. The parameter used for PSO optimization is determined through experimental analysis, and the specific values can be found in Table 3. The initial parameter choices were theoretically grounded and fine tuned. However, the practical adaptation of these parameters evolved empirically, as demonstrated in Table 3. This iterative process ensured the model's alignment with the dynamic nature of plant datasets, highlighting its adaptability and responsiveness to the nuanced complexities of plant images for accurate disease detection.

The algorithm for fine tuning LeafspotNet, the proposed model for leaf spot disease detection, leveraging Conditional GAN and a modified MobileNetV3, is outlined in Algorithm 1 and Algorithm 2.

Algorithm 1. Conditional GAN augmentation for Jasmine leaf spot image generation

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Require: Number of training epochs 100, batch size 64
Initialize Generator G and Discriminator D discriminatory two convolutional layers with 128 neurons each, using a (3, 3) kernel size and a (2, 2) stride to downsample with each layer LeakyReLu activation function
Initialize parameters: learning rate 0.001, loss functions 0.1.
Load and preprocess 2000 images for augmentation
Partition images into training sets into four classes of 250 each
for epoch ← 1 to 100 **do**
  for each batch in training set **do**
    Generate random noise vector 0 to 1 and class vector 100
    Generate fake images of 256x256 pixels
    Get real images and labels from the training set
    Update Discriminator: $D \leftarrow ADAM(D, compute\_discriminator\_loss(D, real, fake)$
    Update Generator: $G \leftarrow ADAM(G, compute\_generator\_loss(D, fake)$
  end for
end for
Evaluate model using metrics like FID less 3, SSIM, SNR score
for iteration ← 1 to 100 **do**
  Generate random noise vector 0 to 1 and class vector 100
  Generate synthetic images: $synthetic\_images \leftarrow G(z, c)$
  Save $synthetic\_images$ for further analysis
end for
Pass augmented images through the classification model

Algorithm 2. Leaf Spot Detection using MobileNetV3

```
MobileNetV3 Architecture Initialization
while Training Epochs do
    for each Layer in MobileNetV3 do
        Perform Depthwise Convolution
        Batch Normalization and ReLU Activation
        Perform Pointwise Convolution
        Batch Normalization and ReLU Activation
    end for
end while
MobileNetV3 Inspired Inverted Residual Block
Incorporate 1x1 Expansion and Projection Convolution Layers
Integrate Depthwise Convolution with 1x1 Kernels
Include Squeeze & Excite Block for Channel-wise Features
Replace ReLU with Swish Activation Function
Introduce Depthwise 1x1 Convolution Layers
Reduce Dimensionality with Max Pooling Layer
Transfer Learning with ImageNet-21k Dataset
Fine-tune Model with Leaf Dataset
Standardize Input Images to 224x224 Pixels
Flatten Output of 1x1 Convolutional Layer
Fine-tuning Parameters:
Learning Rate: 0.001
Batch Size: 32
Fine-tune for Additional Epochs
Initialize PSO Algorithm Parameters
while Not Converged do
    Update Particle Velocities and Positions using Equation (3)
    Evaluate Fitness Values for Each Particle
    Update Personal Best and Global Best Solutions
end while
Optimize Feature Selection for Classification
Utilize Softmax Activation Function
Categorize Leaf Images into Disease Stages
```

The overall working of LeafspotNet is outlined in the flow chart, illustrating the training of the model with both synthesized and real images. The model is subsequently tested with real images to ensure its generalizability in real time situations, as depicted in Fig. 4. Using a fine tuned model suitable for jasmine plant image augmentation and featuring particle swarm optimization for effective feature selection, the approach combines advanced techniques to enhance the robustness and accuracy of disease detection.

Table 3
Parameters of PSO for the feature selection obtained experimentally.

Parameters	Description	Value
N	Size of the population	300
T	Iteration	60
C_1	Cognitive factor	8
C_2	Social factor	7.5
w_{max}	Maximum bounded on inertia weight	0.9
w_{min}	Minimum bounded on inertia weight	0.6
P_{max}	Maximum Velocity	7

3.5. Performance matrices

To evaluate the effectiveness of the CGAN augmentation method, the similarity between the synthesized images and the template images is measured. For this evaluation, two widely used similarity metrics, namely the Peak Signal to Noise Ratio (PSNR) and the Structural Similarity Index (SSIM) (Bejnordi et al., 2017), are employed (Kang et al., 2021). These metrics provide valuable insights into the level of similarity between the generated images and the target images, facilitating a comprehensive assessment of the performance of the CGAN augmentation model.

Precision, Recall, F1 score, and classification accuracy are used to assess the classifier performance. ROC curves are plotted, in which the Area Under Curve (AUC) indicates the classification performance. The Confusion Matrix and Training and Validation accuracy curve are also used to assess the performance of classification.

3.6. Comparative analysis of CNN classification algorithms

To evaluate the effectiveness of our proposed model, a comparison is conducted with widely used CNN classifiers including VGG16, InceptionNetV3, and MobileNetV3 (without customization). These models are pretrained on the ImageNet-21 k dataset and then fine-tuned using our custom leaf dataset. All classifiers are trained for 50 epochs, employing a batch size of 32 to optimize classification performance. The Adam optimizer with a learning rate of 0.001 is utilized for the classification process. By comparing the results of our proposed model with these established CNN models, we aim to assess its relative performance and effectiveness in leaf classification tasks.

3.7. Robustness evaluation of the proposed classifier

The robustness of the proposed classifier is assessed by utilizing images of cassava leaf plants and tomato leaf plants, both affected by blight spot disease. The dataset consists of a total of 9000 images from the cassava dataset and 8000 images from the tomato dataset. This study considers four stages of the blight spot disease in the evaluation process.

3.8. Evaluating the Performance of the Classifier with and without SPO Algorithm

The model is initially trained without the feature selection block, and performance metrics are plotted accordingly. Subsequently, the model is trained again, this time with the inclusion of the feature selection block. However, the tuning parameters remain consistent: the number of epochs is set at 50, the batch size is 32, and the Adam optimizer with a learning rate of 0.001 is maintained throughout the experiment.

3.9. Training techniques employed

To assess the robustness and generality of the proposed classifier, it is fine-tuned with the private Jasmine leaf dataset and the public cassava and tomato leaf dataset. The pre-trained model is fine-tuned independently with all these datasets with the same tuning parameters. In addition, we combined the Jasmine plant with the cassava dataset, then with the tomato dataset and combined all three datasets.

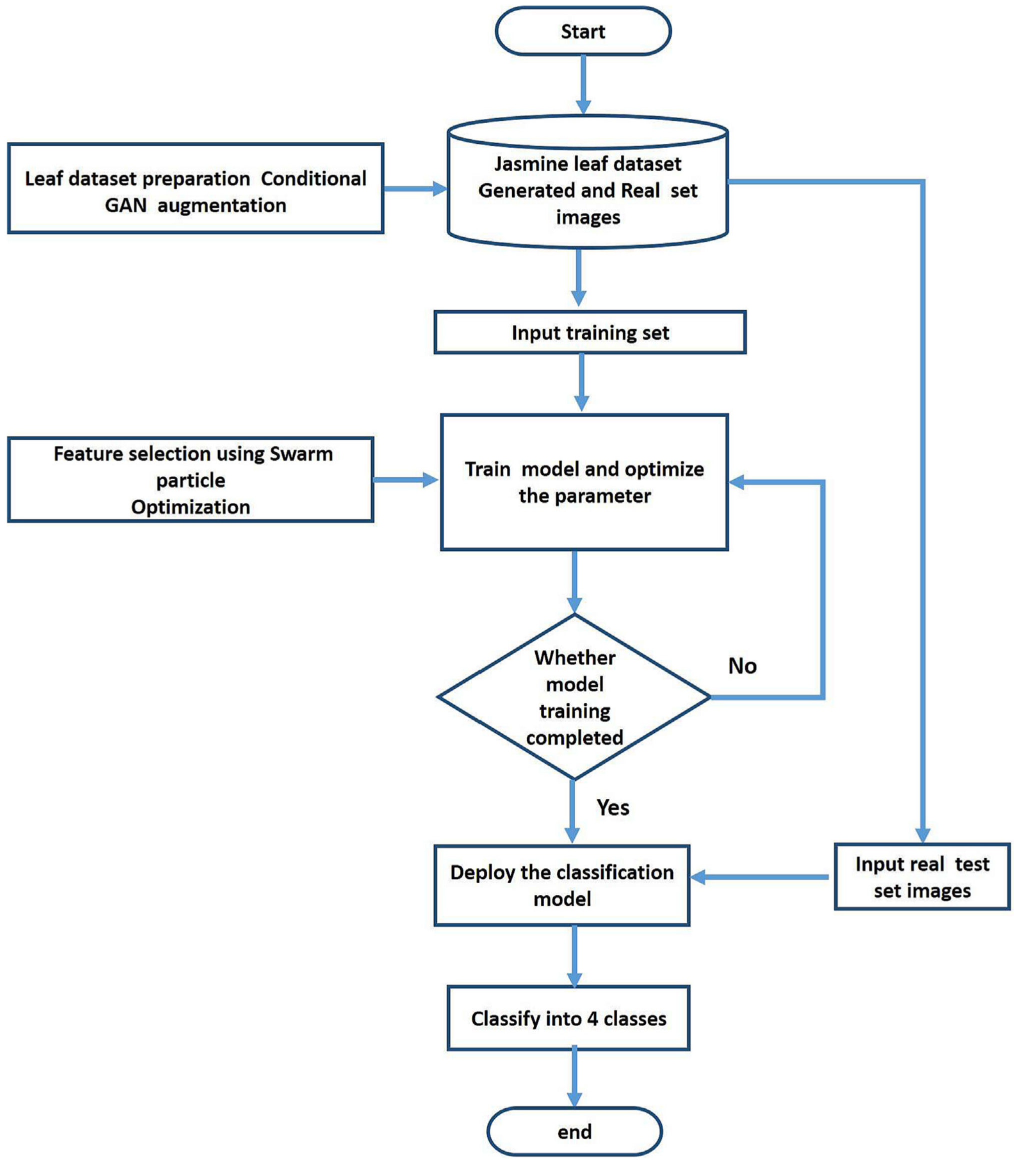

Fig. 4. Overall flowchart of leaf spot disease detection.

3.10. Robustness evaluation of classifier testing with extreme camera angles and challenging conditions

In this study, we conducted robustness testing of our classifier by assessing its performance under various challenging conditions. The Jasmine leaf test dataset used for this evaluation consists of 500 images captured in different scenarios, including shots taken with two different smartphones (Smart phone −1 and Smart phone −2), two distinct cameras (Camera-1 and Camera-2), images with extreme camera angles, diverse lighting conditions, and variations in grain noise. This comprehensive dataset allows us to simulate real world scenarios and assess the classifier's ability to generalize across different conditions. The test conditions are visually illustrated in Fig. 5, showcasing sample images representing the diverse challenges posed to the classifier during robustness testing.

4. Result and discussion

In this section, we reported the results of the CGAN component in dataset augmentation, compared data augmentation techniques in the classification process, evaluated the proposed classifier model for leaf spot disease detection, conducted an ablation study, and compared our methodology with existing methods.

4.1. CGAN component in dataset augmentation

The FID score is a widely accepted metric for evaluating the fidelity of generated images compared to real ones in a dataset. The goal is to train the CGAN to maintain a stable FID score within a specified range, ideally around 3 as shown in Fig. 6. Keeping the FID score within this range indicates that the generated images closely resemble the characteristics of real images, demonstrating high visual quality and diversity. Consistent FID scores reflect the success of the training process in achieving realistic and diverse image generation.

Through the data augmentation process, we obtained approximately 10,000 images, the dataset sample as shown in Fig. 7.

In our study, we utilized CGAN augmentation methods to significantly augment our private jasmine plant leaf dataset, resulting in 2000 images per class. *SSIM* is used to evaluate the preservation of structural information in the generated images compared to the template images. On the other hand, the *P SNR* assesses the retention of color information in the generated images, similar to the template images. The

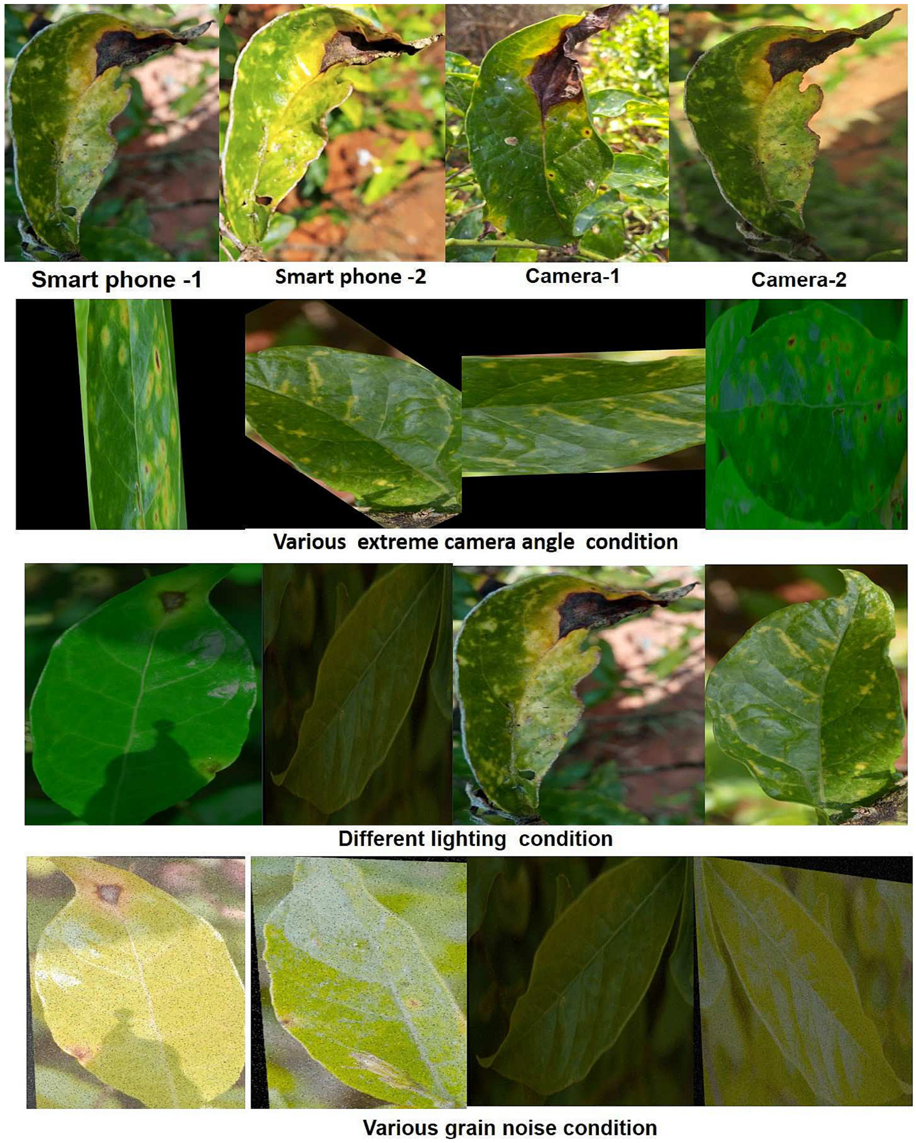

Fig. 5. Jasmine leaf test dataset comprising images captured using various smartphones, cameras, lighting, and grain noise conditions.

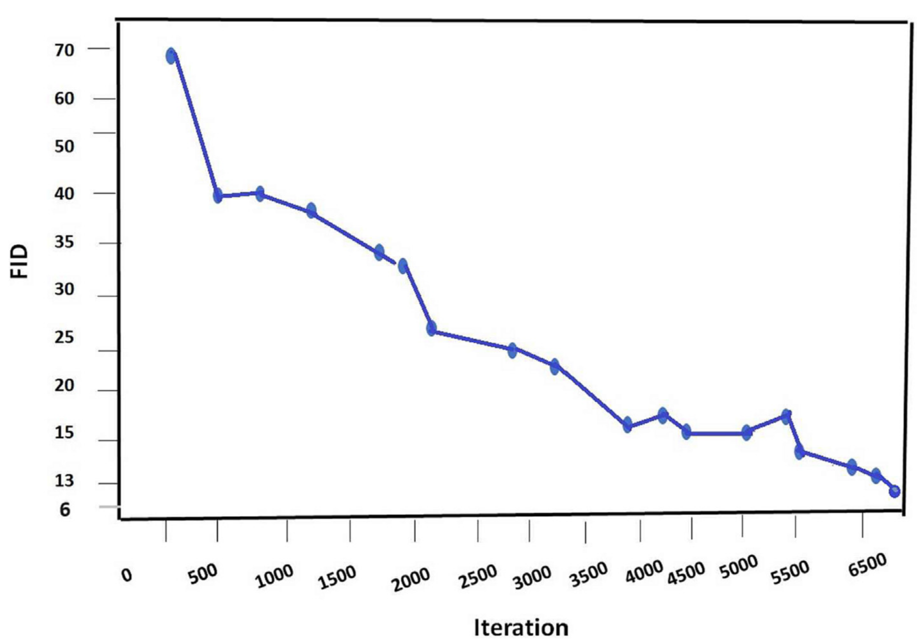

Fig. 6. FID score on Jasmine leaf dataset.

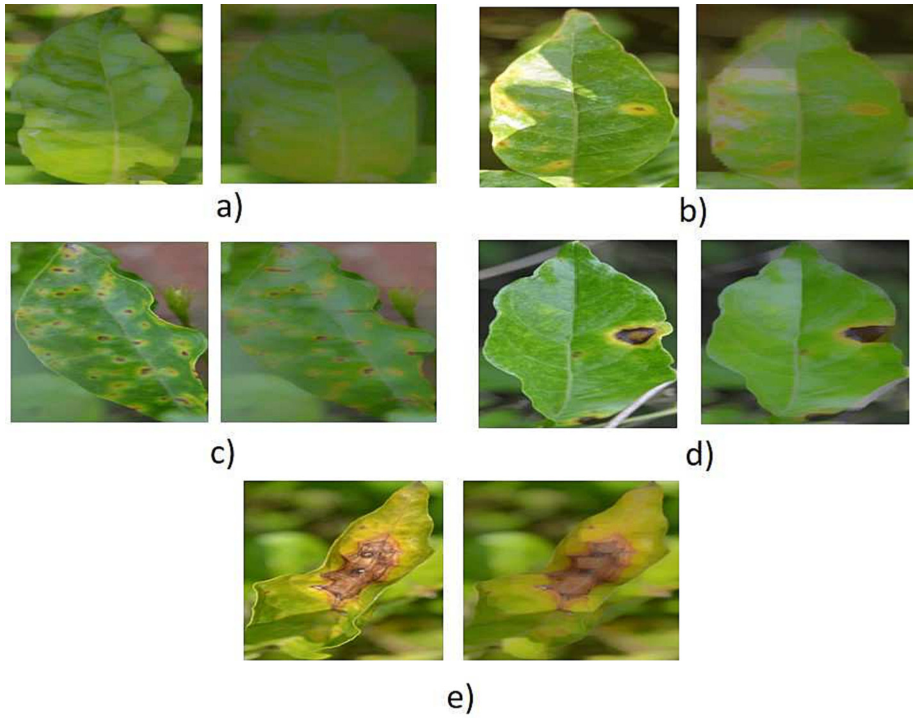

Fig. 7. Augmentated images using CGAN Approach a) Healthy leaf, b) Stage-1, c) Stage-2, d) Stage-3 and e) Stage-4 Jasmine plant leaf disease.

Table 4
Evaluation metrics of methods.

Synthesized image	*SSIM*	*P SNR*
Healthy leaf	0.81 ± 0.02	17 ± 3.1
Stage-1	0.87 ± 0.011	18 ± 4.5
Stage-2	0.89 ± 0.072	23 ± 1.7
Stage-3	0.90 ± 0.072	25 ± 2.4
Stage-4	0.88 ± 0.072	27 ± 6.7

statistical significance of the *SSIM* and *P SNR* results is determined based on an average of 500 test image samples, and the findings are presented in Table 4.

In Table 5, a comparative analysis of various data augmentation techniques applied in previous studies on plant disease detection for the Jasmine leaf dataset is presented. The techniques include cropping and mirroring (Yang et al., 2023), shifting and rotating (Enkvetchakul and Surinta, 2022), Gaussian blurring method (Abayomi-Alli et al., 2021), local based augmentation (Wongbongkotpaisan and Phumeechanya, 2021), and CNN based methods (Sladojevic et al., 2016; Bi and Hu, 2020). Each technique is evaluated based on accuracy, precision, and F1 score. Notably, the proposed CGAN method outperforms other techniques, showcasing a significant improvement in accuracy, precision, and F1 score, with values of 0.93, 0.96, and 0.97, respectively. This underscores the efficacy of the proposed Leadspot Net classifier when integrated with the CGAN approach, highlighting its superior performance in achieving accurate and reliable plant disease classification on the Jasmine leaf dataset.

Table 5
Comparative Analysis of Data Augmentation Techniques Employed in Previous Studies on Plant Disease Detection during the Classification Process for Jasmine leaf dataset.

Technique	Accuracy	Precision	F1 Score
Cropping, Mirroring (Yang et al., 2023)	0.72	0.75	0.77
Shifting, rotating (Enkvetchakul and Surinta, 2022)	0.72	0.71	0.79
Gaussian blurring method (Abayomi-Alli et al., 2021)	0.87	0.85	0.84
CNN method (Bi and Hu, 2020)	0.86	0.85	0.84
Local Based (Wongbongkotpaisan and Phumeechanya, 2021)	0.81	0.83	0.80
Proposed CGAN method	0.93	0.96	0.97
CNN (Sladojevic et al., 2016)	0.82	0.84	0.84

4.2. Evaluation of proposed classifier model for the leafspot disease detection

This expansion of the dataset size yielded notable improvements in the performance of the proposed classifier. However, it also introduced fluctuations and variations in the training and validation accuracy, which ranged from 88% to 90%. These variations can be attributed to the augmented dataset's enhanced feature extraction capabilities, facilitated by adding additional convolution and max pool layers. To visualize the impact, Fig. 8 presents the training and validation accuracy curve for the LeafSpotNet classifier without the feature selection process.

The performance of the proposed LeafSpotNet classifier was evaluated on various datasets. When optimized with the PSO optimization algorithm for the feature selection process, the classifier achieved an impressive classification accuracy of 97% on the Jasmine plant dataset. Furthermore, the LeafSpotNet classifier demonstrated classification accuracies of 94% for the Cassava dataset and 95% for the Tomato leaf dataset. To compare its performance with other CNN classifiers commonly used in leaf disease detection literature, VGG16, InceptionNetV3, and MobileNetV3 were considered. Notably, the LeafSpotNet classifier achieved the highest classification accuracy of 97%, as depicted in Fig. 9.

The Precision, Recall, and F1 Score metrics were plotted to assess the performance of the proposed LeafSpotNet classifier, as well as VGG16, InceptionNetV3, and MobileNetV3 classifiers. As shown in Fig. 10, the graph clearly demonstrates that LeafSpotNet outperformed the other classifiers across these metrics. Notably, when evaluating the results

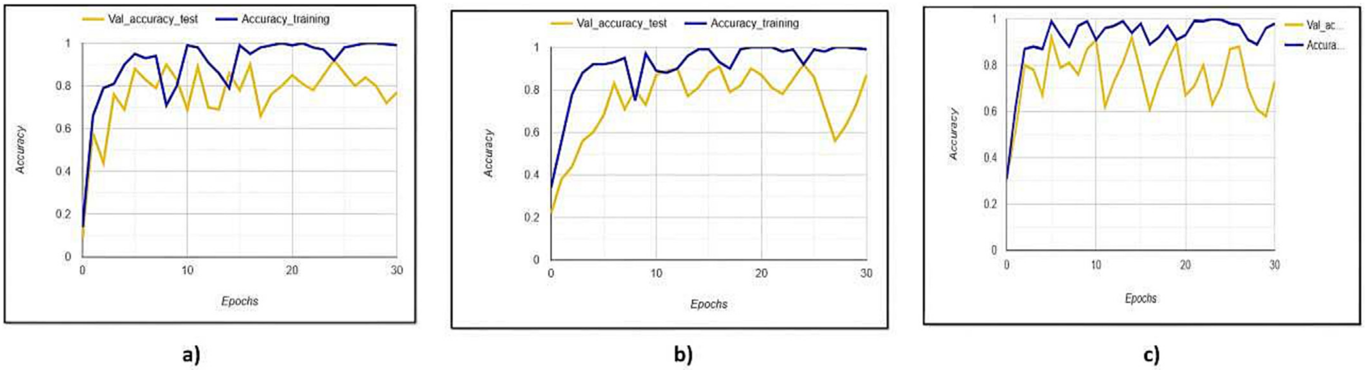

Fig. 8. Training and validation curve of a) Jasmine plant leaf dataset b) Cassava dataset and c) tomato dataset before the PSO optimization algorithm.

on the private dataset, LeafSpotNet exhibited superior performance compared to the public cassava and tomato datasets. The confusion matrix obtained for the test images of the Jasmine plant leaf, Cassava, and Tomato leaf datasets is presented in Fig. 11. A test set comprising 500 images per class was utilized for all the datasets. The confusion matrix provides valuable insights into the classification performance, highlighting the accuracy and misclassification rates for each class in the respective datasets. The training and validation accuracy curve depicted in Fig. 12 demonstrates the classifier's performance with the integration of the PSO optimization algorithm. Notably, the curve indicates the successful mitigation of overfitting issues, as evidenced by the absence of significant fluctuations and a consistent level of accuracy throughout the training process. The utilization of the PSO optimization algorithm has effectively stabilized the accuracy curve, resulting in improved performance and reduced variability.

This study demonstrates that the LeafSpotNet classifier achieves the highest classification accuracy when trained with the private Jasmine plant leaf dataset, outperforming other classifiers. Fig. 13 further illustrates the performance of the LeafSpotNet classifier, with an Area Under Curve (AUC) value of 0.98, which is the highest among the evaluated classifiers. When the Jasmine plant leaf dataset is combined with the tomato leaf dataset for classification, the accuracy of the LeafSpotNet classifier slightly decreases, with an AUC value of 0.90, as depicted in Fig. 14.

Furthermore, the accuracy of the LeafSpotNet classifier increases again when the combined dataset of the Jasmine plant leaf dataset and the tomato leaf dataset is supplemented with the cassava leaf dataset for classification, resulting in an AUC value of 0.95, as illustrated in Fig. 15.

The training methods are depicted in Fig. 16, highlighting the performance of the proposed classifier when trained with different dataset combinations. Interestingly, the classifier trained with the combined Jasmine, Tomato, and Cassava dataset exhibited the highest accuracy of 95%. In contrast, combining the Jasmine plant dataset with the tomato dataset and the Jasmine plant dataset with the cassava dataset resulted in lower classification accuracies of 88% and 82% respectively, indicating the superiority of the combined dataset approach.

In addition, using the GRAD-CAM tool, diseased Jasmine leaf images are visualized, emphasizing the affected areas where the proposed classifier makes the most of its judgment, shown in Fig. 17.

The proposed methodology outshines other models, including those designed for different datasets, in the context of jasmine leaf disease detection. While models proposed by (Abayomi-Alli et al., 2021) and (Atila et al., 2021) demonstrated effectiveness in their respective applications, their performance on our jasmine leaf dataset reveals certain limitations. For instance,(Abayomi-Alli et al., 2021) model, although achieving high precision and accuracy in cassava leaf disease detection, faced challenges in maintaining consistent performance across different image qualities, particularly in low quality conditions. (Atila et al., 2021) approach, known for its robustness in detecting diseases in varied conditions, exhibited a drawback in terms of larger model size. In contrast, our proposed methodology exhibits superior performance in jasmine leaf disease detection, achieving outstanding precision of 0.96, recall of 0.95, F1 score of 0.97, and accuracy of 0.96. The model's efficiency is further highlighted by its relatively low computation time and modest model size, making it well suited for practical implementation in real world agricultural environments. The comprehensive evaluation on our jasmine leaf dataset, as presented in Table 6, demonstrates the

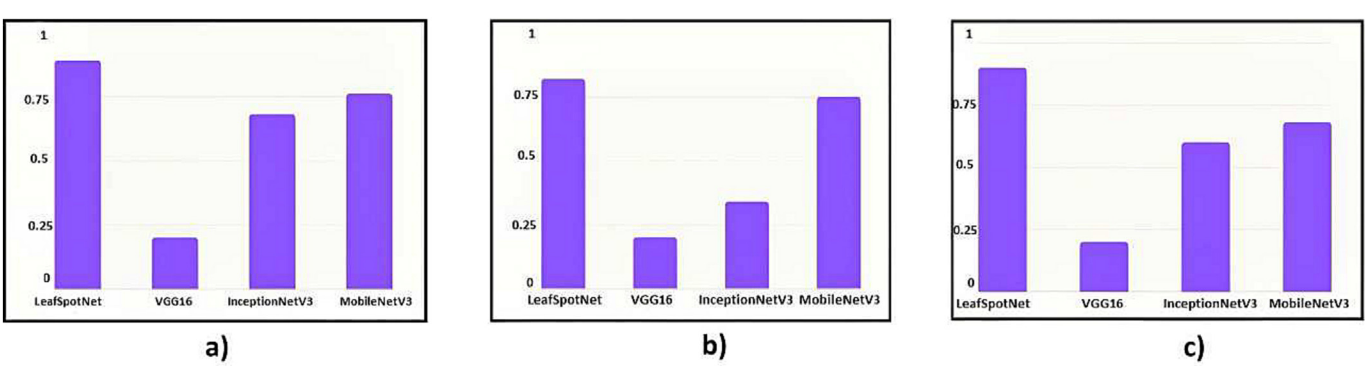

Fig. 9. Classification accuracy graph of a) Jasmine plant leaf dataset b) Cassava dataset and c) Tomato dataset.

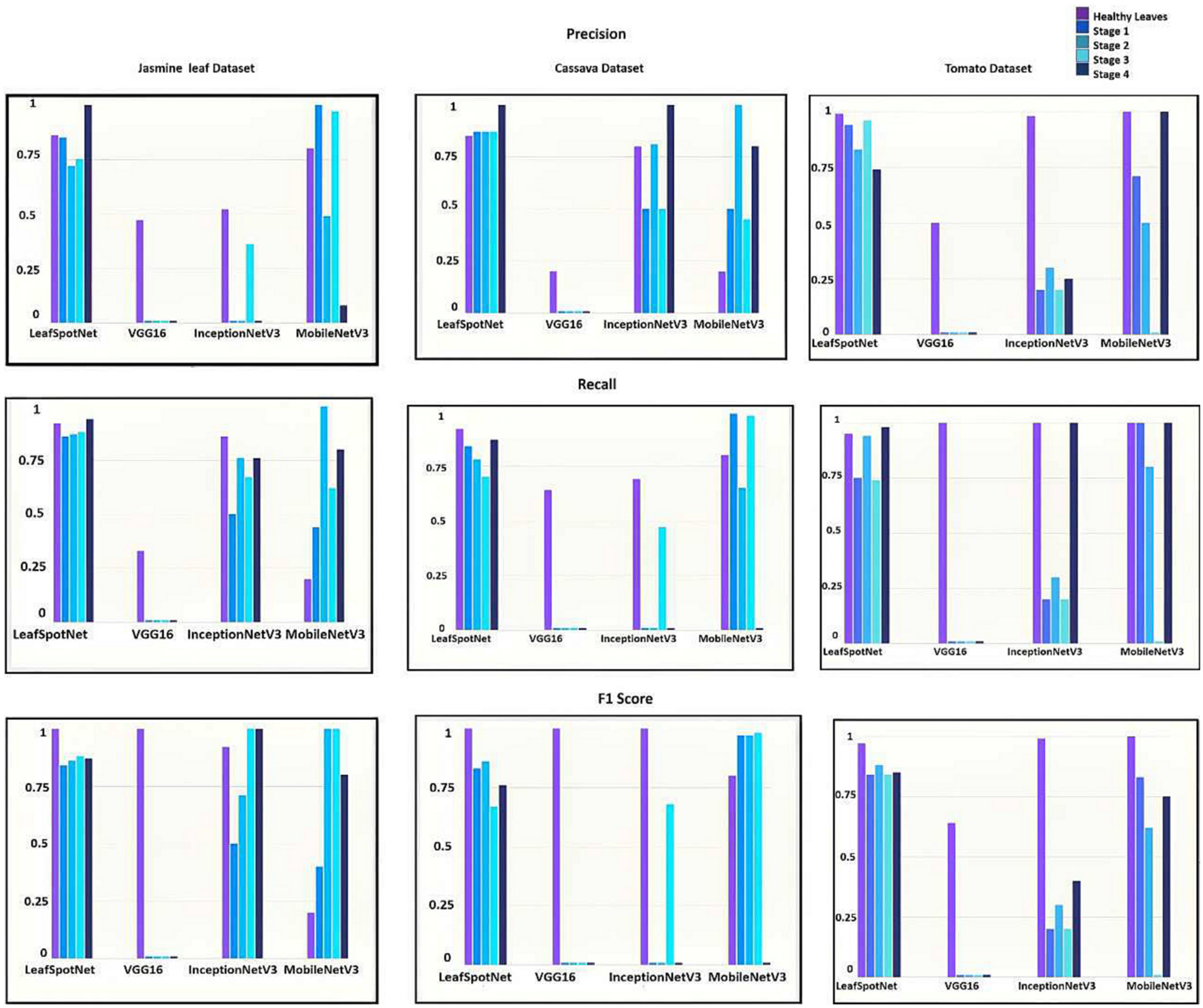

Fig. 10. Performance matrix of propose LeafSpotNet, VGG16, InceptionNetV3 and MobileNetV3 for Jasmine plant leaf, Cassava and tomato leaf dataset.

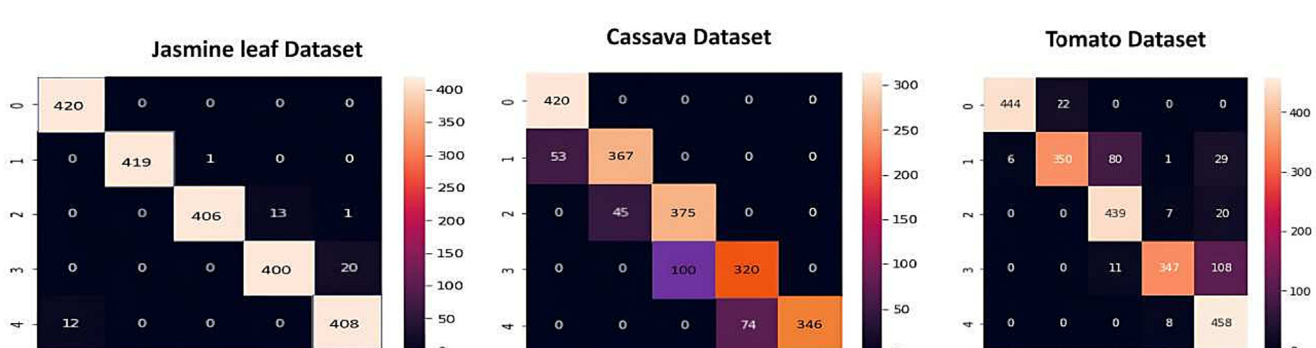

Fig. 11. Confusion matrix obtained for different dataset.

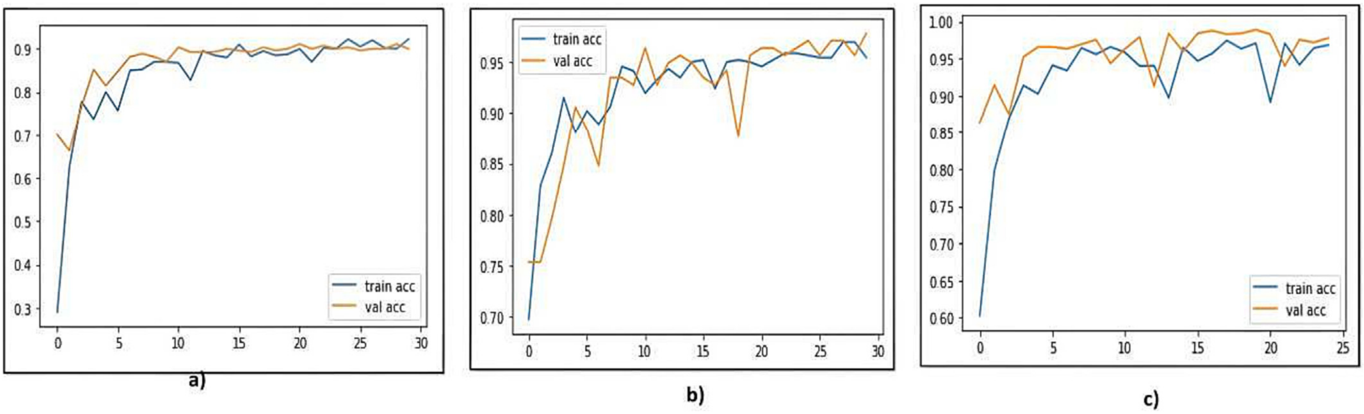

Fig. 12. Training and validation curve of a) Jasmine plant leaf dataset b) Cassava dataset and c) Tomato dataset obtained after the feature selection block.

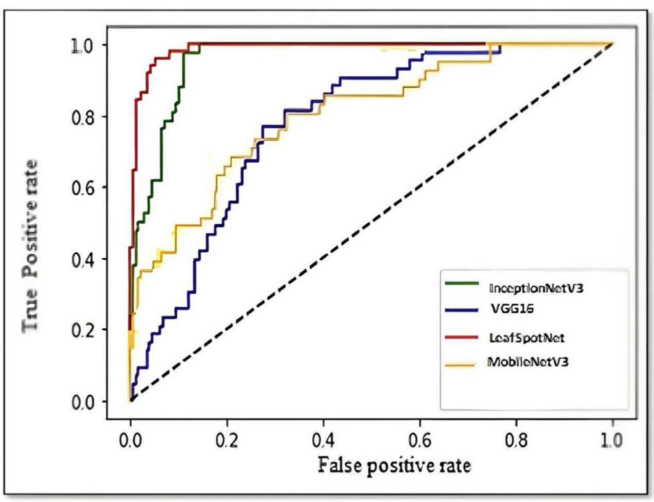

Fig. 13. Precision and Recall curve of various CNN and tomato dataset classfication.

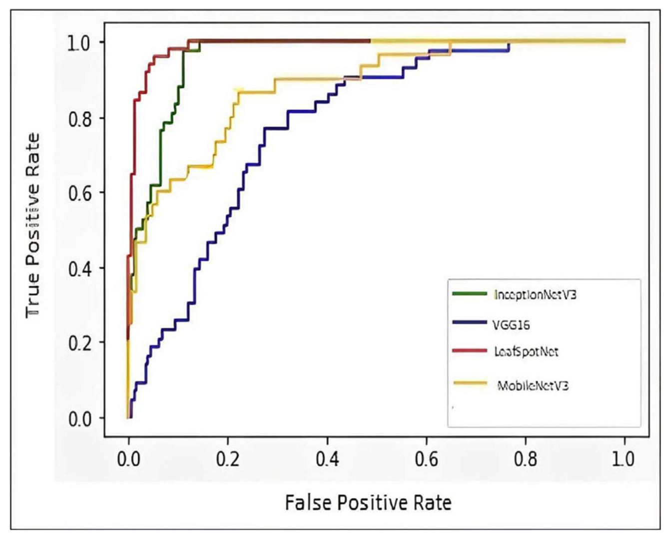

Fig. 15. ROC curve of Jasmine plant leaf, casava and tomato leaf classification.

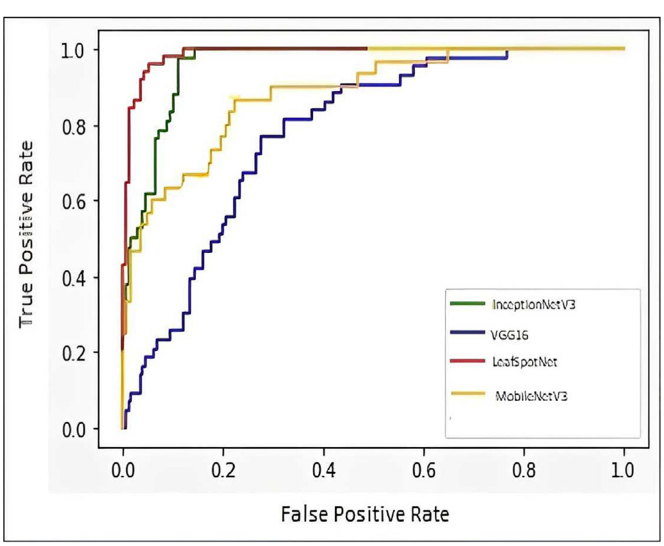

Fig. 14. ROC curve of Jasmine plant leaf classifier for Jasmine plant leaf dataset.

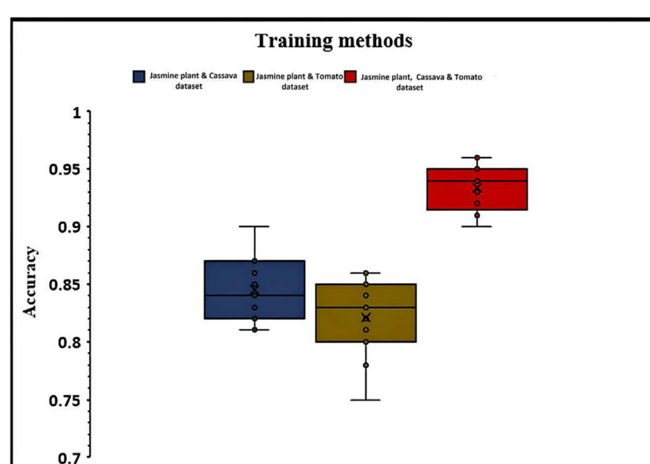

Fig. 16. Training methods used in classification process.

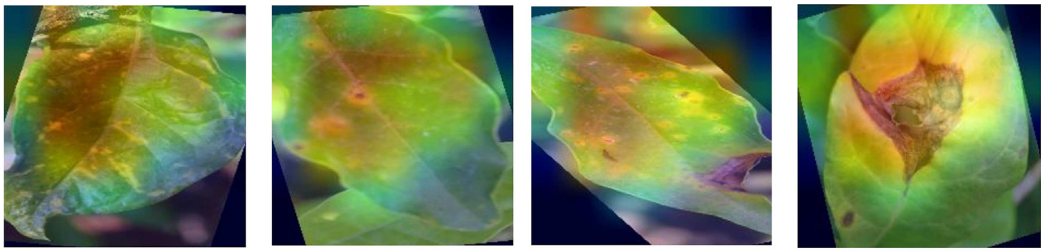

Fig. 17. Jasmine plant leaf visualization using GRAD-CAM tool.

Table 6
Comparision of the performance metrics of existing methods with the proposed methodology for our Jasmine leaf dataset.

Method	Precision	Recall	F1 score	Accuracy	Computation time (Sec)	Model size (MB)
Almadhor et al. (2021)	0.75	0.70	0.68	0.65	360	20
Rehman et al. (2021)	0.72	0.65	0.63	0.61	320	12
Oyewola et al. (2021)	0.75	0.67	0.62	0.61	180	30
Kianat et al. (2021)	0.78	0.81	0.71	0.72	300	16
Singh et al. (2022)	0.72	0.70	0.71	0.76	328	12
Abayomi Alli et al. (2023)	0.81	0.84	0.81	0.78	500	3
Pham et al. (2020)	0.79	0.81	0.82	0.85	620	4
Sambasivam and Opiyo (2021)	0.83	0.80	0.78	0.81	430	14
Sangbamrung et al. (2020)	0.81	0.73	0.78	0.75	120	17
Abayomi-Alli et al. (2021)	0.88	0.81	0.84	0.85	320	12
Atila et al. (2021)	0.89	0.91	0.91	0.93	110	105
Mahum et al. (2023)	0.85	0.81	0.82	0.81	180	37
Khan et al. (2022)	0.81	0.88	0.85	0.83	180	33
Proposed methodology	**0.96**	**0.95**	**0.97**	**0.96**	**30**	**10**

methodology's efficacy and versatility, positioning it as a reliable solution for an accurate and efficient detection of jasmine leaf diseases across diverse conditions and settings.

4.3. Ablation study

The ablation study presented in Table 7 explores the impact of different conditions on the classification performance. Each condition represents a variation in the model setup, including baseline configurations, data augmentation, swarm optimization, and modifications to the MobileNetV3 architecture. Notably, the table highlights that the configuration involving Data Augmentation, Swarm Optimization, and a Modified MobileNetV3 architecture achieves the highest classification accuracy with precision, recall, F1 score, and overall accuracy reaching 0.97, 0.96, 0.97, and 0.98, respectively.

Fig. 8 provides a visual representation of the classifier's accuracy before and after swarm optimization. It illustrates that the training accuracy graph exhibits instability without swarm optimization. In contrast, Fig. 12 depicts a training accuracy curve with a smooth trajectory and validation accuracy, indicating the successful mitigation of overfitting issues when employing Data Augmentation, Swarm Optimization, and Modified MobileNetV3 in tandem. These results underscore the effectiveness of the integrated approach in enhancing the model's classification performance.

4.4. Classifier performance with extreme camera angles and challenging conditions test images

Table 8 presents a detailed comparison of classification accuracy under different test conditions, each of which was visually represented in Fig. 5. The test conditions include various smartphone setups (Smartphone-1 and Smartphone- 2), two camera configurations (Camera-1 and Camera-2), extreme camera angles, varying lighting conditions, and diverse grain noise conditions. Fig. 5 provides a graphical representation of the experimental setup, showcasing the diverse conditions under which the model was tested. Each condition corresponds to a unique setting, allowing for a comprehensive evaluation of the model's performance in real world scenarios. Our extensive highlights the model's impressive resilience across diverse test scenarios, consistently achieving high accuracy.

Notably, Camera-1 demonstrates exceptional performance, with the model achieving an impressive 0.98 accuracy, showcasing its effectiveness in image capture and classification. A significant highlight is the model's robustness under Extreme Camera Angles, maintaining a

Table 7
Ablation study.

Condition	Precision	Recall	F1 score	Accuracy
Baseline (No Augmentation, No Swarm, Original MobileNetV3)	0.81	0.82	0.80	0.82
With Data Augmentation	0. 78	0.76	0.76	0.79
With Swarm Optimization	0.85	0.85	0.87	0.89
Modified MobileNetV3	0.87	0.88	0.86	0.89
With Data Augmentation and Swarm Optimization	0.91	0.90	0.91	0.96
With Data Augmentation and Modified MobileNetV3	0.93	0.94	0.93	0.91
With Data Augmentation and Modified MobileNetV3	0.94	0.95	0.96	0.94
With Swarm Optimization and Modified MobileNetV3	0.93	0.95	0.95	0.95
With Data Augmentation, Swarm Optimization, and Modified MobileNetV3	**0.97**	**0.96**	**0.97**	**0.98**

Table 8
Comparison of Data Augmentation Techniques in the classification process.

TestConditions	ClassificationAccuracy
Smartphone-1	0.95
Smartphone-2	0.93
Camera-1	0.98
Camera-2	0.96
ExtremeCameraAngles	0.93
DifferentLightingConditions	0.94
VariousGrainNoiseConditions	0.96

commendable 0.93 accuracy. This underscores its capability to handle challenging conditions, particularly extreme camera perspectives, showcasing adaptability and generalization. Crucially, the evaluation utilized a dataset of 500 test images, offering a thorough assessment of the model's performance under real world conditions. The demonstrated robustness and reliability affirm the model's suitability for practical and dynamic deployment, emphasizing its exceptional accuracy and effectiveness in addressing diverse testing challenges.

Layer visualizations of the proposed LeafSpotNet, VGG16, InceptionNetV3, and MobileNetV3 classifiers are presented in Fig. 18, Fig. 19, Fig. 20, and Fig. 21 respectively. Furthermore, Fig. 18 showcase the feature maps extracted from different layers of the LeafSpotNet classifier specifically for the Jasmine plant leaf dataset. Notably, the feature maps in the LeafSpotNet classifier exhibit more distinct and evenly distributed patterns, owing to the inclusion of additional custom layers, when compared to the feature maps of the MobileNetV3 model.

5. Conclusion

In conclusion, our study sets out to create a robust classifier for accurately identifying different stages of leaf blight disease in Jasmine plants. The incorporation of a lightweight coupled with particle swarm optimization for feature selection, led to a significant improvement in classification accuracy from 78% to an outstanding 97%. Ablation studies played a crucial role in our evaluation, providing insights into model performance under various conditions. Testing the classifier with different camera angles revealed its robustness. These underscores the model adaptability and reliability across diverse scenarios, crucial for real world applications. The proposed LeafSpotNet classifier, trained on a dataset of 10,000 images using CGAN-based data augmentation, exhibited exceptional performance, notably achieving a remarkable accuracy when tested on the private Jasmine plant leaf dataset. The generalizability of the model was further emphasized through its consistent accuracy

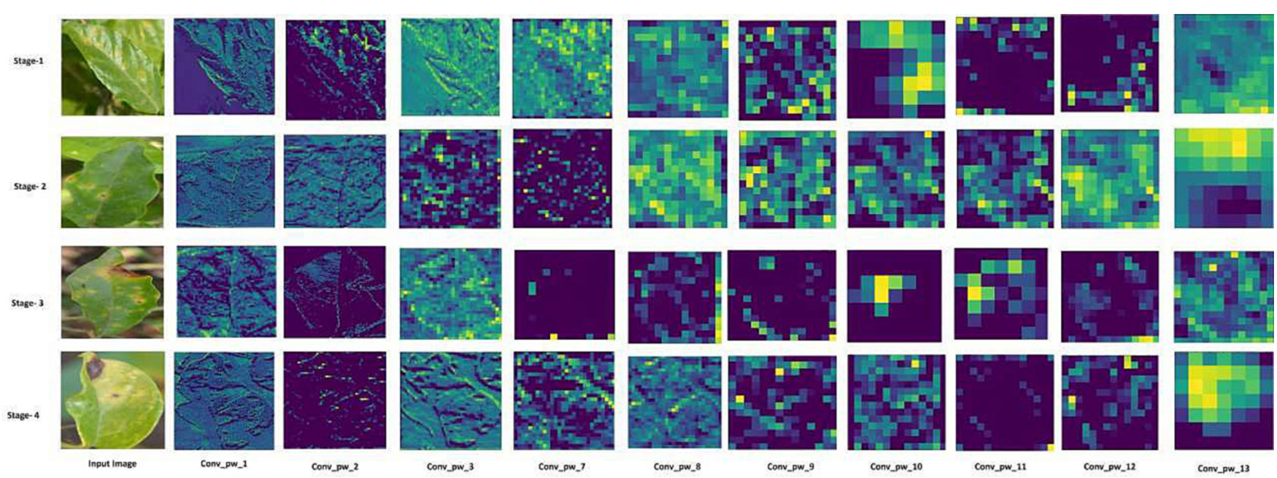

Fig. 18. Layer visualization of LeafspotNet classifier.

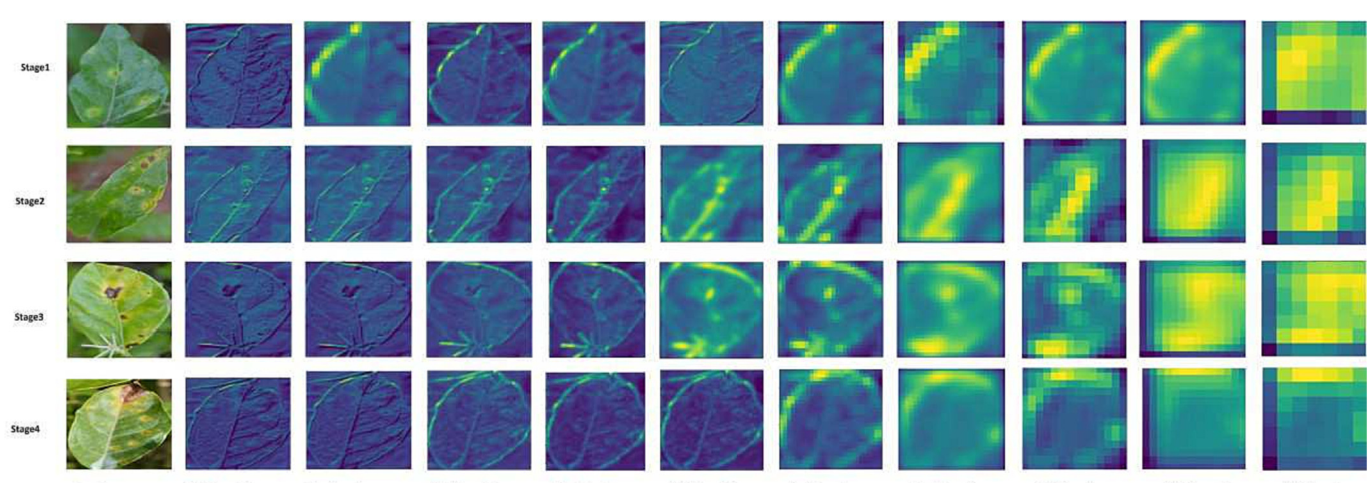

Fig. 19. Layer visualization of VGG16 classifier.

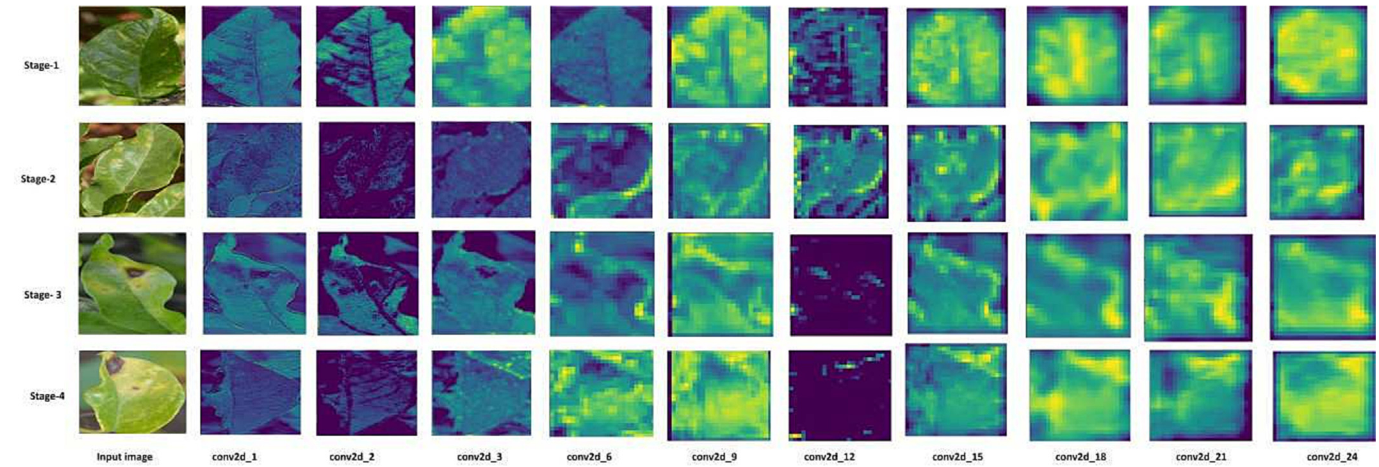

Fig. 20. Layer visualization of InceptionNetV3 classifier.

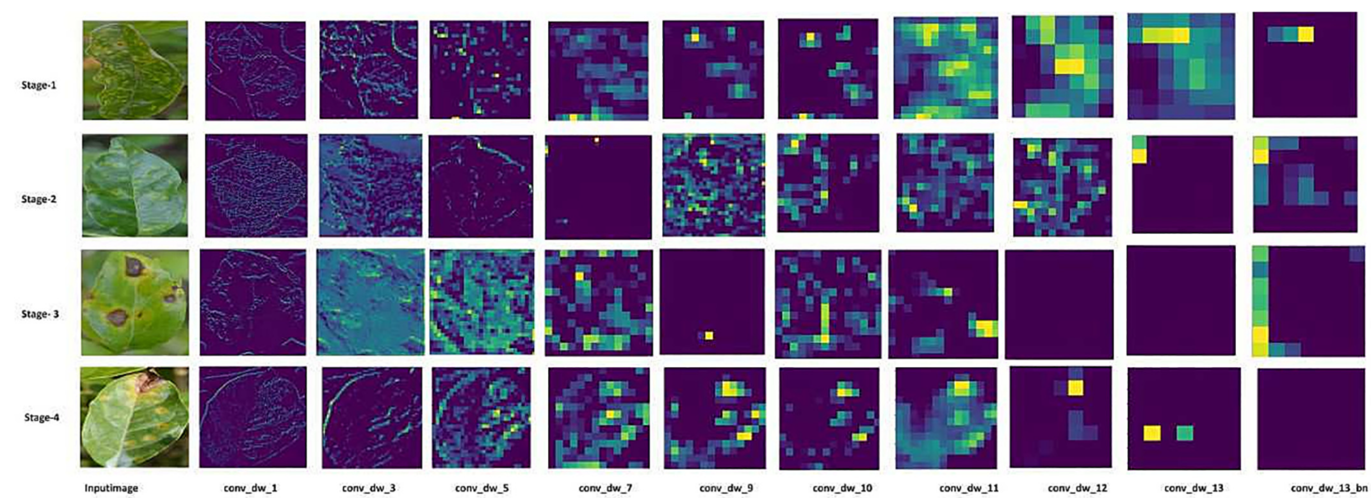

Fig. 21. Layer visualization of MobileNetV3 classifier.

across the Jasmine, Cassava, and Tomato leaf datasets. Comparative analyses with existing image augmentation and classification methods highlighted the superiority of our proposed CGAN model. Its lightweight classification, with a computation time of 30 s and a model size of 10 MB, positions it as an efficient solution for real time applications. The promising scope for deployment in mobile applications holds significant potential for farmers, enabling faster and accurate detection of plant diseases, ultimately facilitating proactive and effective crop management strategies. In summary, the ablation study, robustness testing, and evaluation under various conditions collectively demonstrate the effectiveness, generalizability, and real world applicability of our proposed LeafSpotNet classifier, showcasing its potential as a valuable tool for assisting farmers in timely and accurate plant disease detection. In conclusion, the selection of the MobileNet based LeafSpotNet classifier opens avenues for seamless integration into real time agricultural environments. Leveraging MobileNet's efficiency, the model's optimization for dynamic conditions and mobile deployment stands as a promising future direction. Continuous collaboration with agricultural experts ensures practical alignment, presenting an opportunity to revolutionize plant disease detection for improved crop management.

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Declaration of competing interest

All authors have no competing interests or other interests that might be perceived to influence the results and/or discussion reported in this paper.

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