Tomato Leaf Disease Detection using Generative Adversarial Network-based ResNet50V2

Amit Kumar Pandey, Dhyanendra Jain, Tarun Kumar Gautam, Jitendra Singh Kushwah, Saurabh Shrivastava, Rajeev Sharma and Prashant Vats

***Abstract*—Tomato is a globally grown vegetable and is significantly considered an economic pillar for various states. However, plants are vulnerable to a diversity of illnesses that can damage and decrease healthy plant generation, therefore, the accurate and early identification of these diseases is critically important. The utilization of cutting-edge approaches in computer vision provides a solution for these issues. This paper proposes a Generative Adversarial Network (GAN) for producing synthetic images of tomato plant leaves. The ResNet50V2 is trained with real and synthetic images of tomato leaves to categorize them into ten classes, using PlantVillage dataset. The proposed GAN-based ResNet50V2 model is evaluated on PlantVillage dataset. It attains better results with 99.75% accuracy, 99.28% precision, 99.43% recall, and 99.67% f1-score, thus, ensuring precise and timely detection of tomato leaf disease as opposed to the existing techniques like DenseNet, MobileNetV3, Inception V3 and InceptionResNetV2.**

***Index Terms*—data augmentation, generative adversarial network, leaf disease, ResNet50V2, synthetic images**

I. INTRODUCTION

AGRICULTURE is the main origin of income for a major share of India's population and its extended propagation is significantly vital for the environment [1]. Plant disease detection is a major issue in the field of agriculture and early disease detection helps to prevent its spread over other plants that results in extensive loss [2]. The impact of plant diseases varies from losing smaller parts of the plant to the loss of a whole plant, which substantially affects the agricultural economy [3] [4]. Plant diseases generate observable symptoms on leaves in different forms, hence to recognize a particular disease from all types of symptoms, one needs to be proficient enough to know about crops and their diseases [5]. Use of conventional methods for detecting these diseases is not possible for an entire field of crops. When farmers take help from appropriate human experts for identification and treatment of the diseases, it consumes money and time [6]. Tomatoes are nutritious vegetables that are enriched with nutrients, vitamins, amino acids, minerals, and fibers [7]. The annual production of fresh tomatoes accounts for approximately 159 million, where more than a quarter of 159 million are cultivated for industrial processing [8].

Tomato leaf disease is a growing concern for the agricultural field due to these crops being vulnerable to numerous diseases, which results in substantial decrease of tomato production [9]. The tomato leaf disease is the main cause of economic loss to the farmers. Moreover, tomato productivity is directly related to the agricultural economy [10] [11]. It is a complex task to rapidly recognize tomato leaf disease and introduce suitable activities for tomato manufacture and farmers' productivity [12]. Tomatoes help prevent human diseases like hypertension, constipation, hepatitis, type 2 diabetes, and protect the brain and heart health due to its pharmacological properties [13]. The traditional disease detection technique requires a physical analysis of the affected leaf through chemical investigation or visual information of the diseased region obtained by naked-eye observation, which is a time-intensive process and prone to human faults, thereby resulting in less accuracy and reliability [14]. Farmers generally implement conventional techniques for identifying and treating the disease, for example, by cutting leaves from their fields [15]. As the manual disease identification is a difficult time-consuming task that gives less accuracy, it is done in limited crop regions only [16, 17]. The major contributions of this study are specified as follows:

- The pre-processed data features are selected by using Generative Adversarial Network, which includes Generator and Discriminator models. To prevent the network from over-fitting problems, GAN is utilized as

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a data augmentation procedure for improving the dataset size.

- Then, the pre-trained ResNet50V2 model is employed for tomato disease detection from the leaf images, which helps to reduce overfitting issues.
- The proposed GAN-based ResNet50V2 model's performance is estimated through accuracy, precision, recall, and f1-score.

The remaining parts of the research article are structured as follows: Section 2 describes related works. Section 3 explains the proposed methodology. Section 4 expresses the results and discussion, and lastly section 5 concludes this paper.

II. Related Works

Abbas et al. [18] presented a C-GAN to create synthetic images for detecting tomato disease. Moreover, this research utilized the DenseNet121 model for training, and this model was fine-tuned on actual and synthetic images. The suggested C-GAN-based augmentation approach enhanced the generalizability and prohibited overfitting issues. However, replication of data occurred in DenseNet 121 when the feature maps were spliced with the prior layers. Saeed et al. [19] introduced a smart approach for tomato leaf disease detection using transfer learning. This research utilized pre-trained Convolutional Neural Networks (CNNs) by name of Inception V3 and Inception ResNet V2. At the initial stage, image pre-processing and data augmentation were accomplished. Further, Inception V3 and Inception ResNet V2 were trained based on the transfer learning approach. The foremost layer was removed and was replaced by average pooling, fully connected, and softmax layers. The suggested approach achieved a better classification proficiency by diminishing the dropout rate, but the random connection of feature maps led to overfitting issues in the pre-trained CNN.

Ahmad et al. [20] introduced an efficient approach to categorize the leaf disease symptoms using CNN. Initially, class imbalance problems were resolved in the dataset, and then step-wise transfer learning approach was utilized in the process of reducing the convergence time of CNN. The suggested approach was evaluated using the plant village dataset and pepper disease dataset. The approach proved to be an effective solution based on its achieved accuracy. However, it faced issues related to high running time and computational costs. Zhang et al. [21] introduced IBSA-Net with minor sampled data, for the recognition of tomato leaf disease. IBSA-Net was a combined form of reversed bottleneck network and attention mechanism which was incorporated with hard swish activation and IBMax function. The suggested approach extracted multi-level features and located the disease region with fine granularities. But, due to growth defects in tomato leaves, misjudgment and inappropriate detection were identified.

Pandian et al. [22] introduced a dense CNN to detect plant leaf disease. It was incorporated with five dense blocks, and was referred to as 5DB-DenseConvNet. In addition to these dense blocks, the architecture of 5DB-DenseConvNet also comprised of four transition layers. The size of the dataset was improvised with the help of different augmentation approaches and GAN. The Bayesian approach was deployed for enhancing hyperparameter values of 5DB-DenseNet. Nonetheless, the DenseNet architecture faced issues related to data replication that affected the categorization efficiency of the model. Attallah [23] introduced a tomato leaf disease classification approach using a compact CNN and feature selection. The suggested approach utilized three compact structures of CNN which included deep layers and minimal parameters to reduce the running time and time complexity. Nonetheless, the settings had to be varied for different classes at every iteration which was an exhaustive process.

Ozbilge et al. [24] developed a model for tomato disease recognition, known as Compact CNN. The data augmentation was employed for training the model, through contrast and rotation techniques which enhanced the model's performance. Initially Compact CNN was compared to ImageNet that used transfer learning, and did not require a large complex network to obtain better results. The pre-trained DenseNet201 model accomplished closer results to that of the developed model. The developed model utilized six layers to extract relevant features automatically via its convolutional layer. Nevertheless, in this model, few parameters such as soil, temperature and pH were not considered, which limited its ability to capture difficult features and patterns in the data. Hassan and Maji [25] implemented a deep learning CNN technique for plant disease identification. The standard convolution was changed into depth-wise convolution that minimized the amount of parameters. This model was trained and tested on three datasets. The CNN was developed with the aid of pre-trained models by name of Residual and Inception that extracted features and provided robust result. The developed model had considerably good capability in feature extraction which helped to eliminate the vanishing gradient issues. However, the pre-trained CNN was not adaptable to long-term dependences and sequential data in an input data.

Roy et al. [26] introduced a Principal Component Analysis (PCA) for detection of tomato leaf disease in agro-based industries. The approach was developed through an integration of PCA and Deep Neural Network (DNN), named as PCA-DeepNet. This approach employed GAN to attain a good mixture of datasets. The detection was done through the Faster Region-based CNN (FR-CNN). This model helped to minimize the dimensionality and feature space, to further learn intricate patterns for effective detection. Nevertheless, this approach was computationally demanding and required substantial computational resources in resource-constrained environments. Nandhini and Ashokkumar [27] developed DenseNet-121 with Mutation-based Henry Gas Solubility Optimization (MHGSO) for automatic recognition of plant leaf disease. The MHGSO was deployed to optimize a hyper-parameter of DenseNet-121 to minimize the computation complexity and error occurrences in the CNN. The developed model had the ability to recognize 14 classes in PlantVillage dataset. The architecture of DenseNet-121 allowed the integration of features and utilized lesser parameters than other DL methods. But it required greater number of parameters, which increased the computational cost.

Dhanalakshmi et al. [28] introduced a sequential CNN which was operated on the basis of modified inception. This inception-related sequential network was embedded with the pros of deep leftover and solid networks to minimize range and optimize accuracy, detail flow, and slope. The hyperparameters were utilized to categorize approaches on the basis of their efficiency, using the tomato dataset. Empirical investigation showed that the identified diseases by the suggested method proved that it successfully outperformed the compared approaches in terms of recognition accuracy. The method's performance was exceedingly better than those of the former leaf disease recognition methods, however, the datasets were deficient, the method lacked sufficient computation, and was only moderately robust. Deshpande and Patidar [29] developed a lightweight parallel Deep CNN for identification of tomato leaf disease. Furthermore, GAN was included for generating synthetic data to mitigate the data lacking issues that occurred due to irregular data size. The Plant Village dataset was utilized for classifying different classes of tomato plant samples. The implemented method was rated using the following performance measures: accuracy, recall, precision, and F1 score. The suggested approach offered better accuracy for tomato leaf disease detection when it was differentiated alongside former methods. Also, on an overall basis, the proposed method exceedingly outperformed these former methods. Nevertheless, it has huge computational complexity which affects the model performance. Alruxwaili et al. [30] presented Faster Region-CNN (R-CNN) to categorize the tomato plant leaf sickness utilizing a rapid R-CNN method. This R-CNN offered a deep learning-related Faster R-CNN method to maximize its execution in discovering and managing tomato plant leaf disease. It was compared to some prior recent approaches in which its execution excellently outperformed all other compared approaches.

III. Proposed Methodology

The tomato PlantVillage dataset, which contains 16,012 images of tomato leaves spanning across ten classes, is utilized in this paper. Then, pre-processing is carried out for grayscale conversion and resizing of image. Furthermore, the colored images are converted into black and white images while performing grayscale conversion. The preprocessed data features are selected by using Generative Adversarial Network (GAN), which includes Generator and Discriminator models. To prevent the network from overfitting problems, the GAN is deployed as a data augmentation technique for improving the dataset size. For disease classification, ResNet50V2 is fine-tuned using tomato leaf images. Figure 1 represents the block diagram of proposed methodology.

A. Dataset

The proposed methodology is evaluated by using the publicly accessible tomato PlantVillage dataset [31] containing 16,012 tomato leaf images categorized in ten classes. Among them, nine classes are tomato leaf diseases and one class are healthy leaf images. For quicker computation, every image in the dataset is resized to 224×224. The dataset is divided into three sets of training, testing and validation in the ratio of 60:30:10 with no overlying among the three sets. The description of every class is illustrated in Table 1, and the dataset samples are demonstrated in Figure 2.

TABLE I
The Description of the Tomato PlantVillage Dataset

Classes	Training Set	Testing Set	Validation Set	Total Set
Tomato Mosaic Virus (MscV)	224	112	37	373
Tomato Leaf Mold (LMld)	571	286	95	952
Tomato Early Blight (TEB)	600	300	100	1000
Tomato Target Spot (TTS)	843	421	140	1404
Tomato Two Spotted Spider Mite (SpdM)	1006	503	167	1676
Tomato Septoria leaf spot (SptL)	1063	531	177	1771
Tomato Late Blight (TLB)	1145	573	191	1909
Tomato Bacterial Spot (Bctsp)	1276	638	213	2127
Tomato Yellow Leaf Curl Virus (YLCV)	1925	963	321	3209
Tomato healthy (Hlth)	955	477	159	1591

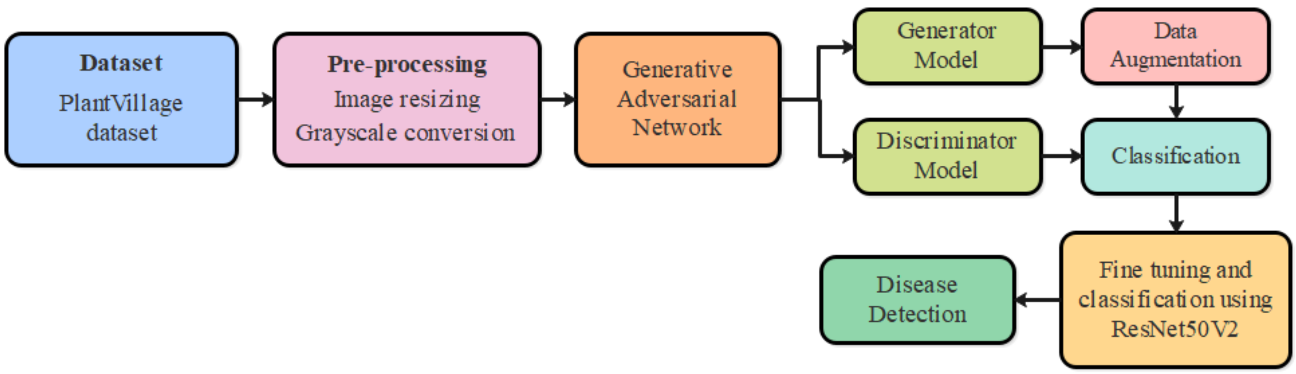

Fig. 1. Block Diagram of Proposed Tomato Leaf Disease Detection

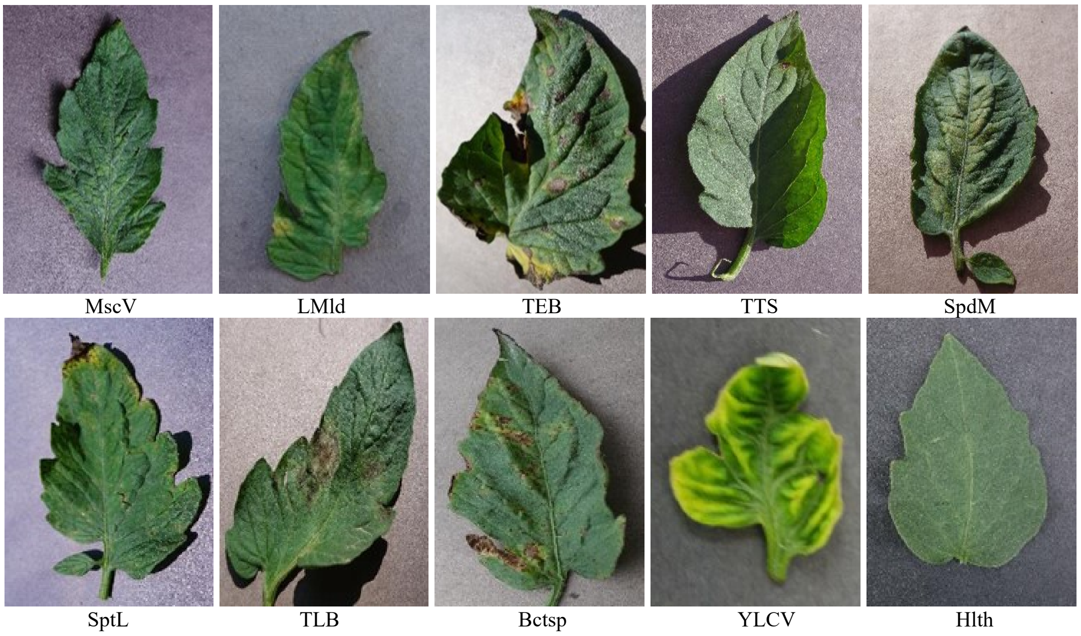

Fig. 2. Dataset Samples

B. Pre-processing

Data preprocessing is accomplished in the PlantVillage dataset by including activities like image resizing and grayscale conversion [32]. The image resizing is performed to modify the dimensions of the image. It involves scaling up or down the image, and maintaining its aspect ratio. Resizing is often performed to meet the requirements of the model and reduce the computational complexity. The grayscale conversion is performed to convert a colored image into black and white version where each pixel represents the light intensity. For each pixel in the resized image, its grayscale intensity is estimated based on the RGB values. It simplifies the data and decreases the image dimensionality which is computationally less expensive for image processing algorithms.

C. Generative Adversarial Network (GAN)

The GAN is a deep learning model which models complicated high-dimensional distributions of real-world data. To prevent the network from overfitting problems, the GAN is utilized as a data augmentation technique for improving the dataset size. In GAN, the convolution layers are utilized to make a matrix image from random noise. It contains both neural networks, Generator (G) and Discriminator (D) [33]. G captures the possible allocation of legitimate data and produces new samples. D is the dual-classifier which determines whether the input is real or generated data. Through the weight loss, the classification result is passed back to G and D. Both networks are trained simultaneously until D is no longer able to discriminate legitimate samples from the generated samples. The D ensures that the images generated through G are potentially near to legitimate. D contains the layers known as input, dense, and embedding layers. After that input, concatenate, and reshape layers follow these 3 convolution layers [34]. Every convolution is followed through Leaky ReLU and the final Leaky ReLU layers are further followed by the dense, flatten and dropout layers. This model contains 771,454 trainable parameters. The layer name and parameter size of D model is presented in Table 2.

The generator contains input layer and dense layer, followed by embedding and Leaky ReLU layers that are further followed by concatenate, dense, and reshaped layers. The concatenation layer includes 4 convolutions, wherein every convolution is followed up with Leaky ReLU, hence the final Leaky ReLU is executed in the last convolution. This G contains 1,735,904 trainable parameters. It takes random noise and latent points as input that produce synthetic images. The D model then distinguishes between legitimate and synthetic images produced through G model. The G model is presented in Table 3.

TABLE II
LAYER NAME AND PARAMETER SIZE OF DISCRIMINATOR

Layers	Input	Embedding	Dense	Reshape	Concatenate	Leaky ReLU	Conv2D	Flatten	Dropout
Parameter Size	[4, 4, 3]	sigmoid activation	[0, 3, 25]	Max (0, x)	[4, 4, 256]	[4, 4, 259]	[32 32], [16 16], [8 8], [4 4] stride= [2 2] same padding	[0, 2048]	[0, 2048]

TABLE III
LAYER NAME AND PARAMETER SIZE OF GENERATOR

Layers	Input	Dense	Embedding	Leaky ReLU	Reshape	Concatenate	Conv2D
Parameter Size	[4, 4, 3]	sigmoid activation	[0, 3, 25]	Max (0, x)	[4, 4, 256]	[4, 4, 259]	[32 32], [16 16], [8 8], [4 4] stride= [2 2] same padding

The optimization goal is to obtain a Nash equilibrium, hence the generated network evaluates the data sample distribution. I denotes data and L is data label for an extra class. Here, I and L are given for discriminatory function, and input noise dispensation of the G model is represented as $q_z(z)$. The D model enhances the possibility of assigning labels properly, to actual and synthetic images produced with the generator model, which are denoted as $log\,D(I/L)$. Whereas, the G model reduces loss that is denoted as $log(1-D(G(z/L)))$. The GAN's objective function is the same as a dual-player minmax game which is formulated in eq. (1),

$$min_G max_D V(D,G) = E_{I\sim p_{data}(I)}\left[log\,D(I/L)\right] + E_{z\sim p_z(z)}\left[log(1-D(G(z/L))\right] \quad (1)$$

Where, $min_G max_D V(D,G)$ is an objective function, p_{data} is defined as real sample distribution, $G(z)$ is a mapping noise function to data space. The proposed methodology uses GAN to produce synthetic tomato images of different diseases. To produce these images, first the tomato leaf images are used for training the proposed methodology. In dataset $DS = \left\{\left(I^{(n)}, L^{(n)}\right)\right\}_{n=1}^{N}$, $I^{(n)}$ and $L^{(n)} \in \{0,1,2,...,9\}$ denote the given image and equivalent labels, respectively. To train the GAN model, the actual tomato images $I^{(n)}$ with the respective labels $L^{(n)}$ are specified as input to the D model. At the same time, label $L^{(n)}$ and noise are specified as inputs for the G model which produces a fake tomato image I_f and sends it to the D model. Then, the D model decides if the image is real or fake. After training the GAN, the tomato leaf synthetic images are obtained that correspond to every disease category.

D. Tomato leaf disease detection with ResNet50V2 model

ResNet50V2 is a CNN architecture that is employed to improve the effectiveness of the CNN model and quicken the computation time [35]. ResNet50V2 is an improved form of ResNet50 and achieves better implementation than ResNet50 and ResNet101. In ResNet50V2, a variation is made in dissemination formulation in the connection between blocks. Additionally, it utilizes computer vision for investigation and for classification of leaf disease images. In transfer learning, a pre-trained model is trained on large dataset and it is fine-tuned for a specific task. The pre-trained model's topmost layer is detached and substituted with a new layer. The added classifier on the topmost of the pre-trained ResNet50V2 model is considered to accommodate network-to-image classification. The output of the pretrained model is passed over a Global Average Pooling 2D layer, thereby minimizing spatial dimensions of the feature map by averaging the width and height axes. This resultant fixed-length feature vector encodes the input image's significant features. The architecture of the ResNet50V2 model is presented in Figure 3.

The feature vector is established with double Fully Connected (FC) layers of 512 and 256 neurons, correspondingly, that learn to depict the high-level feature vector and capture discriminatory data for image classification. After every fully connected layer, batch normalization is attached to preserve the training process and quicken the convergence. By adding an activation function using ReLU, the nonlinearity is established in the network after the second fully connected layer, which further enables the network to obtain distinctive illustrations. At last, the output from the second FC layer is passed over to the FC layer having 10 neurons, while the softmax activation function produces probable allocation output for 10 classes, which is the input image of predicted class label. The parameters of ResNet50V2 model are demonstrated in Table 4.

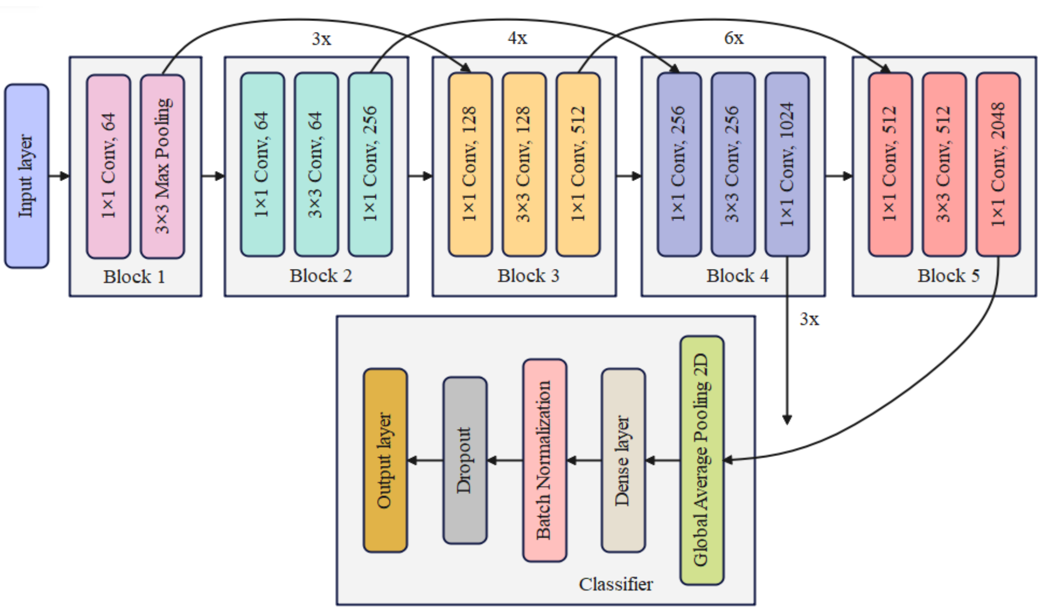

Fig. 3. Architecture of ResNet50V2 model

TABLE IV
PARAMETERS OF RESNET50V2 MODEL

Parameter	Optimizer	Learning Rate (LR)	Momentum	Early Stopping (ES)	Model Checkpoint (MC)	Epochs
Value	SGD	0.0001	0.9	Yes	Yes	100

IV. EXPERIMENTAL RESULT

The GAN-based ResNet50V2 is simulated in Python environment with a system configuration of 16GB RAM, intel core i7 processor and Windows 10 operating system. The parametric measures accuracy, precision, recall and f1-score are assessed to evaluate the model's efficacy. These metrics are mathematically expressed in eqs. (2), (3), (4) and (5),

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1 - Score = 2 \times \frac{Precision \times recall}{Precision + recall} \tag{5}$$

Where, TP, TN, FP and FN correspondingly refer to True Positive, True Negative, False Positive and False Negative.

A. Quantitative Analysis

This section demonstrates quantitative analysis of GAN-based ResNet50V2 through accuracy, precision, recall, and f1-score, as shown in Tables 5, 6, and 7. Table 5 demonstrates quantitative analysis of various feature selections with actual features and table 6 displays the quantitative analysis of various classifiers with optimized features by employing PlantVillage dataset. Table 7 demonstrates quantitative analysis of GAN-based ResNet50V2, devised for tomato leaf disease detection.

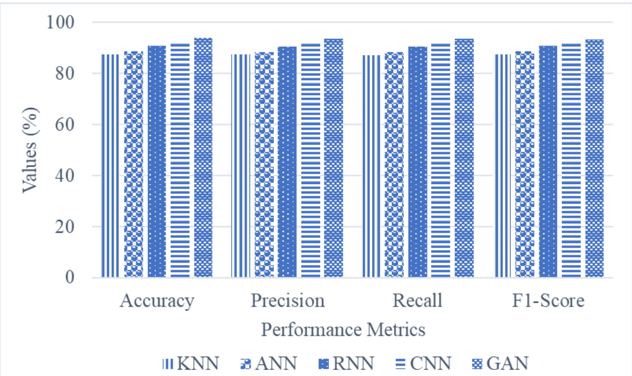

Fig. 4. Performance of feature selection with actual features

Table 5 and Figure 4 denote the feature selection performance with actual features based on the metrics: accuracy, precision, recall and f1-score. The K-nearest neighbor (KNN), Artificial Neural Network (ANN), Recurrent Neural Network (RNN) and CNN performances are matched with GAN. The attained results show that GAN achieves respective accuracy, precision, recall and f1-score values of about 93.92%, 93.77%, 93.65% and 93.41%, which are comparatively higher values than the existing methods.

TABLE V
QUANTITATIVE ANALYSIS OF VARIOUS FEATURE SELECTIONS WITH ACTUAL FEATURES

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KNN	87.64	87.42	87.31	87.52
ANN	88.72	88.56	88.27	88.69
RNN	90.81	90.67	90.46	90.74
CNN	92.58	92.35	92.27	92.10
GAN	93.92	93.77	93.65	93.41

TABLE VI
QUANTITATIVE ANALYSIS OF VARIOUS CLASSIFIERS WITH OPTIMIZED FEATURES

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MobileNet	91.42	91.37	91.19	91.39
AlexNet	92.97	92.59	92.62	92.64
DenseNet	93.74	93.47	93.24	93.58
ResNet50	95.81	95.68	95.51	95.42
ResNet50V2	96.58	96.23	96.47	96.31

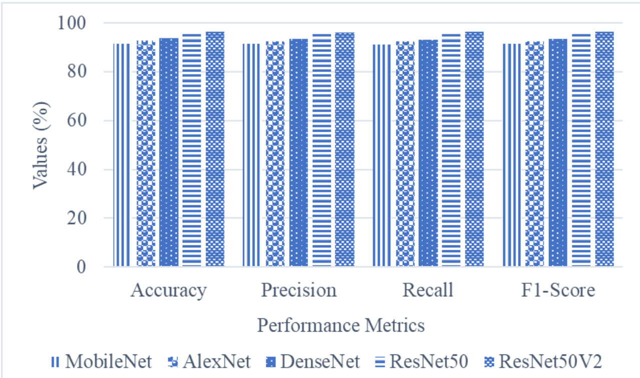

Fig. 5. Performances of classifiers with optimized features

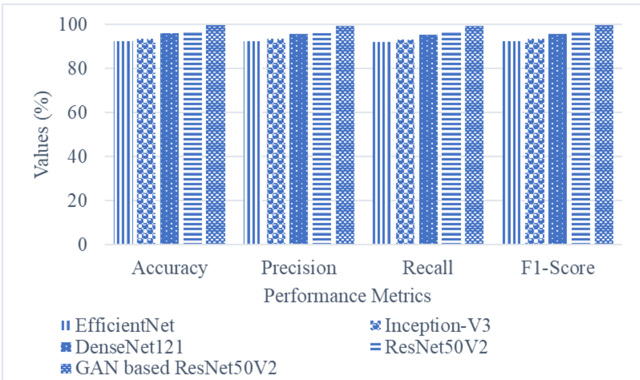

Fig. 6. Performance of proposed GAN based ResNet50V2 model

Table 6 and Figure 5 represent the performances of classifiers with optimized features based on accuracy, precision, recall and f1-score metrics. The MobileNet, AlexNet, DenseNet and ResNet50 performances are matched with ResNet50V2. The attained result shows that

ResNet50V2 achieves respective accuracy, precision, recall and f1-score values of about 96.58%, 96.23%, 96.47% and 96.31%, which is superior to the values of respective metrics attained by the other methods.

TABLE VII
QUANTITATIVE ANALYSIS OF THE PROPOSED GAN-BASED RESNET50V2 MODEL

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientNet-B0	92.34	92.29	92.18	92.31
Inception-V3	93.65	93.41	93.30	93.58
DenseNet121	95.97	95.75	95.51	95.84
ResNet50V2	96.58	96.23	96.47	96.31
GAN based ResNet50V2	99.75	99.28	99.43	99.67

Table 7 and Figure 6 represent the performances of the proposed GAN-based ResNet50V2 through metrics accuracy, precision, recall and f1-score. The same metrics are estimated for the performances of EfficientNet, Inception-V3, DenseNet121, and ResNet50V2, and then are contrasted with the GAN-based ResNet50V2 model. The attained results show that the GAN-based ResNet50V2 model attains the accuracy, precision, recall and f1-score values as 99.75%, 99.28 %, 99.43%, and 99.67%, respectively, which proves that it outperforms the respective measures obtained by the aforementioned, compared existing methods.

B. Comparative Analysis

The comparative analysis of GAN-based ResNet50V2 on the basis of accuracy, precision, recall, and f1-score, is shown in Table 8. The existing results [18-20], and [24-30] are utilized to estimate the ability of the GAN-based ResNet50V2. The results attained in Table 8 show that the GAN-based ResNet50V2 delivers superior performances, as opposed to the compared existing methods. It provides improved metric estimations with an 99.75% of accuracy, 99.28% of precision, 99.43% of recall and 99.67% of f1-score.

C. Discussion

In this section, the advantages of the proposed method over limitations of existing methods are discussed. In C-GAN [18] the replication of data occurred in DenseNet 121 when the feature maps were spliced with the prior layers. The pre-trained CNN [19] had a random connection of feature maps which led to overfitting issues. The CNN [20] faced issues related to high running time and computational costs. The compact CNN [24] did not consider certain parameters, which limited its ability to capture difficult features and patterns in data. The pre-trained CNN [25] was not adapted for handling long-term dependencies and sequential data in the input data. The PCA DeepNet [26] was computationally demanding and required substantial computational resources in resource-constrained environments. The MHGSO optimized DenseNet-121 [27] required more parameters which increased the computational cost. On the contrary, the proposed GAN-based ResNet50V2 model overcomes these existing models' limitations. To produce a network to counter the overfitting problem, the GAN is utilized for data augmentation to improve the dataset size. Additionally, for disease classification, the ResNet50V2 is fine-tuned as per the tomato leaf images.

V. CONCLUSION

This paper proposes Generative Adversarial Network (GAN)-based ResNet50V2 model, for accurate and early detection of tomato plant leaf disease. The image resizing and grayscale conversion are carried out in this experiment for data preprocessing. The image resizing is used to modify the dimensions of the image. Furthermore, the grayscale conversion is carried out for converting colored images to black and white. The preprocessed data features are selected by using a GAN, which includes Generator and Discriminator models. Additionally, in order to prevent the network from overfitting problems, the GAN is employed as a data augmentation technique for improving the dataset size. For disease classification, the ResNet50V2 is fine-tuned with tomato leaf images. The GAN-based ResNet50V2 model is evaluated on PlantVillage dataset, in which it attains better results in the measures of accuracy, precision, recall and f1-score values which are about 99.75%, 99.28%, 99.43% and 99.67% correspondingly. These significantly higher measures ensured precise and timely detection of tomato leaf disease. In the future, disease recognition and detection may be performed on the fruits of the plant.

TABLE VIII
COMPARATIVE ANALYSIS

Author	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Amreen Abbas et al. [18]	PlantVillage Dataset	97.11	97	97	97
Alaa Saeed et al. [19]		99.22	N/A	N/A	N/A
Mobeen Ahmad et al. [20]		99.69	N/A	99.40	99.62
Özbılge et al. [24]		99.70	N/A	N/A	98.49
Hassan et al. [25]		99.39	99.17	99.19	99.18
Kyamelia Roy et al. [26]		99.60	98.55	N/A	98.5
S.Nandhini and K.Ashokkumar [27]		98.7	98.64	98.78	N/A
Dhanalakshmi et al. [28]		99.50	98	97	98
Deshpande and Patidar [29]		98.11	98	98	98
Alruxwaili et al. [30]		97.42	80	75	77
Proposed Method		99.75	99.28	99.43	99.67

REFERENCES

[1] T. Sanida, A. Sideris, M. V. Sanida, and M. Dasygenis, “Tomato leaf disease identification viatwo–stage transfer learning approach,” *Smart Agric. Technol.*, vol. 5, p. 100275, Oct. 2023.

[2] J. A. Pandian, V. D. Kumar, O. Geman, M. Hnatiuc, M. Arif, and K. Kanchanadevi, “Plant disease detection using deep convolutional neural network,” *Appl. Sci.*, vol. 12, no. 14, p. 6982, Jul. 2022.

[3] B. Espejo-Garcia, N. Mylonas, L. Athanasakos, E. Vali, and S. Fountas, “Combining generative adversarial networks and agricultural transfer learning for weeds identification,” *Biosyst. Eng.*, vol. 204, pp. 79–89, Apr. 2021.

[4] S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, “Plant leaf disease detection using computer vision and machine learning algorithms,” *Global Transitions Proc.*, vol. 3, no. 1, pp. 305–310, Jun. 2022.

[5] J. Chen, D. Zhang, M. Suzauddola, Y. A. Nanehkaran, and Y. Sun, “Identification of plant disease images via a squeeze-and-excitation MobileNet model and twice transfer learning,” *IET Image Proc.*, vol. 15, no. 5, pp. 1115–1127, Apr. 2021.

[6] M. H. Saleem, J. Potgieter, and K. M. Arif, “A weight optimization-based transfer learning approach for plant disease detection of New Zealand vegetables,” *Front. Plant Sci.*, vol. 13, p. 1008079, Oct. 2022.

[7] A. Sreedevi and C. Manike, “Development of weighted ensemble transfer learning for tomato leaf disease classification solving low resolution problems,” *Imaging Sci. J.*, vol. 71, no. 2, pp. 161–187, Feb. 2023.

[8] S. R. Reddy, G. S. Varma, and R. L. Davuluri, “Resnet-based modified red deer optimization with DLCNN classifier for plant disease identification and classification,” *Comput. Electr. Eng.*, vol. 105, p. 108492, Jan. 2023.

[9] P. Borugadda, R. Lakshmi, and S. Sahoo, “Transfer Learning VGG16 Model for Classification of Tomato Plant Leaf Diseases: A Novel Approach for Multi-Level Dimensional Reduction,” *Pertanika Journal of Science & Technology*, vol. 31, no. 2, Mar. 2023.

[10] P. Buchke and V. R. Mayuri, “Recognize and classify illnesses on tomato leaves using EfficientNet's Transfer Learning Approach with different size dataset,” Jul. 2023.

[11] A. Tabbakh and S. S. Barpanda, “A Deep Features extraction model based on the Transfer learning model and vision transformer" TLMViT" for Plant Disease Classification,” *IEEE Access*, May 2023.

[12] H. Singh, U. Tewari, and S. Ushasukhanya, “Tomato Crop Disease Classification using Convolution Neural Network and Transfer Learning,” in *2023 International Conference on Networking and Communications (ICNWC)*, IEEE, Apr. 2023, pp. 1–6.

[13] K. Fukada, K. Hara, J. Cai, D. Teruya, I. Shimizu, T. Kuriyama, K. Koga, K. Sakamoto, Y. Nakamura, and H. Nakajo, “An Automatic Tomato Growth Analysis System Using YOLO Transfer Learning,” *Appl. Sci.*, vol. 13, no. 12, p. 6880, Jun. 2023.

[14] M. S. Alzahrani and F. W. Alsaade, “Transform and Deep Learning Algorithms for the Early Detection and Recognition of Tomato Leaf Disease,” *Agronomy*, vol. 13, no. 5, p. 1184, Apr. 2023.

[15] S. U. Rahman, F. Alam, N. Ahmad, and S. Arshad, “Image processing based system for the detection, identification and treatment of tomato leaf diseases,” *Multimedia Tools Appl.*, vol. 82, no. 6, pp. 9431–9445, Mar. 2023.

[16] A. O. Adedoja, P. A. Owolawi, T. Mapayi, and C. Tu, “Intelligent mobile plant disease diagnostic system using NASNet-mobile deep learning,” *IAENG International Journal of Computer Science*, vol. 49, no. 1, pp. 216–231, Mar. 2022.

[17] T. Noulamo, A. Djimeli-Tsajio, J. P. Lienou, and B. F. Talla, “A Multi-Agent Platform for the Remote Monitoring and Diagnostic in Precision Agriculture,” *Eng. Lett.*, vol. 30, no. 3, pp. 972–980, Sep. 2022.

[18] A. Abbas, S. Jain, M. Gour, and S. Vankudothu, “Tomato plant disease detection using transfer learning with C-GAN synthetic images,” *Comput. Electron. Agric.*, vol. 187, p. 106279, Aug. 2021.

[19] A. Saeed, A. A. Abdel-Aziz, A. Mossad, M. A. Abdelhamid, A. Y. Alkhaled, and M. Mayhoub, “Smart Detection of Tomato Leaf Diseases Using Transfer Learning-Based Convolutional Neural Networks,” *Agriculture*, vol. 13, no. 1, p. 139, Jul. 2023.

[20] M. Ahmad, M. Abdullah, H. Moon, and D. Han, “Plant disease detection in imbalanced datasets using efficient convolutional neural networks with stepwise transfer learning,” *IEEE Access*, vol. 9, pp. 140565–140580, Oct. 2021.

[21] R. Zhang, Y. Wang, P. Jiang, J. Peng, and H. Chen, “IBSA_Net: A network for tomato leaf disease identification based on transfer learning with small samples,” *Appl. Sci.*, vol. 13, no. 7, p. 4348, Mar. 2023.

[22] J. Arun Pandian and K. Kanchanadevi, “An improved deep convolutional neural network for detecting plant leaf diseases,” Concurrency and Computation: Practice and Experience, vol. 34, no. 28, p. e7357, Sep. 2022.

[23] O. Attallah, “Tomato leaf disease classification via compact convolutional neural networks with transfer learning and feature selection,” Horticulturae, vol. 9, no. 2, p. 149, Jan. 2023.

[24] E. Özbılge, M. K. Ulukök, Ö. Toygar, and E. Ozbılge, “Tomato disease recognition using a compact convolutional neural network,” *IEEE Access*, vol. 10, pp. 77213–77224, Jul. 2022.

[25] S. M. Hassan and A. K. Maji, “Plant disease identification using a novel convolutional neural network,” *IEEE Access*, vol. 10, pp. 5390–5401, Jan. 2022.

[26] K. Roy, S.S. Chaudhuri, J. Frnda, S. Bandopadhyay, I.J. Ray, S. Banerjee, and J. Nedoma, “Detection of tomato leaf diseases for agro-based industries using novel PCA DeepNet,” *IEEE Access*, vol. 11, pp.14983-15001, 2023.

[27] S. Nandhini, and K. Ashokkumar, “An automatic plant leaf disease identification using DenseNet-121 architecture with a mutation-based henry gas solubility optimization algorithm,” *Neural Computing and Applications*, Vol. 34, pp. 5513–5534, 2022.

[28] R. Dhanalakshmi, K. Balakrishnan, B. B. Sinha, and R. Gopalakrishnan, “Tomato leaf disease identification by modified inception based sequential convolution neural networks,” *The Imaging Science Journal*, vol. 71, no. 5, pp. 408–424, Mar. 2023, doi: https://doi.org/10.1080/13682199.2023.2183318.

[29] R. Deshpande and H. Patidar, “Detection of leaf disease in tomato plants using a lightweight parallel deep convolutional neural network,” Archives of Phytopathology and Plant Protection, vol. 56, no. 9, pp. 707-720, May 2023. https://doi.org/10.1080/03235408.2023.2216359.

[30] M. Alruwaili, M. H. Siddiqi, A. Khan, M. Azad, A. Khan, and S. Alanazi, “RTF-RCNN: An Architecture for Real-Time Tomato Plant Leaf Diseases Detection in Video Streaming Using Faster-RCNN,” Bioengineering, vol. 9, no. 10, p. 565, Oct. 2022, doi: https://doi.org/10.3390/bioengineering9100565.

[31] Dataset Link: https://www.kaggle.com/datasets/emmarex/plantdisease.

[32] G. C. Sunil, Y. Zhang, C. Koparan, M. R. Ahmed, K. Howatt, and X. Sun, “Weed and crop species classification using computer vision and deep learning technologies in greenhouse conditions,” *J. Agric. Food Res.*, vol. 9, p. 100325, Sep. 2022.

[33] X. Liu, T. Li, R. Zhang, D. Wu, Y. Liu, and Z. Yang, “A GAN and feature selection-based oversampling technique for intrusion detection,” *Secur. Commun. Netw.*, vol. 2021, pp. 1–15, Jul. 2021.

[34] L. Dongping, Y. Yingchun, S. Shikai, H. Jun, S. Haoru, Y. Qiang, H. Sunyan, and D. Fei, “Research on Fault Diagnosis based on Improved Generative Adversarial Network under Small Samples,” *IAENG International Journal of Computer Science*, vol. 50, no. 1, pp. 7–13, Mar. 2023.

[35] I. U. Khan, N. Aslam, F. M. Anis, S. Mirza, A. AlOwayed, R. M. Aljuaid, R. M. Bakr, and N. H. A. Qahtani, “Deep Learning-Based Computer-Aided Classification of Amniotic Fluid Using Ultrasound Images from Saudi Arabia,” *Big Data and Cognitive Computing*, vol. 6, no. 4, p. 107, Oct. 2022.

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