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Research Article

An Evolutionary Optimization of Positional-Aware Dual-Attention and Topology-Fusion Generative Adversarial Network for Plant Leaf Disease detection

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ABSTRACT

The classification of crop leaf diseases is the foremost essential task in agricultural activities since it may affect the crop productivity. To achieve this task, a Positional-aware Dual-Attention and Topology-Fusion with Generative Adversarial Network (PDATFGAN) can create super-resolution images of crop leaves robustly. Also, Deep Convolutional Neural Network (DCNN) can classify these enhanced images into different types of leaf diseases. But, the adversarial learning objectives can have non-convergent boundary sets near equilibrium which reduces the generative efficiency. Therefore this proposes a new model called PDATF-Evolutionary GAN (PDATFEGAN) by using different objectives to equally optimize the generator and create the super-resolution images for classification. In this model, an EGAN is constructed which considers an adversarial learning process as an evolutionary problem. A discriminator can act as the atmosphere and a population of generators evolve related to the atmosphere. During every adversarial iteration, the discriminator is learned to identify actual and bogus image samples. Also, the generators who act as parents execute different mutations to produce the offspring and adapt to the atmosphere. To decrease different losses between the created distribution and the image distribution providing to various mutations, different adversarial objective functions are considered. Then, the quality and diversity of images generated by the updated offspring are computed for an optimal discriminator. After that, a weakly-conducting offspring are rejected and the residual well-conducting offspring are preserved according to the idea of survival of the fittest for further learning. Further, the generated super-resolution images are fed to the DCNN to identify and classify the types of leaf diseases. At last, the test analysis shows that the PDATFEGAN achieves better accuracy than the existing models.

Keywords—Crop leaf diseases, PDATFGAN, Super-resolution images, DCNN, Adversarial learning, Evolutionary algorithm, Mutation

I. INTRODUCTION

Leaves are a key component in the cultivation of crops to provide relevant information regarding the quantity and efficiency of agricultural output. Multiple aspects threaten farm productivity, like greenhouse effect, pests and nutrient degradation. Furthermore, the production of a wide range of crops resources and the factor of environmental damage present a major problem to crop leaves infections [1]. Inadequate use of insecticide leads to a failure in recognition of diseases in crops. Plant leaves pathogens were also widely investigated in the research area with a focus on the genes associated with pathogens.

Smart farming uses the innovative tools to enhance recognition process. Visual diagnosis and pathological tests are normally conducted by screening crops whenever essential. Yet, this solution is not effective since it requires more time. To address these challenges, sophisticated and intellectual techniques are necessary to recognize leaf diseases. Traditional machine learning techniques were reported in a number of studies to perform cultivation processes [2]. Presently, a subfield of artificial intelligence such as deep learning has been incredibly efficient in detecting and classifying actual images. From this perspective, agriculture sector has motivated towards deep learning techniques [3] which are used to obtain schematic outcomes for cultivation tasks like seed selection [4], plant labeling [5] and weed recognition [6]. Additionally, recent analysis has also reported on a classification of crop/plant leaf diseases.

Several classical deep learning techniques are employed for categorizing the crop leaf diseases using familiar deep learning structures. Some researchers have been applied updated deep learning structures for improving the performance of recognizing many crop leaves diseases. Accordingly, many DCNN with different optimization schemes are developed to attain successful outcomes in recognizing the leaf diseases [7]. To recognize and categorize the leaf diseases, AlexNet, VGG-16, Inception-V3, Residual Network (ResNet), GoogLeNet and MobileNet-based deep learning structures have been implemented [8].

Moreover, a comprehensive analysis of these structures was presented to clarify the effect of modifying the structures for classifying the leaf infections. But, the images captured from agriculture fields were generally obscure so the precision of pre-learned classifiers were affected. Therefore, the low-resolution or blurry images have to be enhanced to improve the spatial resolution and reproduce the high-frequency details on leaf margins. Accordingly, a DATFGAN [9] framework has been designed to identify the plant leaf diseases. First, the obscure leaf images were translated into the precise and high-resolution images. Next, the weights were assigned to reduce the number of variables and deep structure layers to recognize the types of diseases based on the leaf texture features. Conversely, the goal of GAN was to learn the generator which maps the known latent vector to the actual image vector.

Its learning may also be improved significantly through designing advanced strategies for executing both generator and discriminator effectively. Also, the spatial correlations between the set of training images have to be learned since the diseases can affect only part of the leaf or the whole leaf. To solve this problem, a PDATFGAN framework [10] has been developed which creates a high-quality images by segments and train the spatial correlations between the set of training images. The generator in PGAN was used to produce the images by segments in accordance with their spatial coordinates as the context. The key purpose was to train the spatial coordinates which were orthogonal to the latent vectors and produce the patches at all corresponding spatial positions. Similarly, the discriminator was used to verify whether the nearby patches were homogeneous and continuous across the margins between different patches. Moreover, the created high-quality images are fed to the DCNN to classify the types of leaf diseases. Though the adversarial learning objectives such as mean square error between input and target images can improves the training stability, it can have non-convergent boundary sets near equilibrium.

Hence in this paper, PDATFEGAN model is proposed which uses various objectives for mutually optimizing the generator and creating the super-resolution images. The key objective is to increase both the learning stability and generative efficiency. In this model, an EGAN is constructed which considers an adversarial learning process as an evolutionary problem. Particularly, a discriminator can act as the atmosphere i.e., gives adaptive loss functions and a population of generators develop in response to the atmosphere. During every adversarial iteration, the discriminator is learned to identify actual and bogus image samples. In EGAN, the generators who act as parents conduct different mutations for generating the offspring and adapting the atmosphere. Also, various adversarial objective functions are considered to reduce different losses between the generated distribution and the image distribution providing to various mutations. For a given current optimal discriminator, the quality and diversity of samples created by the updated offspring are measured. At last, weakly-conducting offspring are discarded and the residual well-conducting offspring are preserved based on the theory of survival of the fittest for further learning. After creating the super-resolution leaf images, DCNN is applied to categorize the types of leaf diseases. Thus, PDATFEGAN solves the inherent challenges in the individual adversarial learning objectives and preserves the best offspring generated by various learning objectives.

The remaining sections of the article are: Section II discusses the recent researches on classifying the crop leaf diseases using artificial intelligence techniques. Section III explains the methodology of PDATFGAN and Section IV exhibits its experimental outcomes. Section V concludes the study and recommends the future developments.

II. LITERATURE SURVEY

Ma et al. [11] segmented the cucumber leaf images and augmented them to prevent the overfitting issue. Then, they were classified by the DCNN. However, it cannot able to recognize multiple types of diseases simultaneously and at its early stages. Ozguven & Adem [12] designed a modified Faster R-CNN structure to automatically identifying the leaf spot diseases in sugar beet. But, it needs to optimize the CNN parameters to avoid the misclassifications.

Jaisakthi et al. [13] developed automated system to recognize the diseases in the grape vines using image processing and machine learning algorithm. First, the leaf image was segmented by the grab cut method. After, the infected area from the obtained image was segmented using the global thresholding and semi-supervised methods. Further, the features were extracted and classified by the Support Vector Machine (SVM), adaboost and random forest tree. Conversely, these classifiers take more time for training and overfitting problem was not resolved.

Zhang et al. [14] developed a Global Pooling Dilated CNN (GPDCNN) to identify the cucumber leaf diseases by integrating dilated convolution with global pooling. First, the multi-scale convolutional kernels were used for extracting and merging the multi-scale features of the input image. Then, fully connected layer was used to identify the plant diseases. But, it needs to increase the efficiency by using the probabilistic graphical frameworks.

Dhingra et al. [15] developed a new fuzzy set extended form neutrosophic logic-based segmentation for segmenting the region-of-interests. After that, these images were differentiated by fuzzy membership variables. Then, the features were extracted based on the segmented areas for identifying the infected leaves using different machine learning classifiers. But, the accuracy of these classifiers was not highly effective.

Zhu et al. [16] presented automated identification technique for grape leaf infections depending on the image analysis and Back-Propagation Neural Network (BPNN). The wiener filtering using wavelet transform was used for denoising the infected images. The grape leaf infected areas were segmented by Otsu method and morphological methods were applied for enhancing the lesion shape. Then, Prewitt operator was used for extracting the full edge of lesion area. Further, the three-level BPNN was used to recognize the grape leaf diseases. However, the variances between the morphological characteristics of different lesions were small and so they cannot be completely differentiated by few features.

Liu et al. [17] developed a new Dense Inception CNN (DICNN) to recognize the grape leaf diseases. First, the collected diseased grape leaves images were processed by data augmentation method to create sufficient training images. After that, the digital image processing technique was applied for simulating the images in different cases to enhance the generalization efficiency. Moreover, DICNN was employed which uses the deep separable convolution, Inception structure and dense connection scheme for recognizing the grape leaf diseases. However, it has high time complexity due to the number of convolutional layers in the Inception structure.

Esgario et al. [18] designed an effective and practical method to recognize and estimate the stress severity caused by the biotic agents on coffee leaves. It comprises a multi-task method depending on the data augmentation and CNN. But, the drawback of this method was the low representatively of the dataset which covers only the major biotic stresses that affect the coffee trees.

III. PROPOSED METHODOLOGY

In this section, PDATFEGAN model is described in detail. In PDATFGAN, the generative network G consists of two coordinate systems with shallow-feature extraction network: a fine-grained micro coordinate system for G and a coarse-grained macro coordinate system for D. Also, it considers full images (original (a) and created (x)), macro patches (original (a') and created (x')) and micro patches (created (x'')) [10]. The key goal of G is to produce realistic and flawless full images by gathering a set of x'' entirely with a fusion factor φ and a cropping conversion ψ. Here, ψ is used to crop a' from a for sampling original macro patches in D. But, in this proposed PDATFEGAN, an evolutionary algorithm is developed which evolves a population of generator (G) in a given discriminator (D).

The block diagram of crop leaves diseases classification using PDATFGAN with DCNN model is depicted in Figure 1. Also, Figure 2 shows the adversarial process using PEGAN.

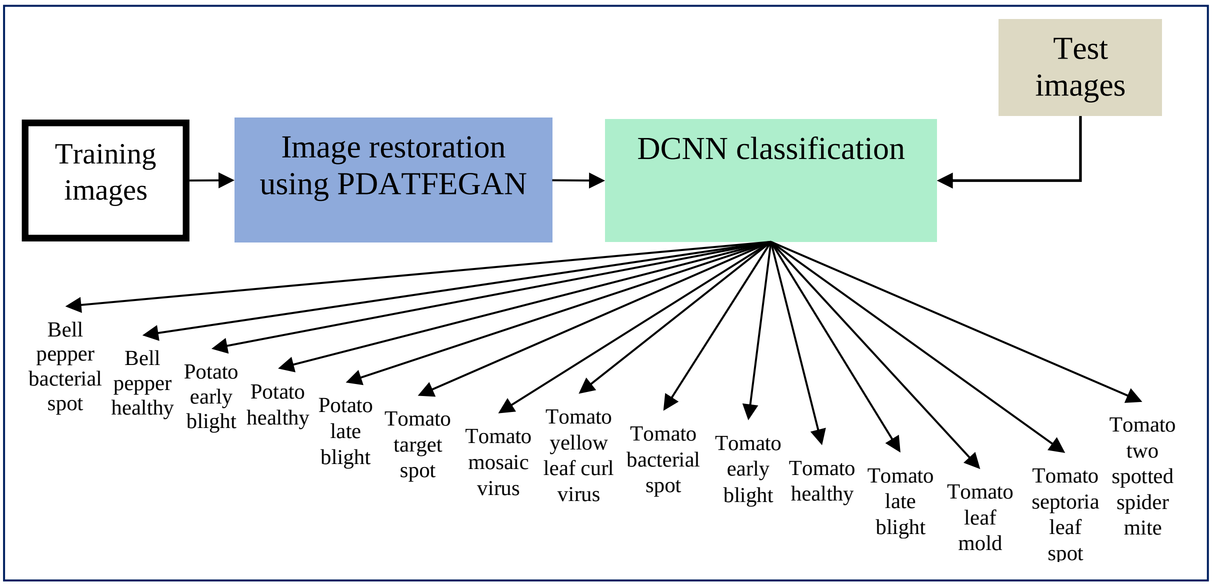

Figure 1. Block Diagram of PDATFEGAN with DCNN Model for Leaf Diseases Classification

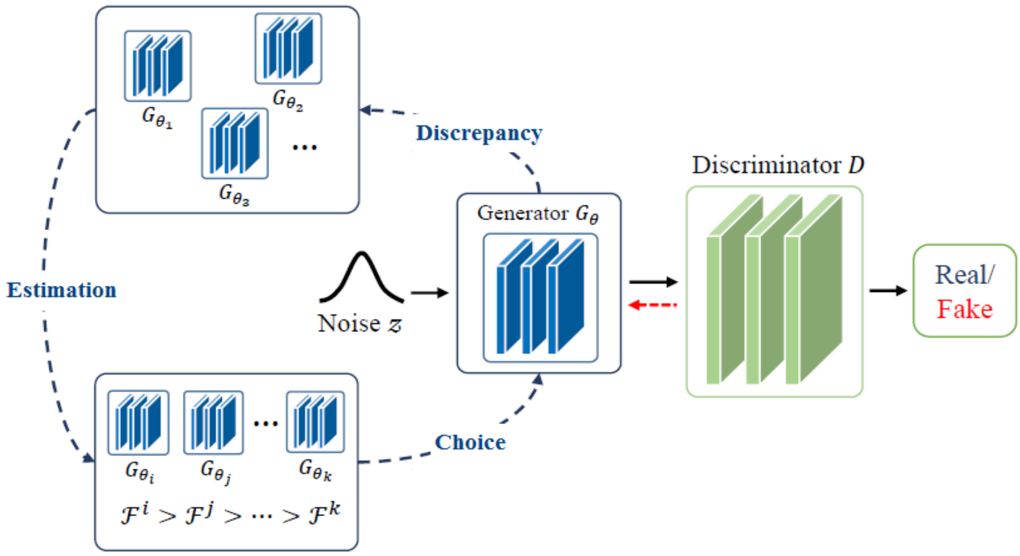

Figure 2. Proposed PEGAN Model

3.1 Evolutionary Algorithm

In this population, every individual indicates a probable solution in a parameter space of G. During the evolutionary task, it is expected that the population regularly adjusts its atmosphere which indicates that the developed generators can constantly create high realistic sample images and finally train the image distribution. Every step during evolution has three different sub-phases:

- Discrepancy: For an individual G_θ in the population, the discrepancy operators are used for generating its offspring $\{G_{\theta_1}, G_{\theta_2}, \dots\}$. Particularly, many duplicates of every individual or patent are generated and each of which are updated by various mutations. After, every updated duplicate is regarded as one child.
- Estimation: For every child, its efficiency or individual's quality is estimated by a fitness factor $\mathcal{F}(\cdot)$ that depends on the current D.
- Choice: Each child can be chosen based on their fitness value and the worst branch is eliminated. The remaining stay alive i.e., free to serve as parents and progress to the next iteration.

After every evolutionary step, the atmosphere D is modified for differentiating the actual macro patches a' and forged macro patches x' created by the developed generators. Also, it supports G to deceive D with seemingly realistic micro patches x'' created by the developed generators i.e.,

$$L_{PEGAN} = \mathop{\mathbb{E}}_{a,c'}\left[\log D\big(\psi(a,c')\big)\right] - \mathop{\mathbb{E}}_{z,C''}\left[\log\left(1 - D\left(\varphi\big(G(z,C'')\big)\right)\right)\right] \tag{1}$$

In Eq. (1), c' and C'' are coordinates for macro patches on D and micro patches on G and z is a latent vector. So, D can frequently give the adaptive losses to force the population of G developed to generate better solutions.

3.2 Mutation

In this process, asexual regeneration is applied with various mutations for creating the next generation's individuals i.e., children. These mutation factors characterize various learning objectives, which try to constrict the gaps between the created distribution and the image distribution from various perceptions. According to Eq. (1), consider that for every evolutionary step, the optimum discriminator $D^*(a) = \frac{a'}{a'+x''}$ is trained to evaluate the related properties of these mutations.

3.2.1 Minimax Mutation

The minimax mutation characterizes the minimax objective function in the standard GAN:

$$\mathcal{M}_G^{minimax} = \frac{1}{2}\mathop{\mathbb{E}}_{z,C''}\left[log\left(1 - D\left(\varphi\big(G(z,C'')\big)\right)\right)\right] \tag{2}$$

For an optimal discriminator D^*, the minimax mutation intends to reduce the Jensen-Shannon Divergence (JSD) between the image distribution and the created distribution. If the support of two distributions lies in two manifolds, the JSD can be fixed providing to the vanishing gradient. When D discards the created samples with a high belief ie., $D\left(\varphi\big(G(z,C'')\big)\right) \to 0$, the gradient leads to vanishing. But, if the created distribution overlaps with the image distribution referring that D cannot fully differentiate actual from bogus samples, the minimax mutation gives powerful gradient and frequently constricts the gap between the image distribution and the created distribution.

3.2.2 Heuristic Mutation

The heuristic mutation intends to increase the log-probability of D being misguided i.e.,

$$\mathcal{M}_G^{heuristic} = -\frac{1}{2} \mathop{\mathbb{E}}_{z,C''} \left[log \left(D \left(\varphi\big(G(z, C'')\big) \right) \right) \right] \tag{3}$$

Compared to the minimax mutation, the heuristic mutation is not saturated while D discards the created samples. As a result, the heuristic mutation prevents vanishing gradient and gives effective G changes. But, for D^*, reducing the heuristic mutation is identical to reducing $[KL(x''\|a') - 2JSD(x''\|a')]$ i.e., inverted Kullback-Leibler (KL) minus 2 JSDs. Naturally, the JSD sign is negative which denotes the approaching these 2 distributions away from every other. Practically, this may tend to learning instability and generator quality changes.

3.2.3 Least-Squares Mutation

In the least-squares mutation, the least-squares objectives are used for penalizing its G to deceive D. The least-squares mutation is formulated as:

$$\mathcal{M}_G^{least-squares} = \mathop{\mathbb{E}}_{z,C''} \left[\left(D \left(\varphi\big(G(z, C'')\big) \right) - 1 \right)^2 \right] \tag{4}$$

The least-squares mutation is non-saturating while D can identify the created sample i.e., $D\left(\varphi\big(G(z, C'')\big)\right) \rightarrow 0$. If D's outcome increases, then the least-squares mutation saturates and move towards 0. So, it will prevent vanishing gradient while D has a considerable gain over G.

3.3 Estimation

In this algorithm, estimation is the process of determining the quality of individuals. The evolutionary direction i.e., individual's choice is determined by creating an estimation or fitness factor which supports to analyze the efficiency of developed individuals i.e., children. This algorithm is focused on quality and diversity of created samples. Initially, the created images from G is fed to D and the mean value of outcome is observed i.e., the quality fitness score as:

$$\mathcal{F}_q = \mathop{\mathbb{E}}_{z,C''} \left[\left(D \left(\varphi\big(G(z, C'')\big) \right) \right) \right] \tag{5}$$

Observe that D is frequently adjusted to be optimal during learning, reflecting the quality of G at every evolutionary or adversarial stage. If G acquires a comparatively high quality score, then its created samples can deceive D and the created distribution is further approximate to the image distribution. Also, the diversity of the created samples are focused and tried to increase the learning stability. The diversity fitness score is described by using the gradient-based regularization term as:

$$\mathcal{F}_d = -\log \left\| \nabla_{\mathrm{D}} - \mathop{\mathbb{E}}_{\hat{x}'}[\log D(\hat{x}')] - \mathop{\mathbb{E}}_{z,C''}\left[\log\left(1 - D\left(\varphi\left(G(z, C'')\right)\right)\right)\right] \right\| \quad (6)$$

In Eq. (6), $\hat{x}' = \varepsilon x' + (1-\varepsilon)x'$ is computed between randomly coupled x' and a' with a random number $\varepsilon \in [0,1]$. The log gradient of changing D is used for computing the diversity of created samples. If the modified G gets a comparatively high diversity score, which relates to small D gradients, its created samples lead to spread out sufficiently for preventing D has clear countermeasures. So, D can update smoothly which supports to increase the learning stability. By using these 2 fitness scores, the estimation factor of this evolutionary algorithm is provided as:

$$\mathcal{F} = \mathcal{F}_q + \gamma \mathcal{F}_d \quad (7)$$

In Eq. (7), $\gamma \geq 0$ balances generative quality and diversity efficiently. Generally, a quite high fitness score $\mathcal{F}$ tends to higher learning efficiency and better generative effectiveness. Thus, the super-resolution images of plant leaves are obtained by the PDATFEGAN.

3.4 Leaf Diseases Classification using DCNN

Further, different DCNN classifier models: DenseNet-121, MobileNet V2 and ShuffleNet V2 are performed for classification of leaf diseases. These models maintain most of the weights during learning process and trains only the softmax layers. Adam is employed as an optimizer and cross-entropy is considered as a loss factor. Table 1 presents the training details of these classifiers. Eventually, such trained models are applied to categorize the test leaf images into 15 types of diseases: bell pepper bacterial spot, bell pepper healthy, potato early blight, potato healthy, potato late blight, tomato target spot, tomato mosaic virus, tomato yellow leaf curl virus, tomato bacterial spot, tomato early blight, tomato healthy, tomato late blight, tomato leaf mold, tomato septoria leaf spot and tomato two spotted spider mite.

Table 1. Training Parameters

Model	Learning rate	Batch size	Epochs
DenseNet-121	0.0005	20	50

MobileNet V2	0.0001	20	60
ShuffleNet V2	0.0001	20	70

Algorithm for PDATFEGAN Model:

Input: PVD image dataset

Output: Classified categories of leaf diseases

Begin

$\boldsymbol{for}(each\ training\ leaf\ image)$

Feed them into the PEGAN as micro image patches;

Initialize the batch size, the discriminator's updating steps per iteration n_u, the number of parents n_p, the number of mutations n_m, Adam hyper-parameters α, β_1, β_2, the hyper-parameter γ of estimation factor;

Set initial discriminator's parameters ω_0 and initial generator's parameters $\{\theta_0^1, \theta_0^2, \dots, \theta_0^{n_p}\}$;

$\boldsymbol{for}(number\ of training\ iterations)$

$\boldsymbol{for}(k = 0, \dots, n_u)$

Sample a batch of training images and noise samples;

$$g_\omega \leftarrow \nabla_\omega \left[\frac{1}{m}\sum_{i=1}^{m} \log D_\omega\left(a'^{(i)}\right) + \frac{1}{m}\sum_{j=1}^{n_p}\sum_{i=1}^{m/n_p} \log\left(1 - D_\omega\left(G_{\theta^j}\left(z^{(i)}\right)\right)\right)\right];$$

$\omega \leftarrow Adam(g_\omega, \omega, \alpha, \beta_1, \beta_2);$

$\boldsymbol{end\ for}$

$\boldsymbol{for}(j = 0, \dots, n_p)$

$\boldsymbol{for}(h = 0, \dots, n_m)$

Sample a batch of noise samples;

$$g_{\theta^{j,h}} \leftarrow \nabla_{\theta^j} \mathcal{M}_G^h \left(\left\{ z^{(i)} \right\}_{i=1}^{m}, \theta^j \right);$$

$$\theta_{child}^{j,h} \leftarrow Adam\left(g_{\theta^{j,h}}, \theta^j, \alpha, \beta_1, \beta_2\right);$$

$$\mathcal{F}^{j,h} \leftarrow \mathcal{F}_q^{j,h} + \gamma \mathcal{F}_d^{j,h};$$

$\boldsymbol{end\ for}$

$\boldsymbol{end\ for}$

$$\left\{\mathcal{F}^{j_1,h_1}, \mathcal{F}^{j_2,h_2}, \dots\right\} \leftarrow sort\left(\left\{\mathcal{F}^{j,h}\right\}\right);$$

$$\theta^1, \theta^2, \dots, \theta^{n_p} \leftarrow \theta_{child}^{j_1,h_1}, \theta_{child}^{j_2,h_2}, \dots, \theta_{child}^{j_{n_p},h_{n_p}};$$

$\boldsymbol{end\ for}$

Acquire the super-resolution micro patches of a given leaf image;

Fuse the created super-resolution micro patches;

Get the entire leaf images;

Train the DesneNet-121, MobileNet V2 and ShuffleNet V2 classifiers;

$\boldsymbol{end\ for}$

Test these classifiers using testing images;

Classify the types of leaf diseases;

End

IV. EXPERIMENTAL RESULTS

This section presents the efficiency of PDATFEGAN by executing it in Python 3.7.8 with the consideration of plant leaf images and their related classes obtained from the PlantVillage Dataset (PVD) at https://www.kaggle.com/emmarex/plantdisease. This dataset encompasses 20636 healthy and unhealthy leaf images of tomato, bell-pepper and potato. This study considers 2250 leaf images with 15 different labels for evaluating the PDATFEGAN model. Among this, 1500 leaf images are taken for training i.e., 100 images from every label are chosen randomly and 750 leaf images are taken for testing i.e., 50 images from every label.

The analysis is conducted in terms of precision, recall, f-measure and accuracy to understand its enhancement on crop leaf disease classification model. Figure 4 displays the sample leaf images for each type of disease.

Bell pepper healthy

Bell pepper bacterial spot

Potato healthy

Potato early blight

Potato late blight

Tomato healthy

Tomato target spot

Tomato mosaic virus

Tomato yellow leaf curl virus

Tomato bacterial spot

Tomato early blight

Figure 4. Sample Leaf Images for Various Types of Diseases

Precision is determined by

$$Precision = \frac{No.of\ exactly\ categorized\ unhelthy\ leaves}{No.of\ exactly\ categorized\ unhelthy\ leaves + No.of\ inexactly\ categorized\ unhelthy\ leaves} \quad (8)$$

Recall is determined by

$$Recall = \frac{No.of\ exactly\ categorized\ unhealthy\ leaves}{No.of\ exactly\ categorized\ unhealthy\ leaves + No.of\ inexactly\ categorized\ healthy\ leaves} \quad (9)$$

F-measure is determined by

$$F - measure = 2 \times \frac{Precision \cdot Recall}{Precision + Recall} \quad (10)$$

Accuracy is determined by

$$Accuracy = \frac{TP + True\ Negative\ (TN)}{TP + TN + FP + FN} \tag{11}$$

The comparative results of ShuffleNet V2, DenseNet-121 and MobileNet V2 executed on PVD raw dataset, augmented dataset from PDATFGAN and PDATFEGAN are given in Table 2 and the accuracy analysis is shown in Figure 3.

Table 2. Analysis of Executed Leaf Disease Classification Models on PVD

Models	Evaluation Metrics	Raw dataset	Dataset obtained from PDATFGAN	Dataset obtained from PDATFEGAN
ShuffleNet V2	Precision (%)	89.54	91.48	92.32
	Recall (%)	89.58	91.51	91.37
	F-measure (%)	89.57	91.50	91.84
	Accuracy (%)	89.58	91.52	92.36
DenseNet-121	Precision (%)	88.41	92.70	93.21
	Recall (%)	88.43	92.73	93.31
	F-measure (%)	88.42	92.72	93.26
	Accuracy (%)	88.47	92.74	93.26
MobileNet V2	Precision (%)	90.62	92.83	93.51
	Recall (%)	90.65	92.87	93.62
	F-measure (%)	90.64	92.85	93.56
	Accuracy (%)	90.66	92.87	93.58

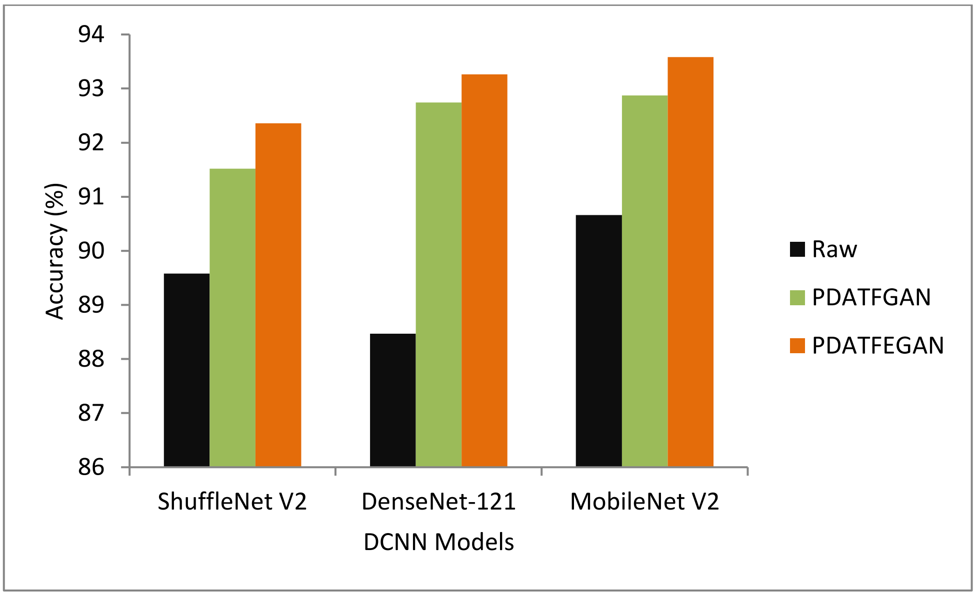

Figure 3. Comparison of Accuracy

The comparative analysis points out that the MobileNet V2 classifier gives an improved performance than the other classifiers on both original and augmented datasets. As far as the plant leaf disease classification model is analyzed, the MobileNet V2 with PDATFEGAN model is highly useful in terms of accuracy.

V. CONCLUSION

In this paper, a PDATFEGAN was proposed which constructs an EGAN to consider an adversarial learning as an evolutionary problem. In this model, the discriminator was acted as the atmosphere and a population of generators was developed according to the atmosphere. During every adversarial iteration, the discriminator was learned to recognize original and false image samples. Also, the generators who act as parents were used to perform various types of mutations for creating the offspring. Various adversarial objective functions were considered for reducing the losses between the created distribution and the image distribution. Moreover, the quality and diversity of images generated by the updated offspring were determined for an optimal discriminator. Then, a weakly-conducting offspring were rejected and the residual well-conducting offspring were preserved for further learning. After, DCNN-based classifier is applied to categorize the crop leaf diseases by using the created leaf images. To conclude, the investigational outcomes demonstrated that the PDATFEGAN with ShuffleNet V2, DenseNet-121 and MobileNet V2 classifiers attains a mean accuracy of 92.36%, 93.26% and 93.58%, accordingly than the PDATFGAN with these classifiers. So, it indicates that the MobileNet V2 classifier with PDATFEGAN model realizes the maximum efficiency compared to the other models.

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