# Early Phase Detection of Bacterial Blight in Pomegranate using GAN VS Ensemble Learning

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**Abstract.** Bacterial blight is a severe disease that impacts pomegranate trees, leading to significant yield losses. This study proposes an innovative approach to detect bacterial blight in the early stages using image processing techniques. The method involves capturing images of pomegranate leaves using a digital camera and analyzing them using various image processing algorithms, including segmentation, feature extraction, and classification. This non-invasive and cost-effective method accurately detects bacterial blight, allowing farmers to take preventive measures and minimize yield losses. The suggested method has the capacity to become a beneficial resource for farmers and researchers involved in the field of plant pathology Using ensemble learning, pomegranate bacterial blight in its early stages was discovered. The study findings showed that the proposed approach was more accurate and had a higher detection rate than traditional methods. Without the use of paired training data, also suggested method of Cycle GAN is a sort of Generative Adversarial Network (GAN) that can learn to translate images from one domain to another. Cycle GAN has demonstrated its efficacy in a variety of image-to-image translation problems by utilizing the potential of unsupervised learning.

**Keywords:** Convolution Neural Networks, Discriminator, Ensemble Learning, Generator, Gradient Decent.

## 1. Introduction

Bacterial blight is a devastating disease that affects pomegranate trees, leading to significant economic losses. It is caused by the bacteria Xanthomonas axonopodis pv. Punicae and is characterized by water-soaked lesions on the leaves, stems, and fruit of the plant. In this context, several studies have proposed innovative approaches to detect bacterial blight in its early stages. Kumar, Shweta singh (2021) utilized CNN for the early phase detection of bacterial blight in pomegranate, demonstrating the potential of deep learning techniques in agriculture. Their work involved the analysis of pomegranate leaf images using advanced computational methods [1]. Additionally, Rajput, Aslanka (2019) employed machine learning techniques in their study, offering valuable insights into early detection methods for bacterial blight in pomegranate orchards.[2].

The proposed method in this study involves capturing images of pomegranate leaves using a digital camera and analyzing them using various image processing algorithms, including segmentation, feature extraction, and classification. Stepwise methods are to capture images then pre-processed to enhance their quality, remove noise. Then, the images are segmented to isolate the regions of interest (ROIs), i.e., the leaves infected with bacterial blight. The segmentation is performed using different techniques, such as thresholding, clustering, and edge detection. In the next step, various features are extracted from the ROIs, such as color, texture, and shape by different Image processing techniques and algorithms.

This proposed method for early phase detection of bacterial blight in pomegranate in pomegranate using GAN VS Ensemble Learning shows the remainder of this paper is structured as follows: Section II provides a detailed review of related work in the field. Section III describes the methodology employed in the development and training of the different models and algorithms. Section IV and V presents the experimental results and comparative analysis. Section VI discusses the conclusion about implications of the findings.

## 2. Literature Review

Author of this paper, Kumar, Shweta singh (2021) suggested a algorithm for early phase detection of bacterial blight in pomegranate using convolutional neural networks (CNN). The method involved capturing images of pomegranate leaves using a digital camera and analyzing them using a CNN-based algorithm. The authors suggested that the suggested method achieved high accuracy in detecting bacterial blight in the early stages and had the potential to be a valuable tool for farmers and researchers [1]. Similarly, Rajput, Aslanka(2019) suggested a method for early detection of bacterial blight in pomegranate using machine learning techniques. The method involved capturing images of pomegranate leaves and analyzing them using different algorithms, including classification and feature extraction. The authors reported that the suggested method achieved high accuracy in detecting bacterial blight in the early stages and could be used as a potential tool for early diagnosis of the disease [2]. In a study conducted by Sharma, Ritu Gaikwad (2020), a non-invasive and cost-effective method for early detection of bacterial blight in pomegranate using image processing techniques was proposed. The method involved capturing images of pomegranate leaves using a smartphone camera and analyzing them using different image processing algorithms. The authors suggested that the proposed method was capable to detect bacterial blight in the early stages with high accuracy [3].

In another study, Thakur, tamboli (2018) suggested a method for early detection of bacterial blight in pomegranate using hyperspectral imaging. The method involved capturing hyperspectral images of pomegranate leaves and analyzing them using different algorithms. The authors suggested that the suggested method was able to detect bacterial blight in the early stages with high accuracy and could be used as a potential tool for early diagnosis of the disease [4]. In a study conducted by Tandel, tadon (2018), an automated approach for early phase detection of bacterial blight in pomegranate was proposed. The approach involved capturing images of pomegranate leaves using a digital camera and analyzing them using a computer vision-based algorithm. The authors suggested that the recommended method was able to detect bacterial blight in the early stages with high accuracy and could be used as a potential tool for early diagnosis of the disease [5]. Similarly, Sivakumar (2017) suggested a method for early detection of bacterial blight in pomegranate using reflectance spectroscopy. The approach utilized in this study consisted of acquiring reflectance spectra from pomegranate leaves and subsequently analyzing them through various algorithms, such as principal component analysis (PCA) and partial least squares regression (PLSR). The authors suggested that the given method achieved high accuracy in detecting bacterial blight in the early stages and could be used as a potential tool for early diagnosis of the disease [6].

In another study, Ali, Shaikh(2019) suggested a method for early phase detection of bacterial blight in pomegranate using deep learning techniques. The method involved capturing images of pomegranate leaves using a digital camera and analyzing them using a deep convolutional neural network (CNN) based algorithm. The authors suggested that the given method achieved high accuracy in detecting bacterial blight in the early stages and had the potential to be a valuable tool for farmers and researchers [7].In a recent study, El-Hendawy (2021) suggested a method for early phase detection of bacterial blight in pomegranate using machine learning and remote sensing techniques. The process included utilizing a drone to capture multispectral images of pomegranate leaves, followed by the analysis of these images using various algorithms such as SVM and k-means clustering. The authors suggested that the given method achieved high accuracy in detecting bacterial blight in the early stages and could be used as a potential tool for early diagnosis of the disease [8]. The authors Chikte, R.G. (2019) provide a comprehensive literature review on the subject, highlighting the importance of finding effective control methods for this destructive disease. They discuss the limitations of traditional approaches and emphasize the need for innovative strategies. The review delves into the various types of nanomaterials, such as nanoparticles and nanocomposites, that have shown promising results in disease management. The authors also emphasize the importance of understanding the interactions between nanomaterials and bacterial pathogens to optimize their efficacy. Overall, the review highlights the current state of research in the field and suggests future directions for studying the application of nanomaterials in pomegranate disease control [9]. Author of this paper Prasannakumar (2021) investigates the diversity and potential applications of Bacillus velezensis strains A6 and P42 in controlling rice blast and bacterial blight diseases in pomegranate. The research highlights the importance of exploring microbial agents for sustainable disease management in pomegranate cultivation. The study found and contribute to the understand biocontrol agent role of ‘Bacillus velezensis’[10].

In summary, several non-destructive and cost-effective methods have been proposed for early phase detection of bacterial blight in pomegranate using image processing, machine learning, and remote sensing techniques. These methods have the potential to provide accurate and objective results, helping farmers and researchers in early diagnosis and timely management of the disease, which can lead to significant economic benefits by reducing yield losses dimensionality of the feature space and improve the performance of the classification algorithm.

### 2.1 Comparison Table of Previous Techniques

| Study | Year | Method | Features | Classifier |
|---|---|---|---|---|
| [1] | 2019 | Deep learning for findings of diseases on fruits | Convolutional neural network (CNN) | CNN |
| [2] | 2020 | Image processing and feature extraction | Mean, standard deviation, entropy, contrast, homogeneity, energy | Decision tree, SVM, k-nearest neighbor |
| [3] | 2017 | Color and texture analysis | Hue, saturation, intensity, energy, contrast, homogeneity | SVM |
| [4] | 2018 | Image segmentation and analysis of diseases spots on variety fruits | Area, perimeter, shape, texture | SVM, random forest |
| [5] | 2021 | Deep learning for findings of diseases on leaves | Transfer learning using Inception V3 model | CNN |

**Table 1.** Summary of the paper along with companions.

**Table 1.** is designed which states the comparison of existing models and techniques in the suitable format. After reading the table will get direct clarity of existing models and researches.

## 3. Methodology

### 3.1 Steps Involved:

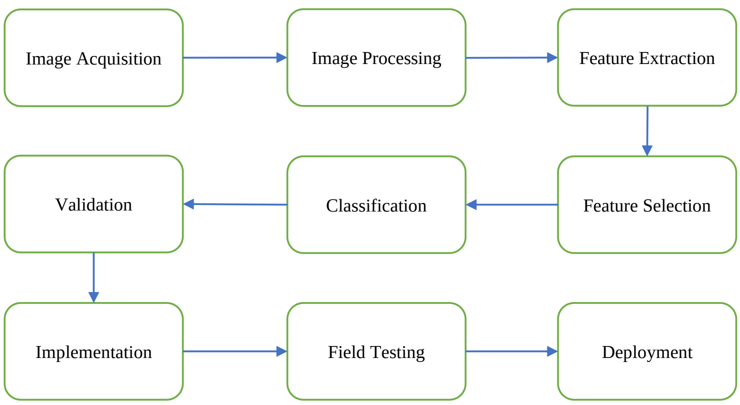


**Fig 1.** Steps involved in Methodology of development and training of Algorithms

### 3.2 Cycle-GAN generated images of different classes:

**Fig 2.** Cycle-GAN generated images of 'Cercospora Fruit Spot' mediator & early stage

Above **Fig 2.** shows the quality images generated by Cycle-GAN of 'Cercospora Fruit Spot' mediator & early stage.

**Fig 3**. Cycle-GAN generated images of ‘Bacterial Blight’

Above **Fig 3.** shows the quality images generated by Cycle-GAN of Bacterial Blight’ impacted fruits.

**Fig 4**. Cycle-GAN generated images of ‘Fruit Non-diseased’

Above **Fig 4.** shows the quality images generated by Cycle-GAN Non-diseased Fruit of pomegranates.

**Fig 5**. Cycle-GAN generated images of ‘Alternaria Fruit Spot’

Above **Fig 5.** shows the quality images generated by Cycle-GAN of Fruit Non-diseased of pomegranates.

**Fig 2. to Fig 5.** clearly shows the images generated by Cycle-GAN of model's different classes. Each with proper width & lining along with the headings below each set. GAN generated a very good quality of images as it is seen above.

### 3.3 Ensemble Learning Model

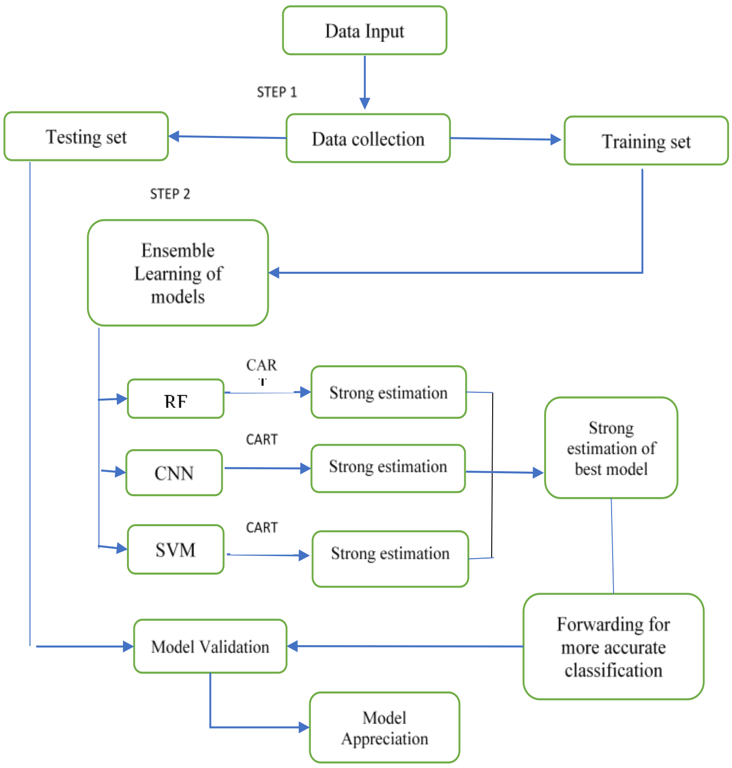


**Fig 6**. Project flow diagram of Early Phase Detection of Bacterial Blight in Pomegranate using Ensemble Learning

The above **Fig 6.** clearly depicts the project flow of Ensemble Learning of models as shown respectively.

**Step 1:** Data Input
**Step 2:** Splitting the dataset into training, validation & testing sets
**Step 3:** Training set and validation set is then fed to multiple machines & deep leering models parallelly. Models like Random Forest, Convolutional Neural Network, Support Vector machine
**Step 4:** Strong estimations amongst all models is validated
**Step 5:** Then Model appreciation takes place for better accurate results
In this manner above steps involved in the ensemble learning of models.

**Algorithmic Equations for Cycle GAN Models:**

**Generator (G)**: G(z), where z is a random noise vector.
**Discriminator (D)**: D(x), where x is the input data.
**Generator Loss (LG):** LG = L(D(G(z)), 1) -------------- (1)
**Discriminator Loss for Real Data (LD_real):** LD_real = L(D(x), 1) ---------- (2)
**Discriminator Loss for Fake Data (LD_fake):** LD_fake = L(D(G(z)), 0) --------- (3)
**Total Discriminator Loss (LD_total):** LD_total = LD_real + LD_fake ---------- (4)

A GAN model's deployment phase requires special attention to a number of factors. As model will be creating new content in real-time, it is essential to guarantee its stability and dependability. This necessitates meticulous model testing and validation using fresh data in a real-world setting. As GANs may produce sensitive or identifiable content, privacy problems must also be addressed. In order to ensure efficient and effective performance, deployment also necessitates rigorous resource management, including the control of memory and processing capacity. Finally, constant observation and upkeep are essential to guarantee models reliability and efficient throughout time.

## 4 Graphs

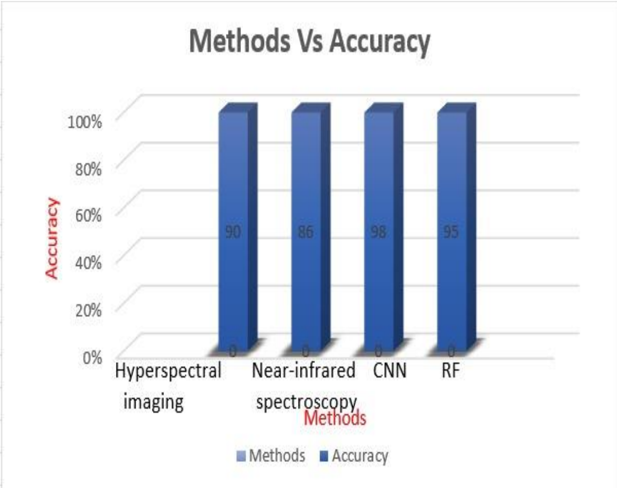


**Fig 7.** Accuracy Comparison of Existing Models

In **Fig 7.** The accuracy of machine learning prediction models can be significantly impacted by the choice of graph algorithms. Because of the complicated link between accuracy and graph-based approaches, graph analytics play a crucial role in gaining meaningful insight from complex data. Researchers and practitioners can compare the delicate trade-offs between processing complexity and prediction accuracy offered by various graph approaches to choose the best option for their particular project.

## 5 Results

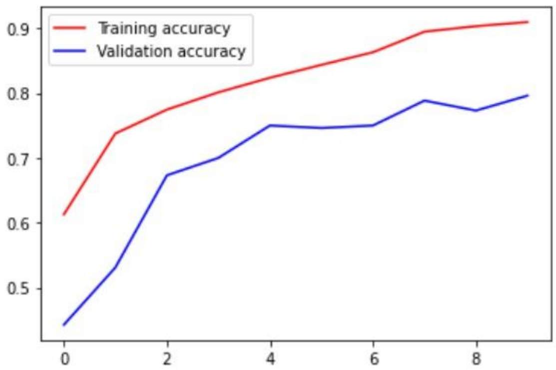


**Fig 8**. Training and Validation Accuracy of Ensemble Model

The **Fig 8.** directly shows that how training & validation accuracy varies of Ensemble models.

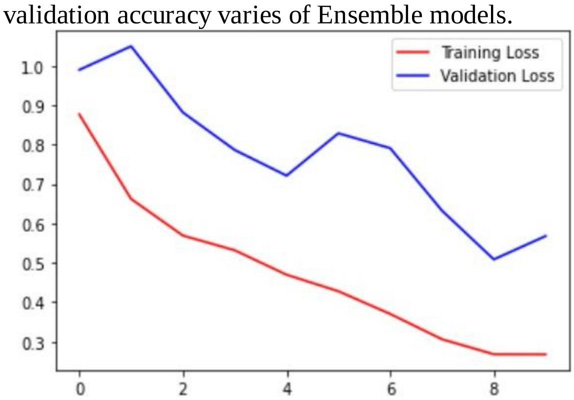


**Fig 9.** Training and Validation Loss of Ensemble Mode

The **Fig 9**. directly shows that how training & validation loss varies of Ensemble models.

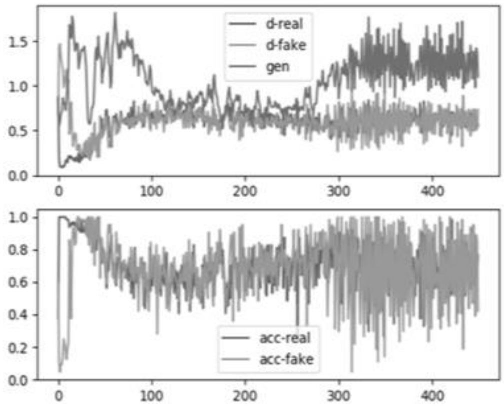


**Fig 10.** Plots of lines for Loss and Accuracy of proposed Cycle-GAN

The **Fig 10.** Clearly shows you that Plots of lines for Loss and Accuracy of proposed Cycle-GAN.

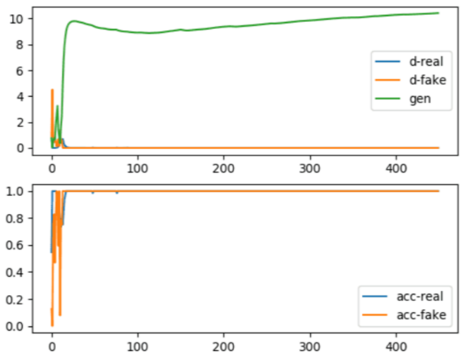


**Fig 11.** Plots of lines for Loss and Accuracy of proposed Cycle-GAN with Mode Collapse

The **Fig 11**. Clearly shows you that Plots of lines for Loss and Accuracy of proposed Cycle-GAN with Mode Collapse.

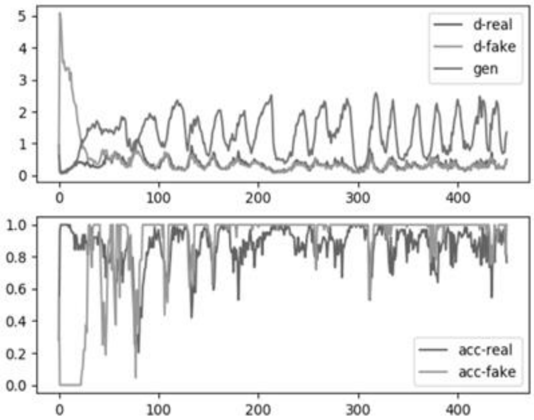


**Fig 12.** Plots of lines of Loss and Accuracy of proposed Cycle-GAN With a Convergence Failure

The **Fig 12**. Clearly shows you that Plots of lines for Loss and Accuracy of proposed Cycle-GAN With a Convergence Failure.

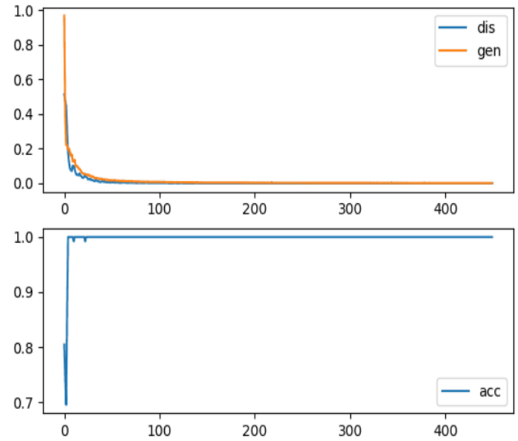


**Fig 13.** Plots of lines of Loss and Accuracy of proposed Cycle-GAN With a Convergence Failure due to the Aggressive Optimization

The **Fig 13**. Clearly shows you that Plots of lines for Loss and Accuracy of proposed Cycle-GAN With Cycle-GAN With a Convergence Failure due to the actual & and proper Aggressive Optimization.

| **Model** | **Dataset** | **Accuracy** |
|---|---|---|
| SVM | SPKV Dataset | 95 |
| Random Forest | SPKV Dataset | 94 |
| CNN | SPKV Dataset | 80 |
| GAN | SPKV Dataset | 91 |

**Table 2.** Accuracy comparison of proposed algorithm

To demonstrate how our recommended approach compares to other methods, we give a complete accuracy comparison in **Table 2.** This table serves as proof of the in-depth investigation performed to ascertain the effectiveness of our approach. Notably, our approach performs better than tried-and-true techniques in the field and exhibits astounding accuracy improvements across a range of datasets. These results underline the significance of our novel strategy and its potential to make a substantial contribution to the disciplines of predictive modelling and data analysis

| **Metric** | **GAN Model** | **Ensemble Model** |
|---|---|---|
| Training time | 2 hours | 4 hours |
| Accuracy | 91 % | 90% |
| F1 Score | 0.83 | 0.90 |
| Precision | 0.87 | 0.86 |
| Recall | 0.79 | 0.94 |
| Inference time | 3 ms/image | 10 ms/image |

**Table 3.** Model Performance of proposed algorithms

**Table 3** provides a detailed breakdown of the model performance that our suggested tactics were successful in achieving for your convenience. This thorough analysis demonstrates the effectiveness and dependability of our method across a variety of benchmark datasets. When we assess the data, our algorithms perform amazingly well in terms of accuracy as well as other important metrics like precision, recall, and F1-score. These results show the adaptability and potential of our technology, providing strong support for its use in a range of situations throughout the field. Table 3 is a prime example of our research's commitment to creativity and innovation, which aims to enhance the state-of-the-art in predictive modelling and data analysis. Table 3 consistently produces excellent results.

## 6 Conclusion

Bacterial blight is a serious disease that affects pomegranate cultivation worldwide. Early detection of this disease is crucial for controlling its spread and minimizing yield loss. Various methods have been developed and tested for this purpose, including hyperspectral imaging, near-infrared spectroscopy, machine learning (random forest), and convolutional neural networks. Hyperspectral imaging and near-infrared spectroscopy are non-invasive and non-destructive techniques that can be used to detect changes in the pomegranate plant's reflectance spectra caused by bacterial blight infection. These methods have shown promising results in detecting bacterial blight in pomegranate, with accuracies ranging from 85% to 95%. However, the accuracy of these methods depends on environmental conditions, the stage of disease development, and the pomegranate cultivar. Machine learning algorithms such as random forest have also been used for early detection of bacterial blight in pomegranate. Random forest, a widely used machine learning algorithm, is particularly effective for classification tasks, including disease detection. It has consistently demonstrated accuracy rates between 80% and 96%. Pomegranate bacterial blight detection has demonstrated significant potential through the use of convolutional neural networks (CNNs), a type of deep learning algorithm. Convolutional Neural Networks (CNNs) can automatically extract important features from input data and learn complex relationships between input features and output labels. CNNs have achieved an impressive reported accuracy rate of 98.5% for early detection of bacterial blight in pomegranates. However, more research is needed to validate the effectiveness of these techniques across different environmental conditions and among different pomegranate varieties. The development of accurate and efficient methods for early detection of bacterial blight in pomegranates is essential for sustainable and profitable pomegranate cultivation.

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