



Data Article

Grapes leaf disease dataset for precision agriculture



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ABSTRACT

Grapes are widely cultivated fruit crops, essential for fresh consumption, winemaking and dried product production. However, their yield and quality are significantly impacted by various fungal diseases. This paper provides a large dataset of 2,726 high-quality grape leaf disease images collected from grapes farm of Nashik, India in two years of span 2023 to 2025. The dataset is precisely annotated under the guidance and observation of agriculture domain expert and organized in a well-defined folder structure. The dataset captures the two major categories healthy leaves and unhealthy leaves, during cultivation period. A primary directory containing two main classes Healthy Leaf Images and Unhealthy Leaf images. Further unhealthy class is divided into three subfolders for disease class, namely Downy Mildew, Powdery Mildew and Bacterial Leaf Spot. These are the major fungal disease observed on grape crop causes substantially crop losses and ultimately impact on the yield production. Timely identification of these diseases can significantly reduce the risk of crop loss and help to improve quality of fruit with maximum yield production. This High-quality annotated image dataset can help to design standard advanced AI models for automated disease detection, classification, and prediction. The

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dataset was validated through a transfer learning approach using the ResNet-18 algorithm and demonstrated the remarkable classification accuracy of **96 %**. These results validate the dataset's quality and its suitability for deep learning-based grape disease detection. Overall, this open-access resource provides a valuable foundation for computer vision, machine learning, and agricultural technology researchers aims to enhance disease management practices in grape production. thus, this is an effective source of data for future studies and real-world applications in sustainable grape production.

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Specifications Table

Subject	Precision Agriculture, Disease Classification, Computer Vision
Specific subject area	Grape's Disease Dataset for Computer Vision
Type of data	Image Data
Data collection	Dataset Offers a collection of 2726 high-quality grape leaf diseases images, including Downy Mildew, Powdery Mildew, and Bacterial Leaf Spot, with Healthy Leaf Images captured from grape farm at the Niphad region located in Nashik District 422303, Maharashtra, India. It focuses on frequently observed and harmful diseases in grapes leaf's, which certainly cause huge losses. For each category, images are well organised in separate folders. Images are saved in high quality JPEG format and resized to a uniform resolution of 256*256 pixels for efficient storage and pre-processing. Images were labelled sequentially for clear association within the dataset.
Data source location	Niphad Grapes farms, located at District Nashik 422209, MH-India Longitude and Latitude: 20.0771° N, 74.1094° E
Data accessibility	Repository Name: Niphad Grape Leaf Disease Dataset (NGLD) DOI: 10.17632/8nnd2ypcv3.5 Direct URL to Data: https://data.mendeley.com/datasets/8nnd2ypcv3/5

1. Value of the Data

- *Comprehensive Dataset:* The Dataset is comprehensive and consists of 2726 high-quality images, in four subfolder such as Downy Mildew, Powdery Mildew, Bacterial Leaf Spot and Healthy Grapes Leaf. Unlike existing public datasets that primarily focus on diseases such as Esca, Black Rot, and Leaf Blights, this dataset specifically targets Downy Mildew, Powdery Mildew, and Bacterial Leaf Spot, which are commonly observed leaf diseases on grapes plant. This specificity makes it a valuable resource for developing targeted disease detection models tailored to real-world agricultural challenges.
- *Binary Classification:* The Dataset mainly categorizes into two major categories first one is healthy grapes leaves having 1254 images and unhealthy grapes leaves (three diseases combined 966+406+100) having 1472 images. This balance ensures effective training of machine learning models for distinguishing healthy and diseased leaves, making it suitable for early disease detection systems [1].
- *Multi-Class Classification:* The unhealthy leaves in dataset represents 3 diseases classes namely Downy Mildew, Powdery Mildew and Bacterial Leaf Spot to build multi-class classification models, enabling precise diagnosis and management of grape diseases.
- *Potential Class Imbalance Consideration:* The dataset is structured to maintain balance for binary classification (Healthy & Diseased), The variation in the number of disease-specific im-

ages reflects the natural occurrence of these diseases under real-world environmental conditions. Under representation of specific diseases matches the frequency with which they are actually seen in the period during which the data is collected to ensure that the data set does accurately represent seasonally occurring disease. Retaining the original distribution allows machine learning models to learn from real-world patterns rather than artificially balanced data, enhancing the reliability of AI-driven disease detection. Furthermore, the dataset supports unbiased risk assessment, enabling researchers to analyze disease severity, occurrence rates, and seasonal variations. Since data was collected over growing seasons from June 2023-January 2025. This provides insights into disease progression, environmental influences, and temporal trends. Preserving the dataset in its original form ensures its research value as a benchmark for evaluating new machine learning models in grape disease classification. However, researchers can apply various GAN techniques for synthetic data generation, class balancing while preserving the dataset's authenticity and applicability.

- *Controlled Environment:* The dataset collected from single- grapes plot during two consecutive years of grapes cultivation season which provides a controlled study environment while still capturing natural disease variability and progression [2].
- *Region-specific:* Nashik district is the major grapes producer of the Asian region, the dataset collected from this region supports researcher to analyse the regional agricultural challenges ultimately contributing to enhanced grapes crop yield for agricultural sustainability [3,4].
- *Application in Precision Agriculture:* Dataset is collection of high-quality annotated images support advanced AI models for early disease detection and prediction systems in precision agriculture. It also enables comparisons with other grape-growing regions, helping in guiding scalable globally informed strategies for sustainability [5].
- *Data Diversity:* The dataset consists of four categories, three for grapes leaf diseases and one for healthy leaves that provide essential diversity for training and testing machine learning models thereby enabling high accuracy is disease detection and classifications, moreover, using transfer learning approaches can significantly reduce development time as these methods leverage existing image recognition capabilities and can be adapted to various other tasks.
- *Well-Formatted Dataset:* The standardized dataset with 256*256-pixel resolution with 96 dpi well suited for development of efficient machine learning models the datasets structures encourage studies on disease progression detection for risk analysis and high-level screening emphasizing preventive disease control strategies.

2. Background

Grapes (*Vitis vinifera*) are an important fruit crop cultivated worldwide for fresh consumption, winemaking, juice production, and dried products such as raisins and sultanas. They hold significant economic value in the agriculture and food industries [6]. However, grape crops are highly susceptible to various fungal, bacterial, and viral diseases, which can lead to severe yield losses and reduced fruit quality. Some of the widespread grape leaf diseases are Downy Mildew, Powdery Mildew, and Bacterial Leaf Spot, which easily propagate in the favourable environment conditions, thus effective disease management becoming an essential component of grape cultivation [7,8].

Early detection and classification of these diseases are important in the prevention of outbreaks and minimizing agricultural losses [9,10]. Traditional disease detection methods, such as laboratory testing and visual observation in the field, are usually time-consuming and labour-intensive [11]. A well-organized dataset of diseases of grape leaves can improve the efficiency of disease detection through the provision of labelled and categorized images of healthy and unhealthy leaves [12]. Such a dataset is an effective instrument for researchers, agronomists and plant pathologists to analyze disease patterns, to improve diagnostic methods as well as to create effective disease management methods [13,14].

A properly annotated and documented data set facilitates more accurate measures of disease severity, thus supporting the development of integrated pest management (IPM) strategies, improving treatment protocols, and reducing the misapplication of pesticides. By facilitating a better understanding of diseases in grape crops, this data set significantly supports in the development of sustainable agriculture practices and the protection of grape crops from severe losses.

3. Data Description

The grape leaf image dataset is crucial for crop health monitoring and decision support in precision agriculture using cutting-edge technologies like computer vision, internet of things, machine learning and AI solutions. The dataset offers a diverse image set of grape leaf visual information allowing researcher to detect healthy and unhealthy leaves. The set of high-quality, well-structured image offers a chance to researchers and professionals to derive the insights and visual patterns to improve the efficiency and robustness of advanced AI models for crop health monitoring.

The Grape Leaf Disease Dataset is a collection of high-quality images specially designed for machine learning use for grape leaf disease classification. It contains images of healthy and unhealthy grape leaves, unhealthy leaf images are further divided into three disease categories such as Downy Mildew, Powdery Mildew, and Bacterial Leaf Spot which are the common disease observed on grapes leaf with seasonal variation. Every image is resized to 256*256-pixel resolution, at 96 dpi to ensure and preserved uniformity in the dataset. The images are saved in RGB format as high-quality JPEGs, maintaining important visual information and optimizing storage space. The dataset has a structured directory structure, with each disease class having a specific folder with clearly labelled images.

The “Niphad Grape Leaf Disease Dataset” serves as a valuable resource for machine learning and computer vision applications in plant disease classification and prediction, contributing to sustainable agricultural practices [15,16]. The dataset comprises high-quality images with a uniform background, ensuring clarity and robustness for real-time applications [17]. All images were captured directly from grape fields in Maharashtra, maintaining authenticity and reliability. This dataset includes commonly observed and highly impactful grape crop diseases that occur during the cultivation period under favourable environmental conditions. A total of 2,726 images have been manually acquired and categorized into four distinct classes—Downy Mildew, Powdery Mildew, Bacterial Leaf Spot, and Healthy Leaves—with the assistance of domain experts from a grape research centre, Pimpalgaon Baswant, Nashik District, Maharashtra, India.

Since these diseases are seasonal, their occurrence varies depending on climatic conditions. Over the past two years, Bacterial Leaf Spot was observed at a significantly lower frequency, leading to fewer corresponding images in the dataset. This limited representation is due to variations in environmental factors that influence disease prevalence during the growing period. However, the dataset still provides a well-structured and diverse collection for training and evaluating classification models. Table 1 provides a detailed breakdown of image distribution across categories.

Table 1
Breakdown of image distribution of the dataset.

Sr. No	Class	Sub Class	No. of Images
1	Healthy Grapes Leaf	-	1254
2	Un-healthy Grapes Leaf	Downy Mildew	966
		Powdery Mildew	406
		Bacterial Leaf Spot	100
Total Number of Images:			2726

Table 2

Image acquisition steps.

Sr. No.	Activity	Duration	Specification
1	Image Acquisition	June2023-January 2025	During daytime field/farm visits to capture images.
2	Pre-Processing	January 2025	The images suitable for the dataset were selected from collected images and were pre-processed.
3	Dataset Published	February 2025	Dataset Published on Mendeley Platform: https://data.mendeley.com/datasets/8nnd2ypcv3/5

4. Experimental Design, Materials and Methods

This section provides detail description of grape leaf image data acquisition process with experimental design, data pre-processing and classification. Table 2 represents summarized the image data acquisition process undertaken by this project.

The Grapes Leaf dataset is preparation mainly categorize in two phases. First section consists of grapes leaf acquisition process and second phase includes image pre-processing to data classification steps as shown in Fig. 1.

4.1. Image acquisition process

a) Grape field visit

We have selected the grape farm from Nashik district to collecting the grape leaf images for our proposed research work. This dataset is collected from grapes farms during the period of June 2023 to January 2025, ensuring a diverse dataset across multiple seasons. The periodical field visit in susceptible environmental condition has planned and executed to collect the healthy and infected leaves with diverse diseases. The visits were scheduled based on critical crop growth stages and disease susceptibility periods to ensure comprehensive data collection.

b) Selection of leaves

To prepare the dataset for the proposed research work the grape leaves are selected in two measure categories i.e. healthy and unhealthy (infected) leaves. The grape leaves were collected after observing environmental conditions susceptible to diseases such as downy mildew, powdery mildew, and bacterial leaf spot. The selection was not primarily dependent on the leaf growth stage. Downy mildew infections were noted under high humidity and mild to warm temperatures. Powdery mildew was commonly observed in warm, dry climates with moderate humidity, while bacterial infections appeared in high-moisture conditions combined with warm temperatures [10]. These infections were recognised throughout the growing season, from pruning to harvest. This ensured that the dataset represents a wide range of real-world variations, making the model more generalizable. All images were captured under natural lighting conditions, maintaining consistent angles and distances from the leaf surface to ensure uniformity.

All leaves were collected under the supervision of an agricultural expert, and images were captured in daylight conditions to ensure clear visibility.

c) Image capturing

The selected grape leaves images have captured using the two devices which are and Real me 8s 5G Mobile having best resolution rear cameras. The detailed description of camera devices are as follows:

i) Make and Model: Real me 8s 5G Android Mobile.

- Rear Primary Camera: It has 64MP + 2MP + 2MP camera with 1/5-inch Sensor Size, 3P Lens.

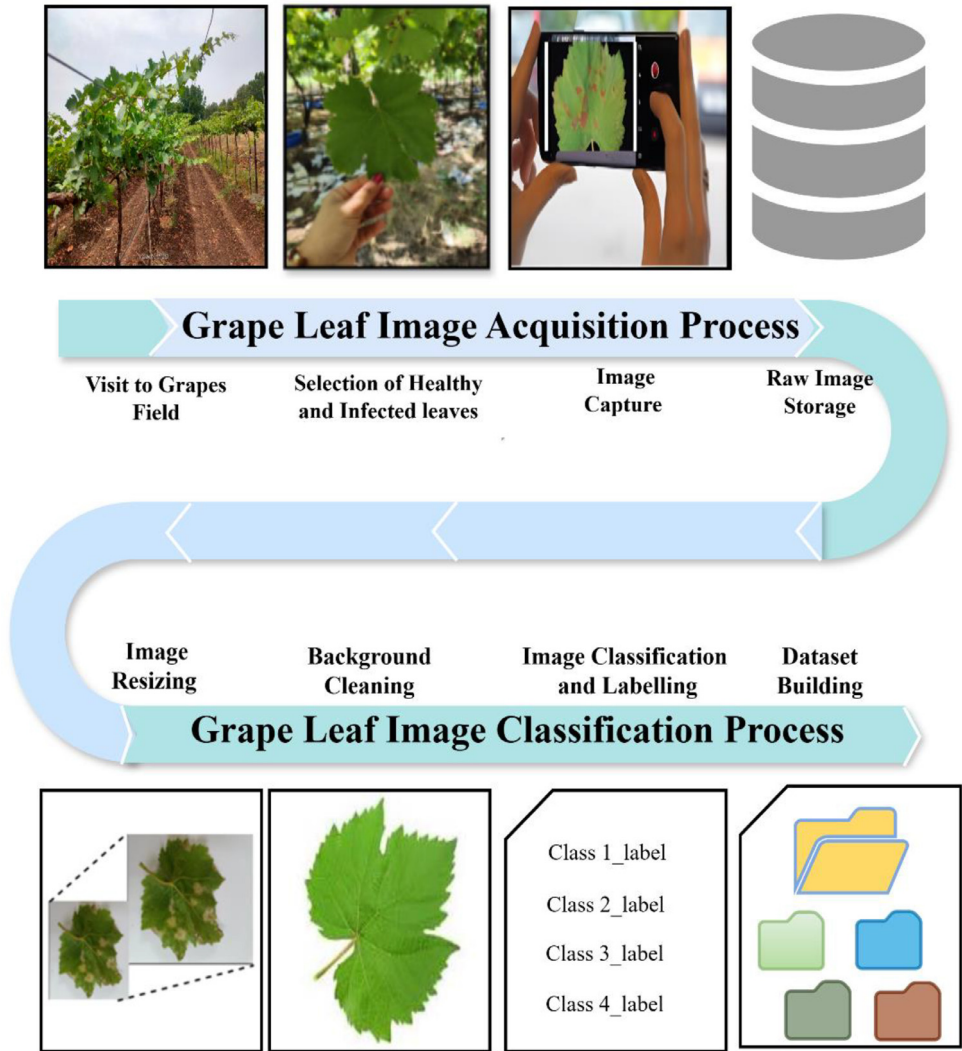


Fig. 1. Grape leaf image acquisition to image classification process.

- Triple rear camera setup with a 64MP primary sensor (PDAF, EIS), 2MP portrait, and 2MP macro lens, featuring a CMOS sensor for enhanced imaging. The primary camera offers f/1.8 aperture, 80.5°FOV, and a 6P lens for detailed and sharp photos.
- ii) Make and Model: Samsung S21 FE 5G Mobile
- Rear Primary Camera: It has 12MP + 12MP + 8MP (OIS) camera with f/1.8-aperture lens.
 - Triple rear camera setup with a 12MP main sensor (f/1.8, Dual Pixel AF, OIS), 12MP ultra-wide lens (123°FOV), and 8MP telephoto lens (3X optical zoom, 30X space zoom, OIS) for versatile photography.
- d) Raw image data storage
- The captured images were initially stored as raw images on a local drive for further pre-processing and analysis. During this stage, a quality check was performed to ensure the usability of the dataset for machine learning applications. Blurry, low-resolution, or poor-quality

images were identified and removed to maintain dataset integrity. Only high-quality images with clear details were retained for subsequent processing steps, ensuring reliable feature extraction and accurate model training.

4.2. Image preprocessing steps

a) Image resizing

To maintain consistency across the dataset for research purposes, the stored raw images were resized to a standardized dimension of 256×256 pixels at 96 dpi. By choosing smaller image dimensions 256×256 pixels at 96 dpi, the dataset remains well-structured, computationally optimized, and suitable for deep learning applications while preserving crucial image details. The 96-dpi setting is appropriate for digital analysis, offering a practical balance between image clarity and storage efficiency.

b) Background removal

To improve classification efficiency, the resized grape leaf images are proceeded with background removal to provide a uniform background, enhancing grape leaf focus and noise reduction. The uniform background plays a significant role in emphasizing appropriate features and lessening interference by non-leaf features. We used the popular web tool Remove.bg to extract unwanted backgrounds from chosen images and make the dataset more appropriate for image-based machine learning, deep learning, and image analysis research. This step of preprocessing further improves the dataset's applicability for building solid disease classification models.

c) Image classification and labelling

These selected images were then manually classified into healthy and three disease classes under the guidance and observation of domain expert from the Grapes Research Centre. The infected images are further classified in three sub classes namely Downy Mildew, Bacterial Leaf Spot and Powdery Mildew. The Fig. 2 represents the sample images from four different classes of dataset. Accurate image labelling supports to develop supervised learning for model.

d) Dataset building

In the final stage of database preparation, all label and classified images are stored in well-structured format at local drive for future research and analysis. The final dataset is published at free and secured cloud-based communal repository Mendeley Data [1] to assist the research community in precision agriculture. The Fig. 3 Represents the structural organization of the dataset for accumulated navigation.

This meticulous image pre-processing and dataset building process not only prepares the data for complex models but also lays the foundation for seamless analysis throughout our research, enhancing both the reliability and effectiveness of our data.

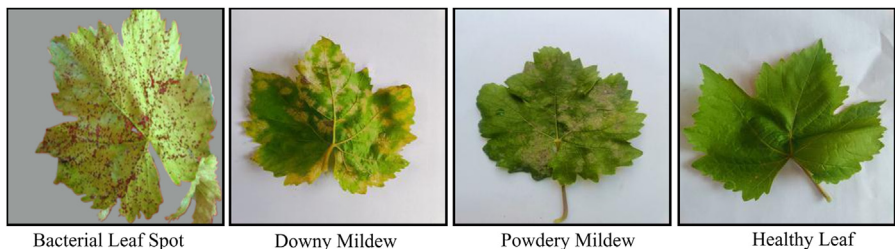


Fig. 2. Sample Images of Each Class.

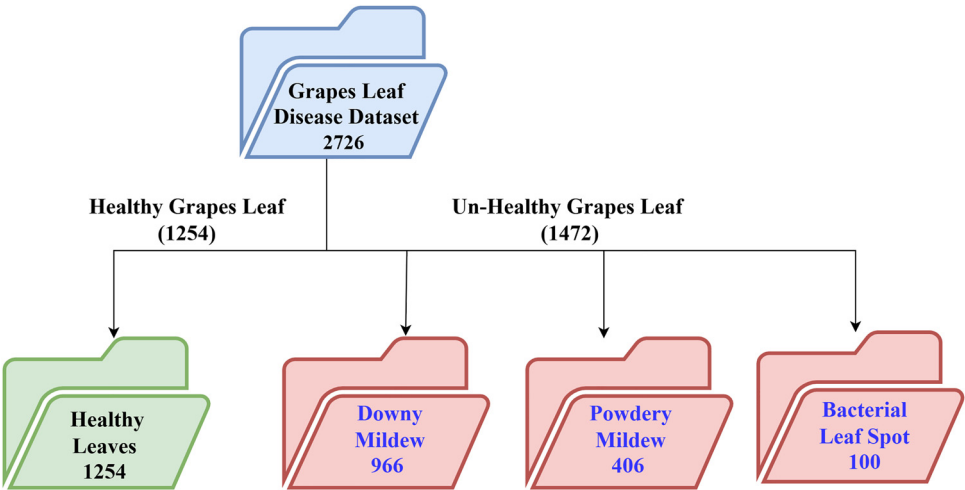


Fig. 3. Disease wise organized dataset.

4.3. Highlighting the datasets value

To analyze the quality of the dataset, a classification was performed using transfer learning approach on the pretrained version of ResNet-18 to take advantage of visual features learned from a large and diverse dataset. To adapt it to our task, we replaced the final classification layer with a new one that matches the number of classes in our dataset. We kept all the other layers frozen during training, so only the final layer was updated. This made training faster and helped prevent overfitting, which is especially important when working with smaller datasets.

The model was trained and tested on the dataset for image classification of grape leaves into four categories: Powdery Mildew, Downy Mildew, Bacterial Leaf Spot, and Healthy Leaves. The model was trained for 10 epochs using the hyperparameters configuration such as learning rate, optimizer, batch size, loss function, regularization settings, and training duration outlined in Table 3.

To ensure a balanced and fair evaluation, the dataset was split into 70% training, 15% validation, and 15% testing sets using stratified sampling, preserving class proportions across all subsets.

To thoroughly understand how well the model performs, we evaluated it using standard metrics like precision, recall, F1-score, and overall accuracy, as shown in Table 4.

The model performed impressively across most disease categories, maintaining consistently high scores. Most importantly, it achieved an overall accuracy of **96%**, which reflects its strong

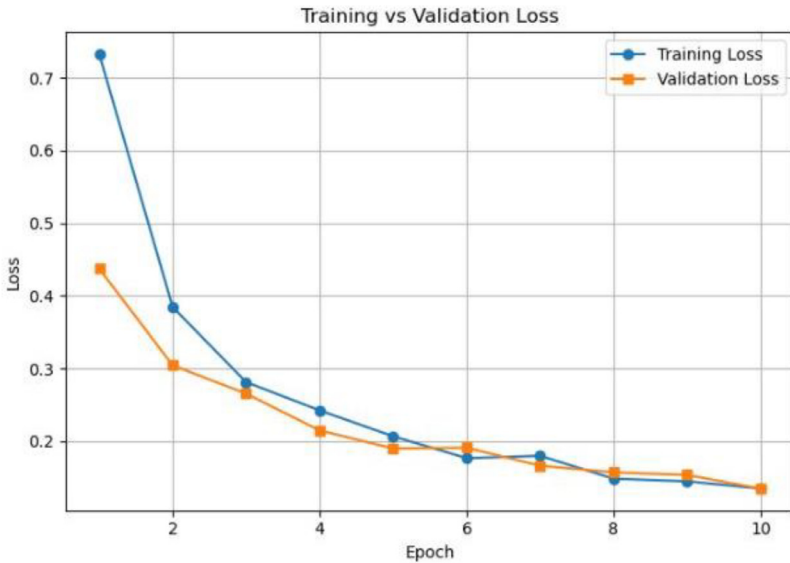
Table 3
Hyperparameters used in model training.

Hyperparameter	Value	Description
Model Architecture	ResNet-18 (pretrained)	Base CNN model with ImageNet weights
Trainable Layers	Final fully connected (fc) layer only	Other layers frozen during training
Optimizer	Adam	Adaptive Moment Estimation optimizer
Learning Rate	0.001	Controls step size during optimization
Batch Size	32	Number of samples per training iteration
Epochs	10	Number of full passes over the training dataset
Loss Function	CrossEntropyLoss	Standard for multi-class classification
Weight Decay (L2)	1e-5	Regularization term to reduce overfitting

Table 4

Performance analysis on the validation set.

Class/Metric	Precision	Recall	F1-Score	Support
Bacterial Leaf Spot	0.92	0.71	0.80	17
Downy Mildew	0.99	0.94	0.96	150
Healthy Leaves	0.95	0.99	0.97	182
Powdery Mildew	0.92	0.97	0.94	59
Accuracy		0.96		408
Macro Avg	0.95	0.90	0.92	408
Weighted Avg	0.96	0.96	0.96	408

**Fig. 4.** Training and validation loss curve.

ability to correctly identify grape leaf diseases. These results not only show the model's reliability but also highlight the NGLD dataset's strength in supporting accurate and meaningful disease classification.

Additionally, We plot the training vs. validation loss curve to get a clear idea of how well the model is learning and whether it's generalizing properly to new, validation data. This graph is especially useful for identifying problems like underfitting or overfitting. As shown in Fig. 4, both the training and validation losses steadily decrease and closely follow each other throughout the training process.

This smooth, parallel decline suggests the model is learning effectively and isn't overfitting. The consistent performance of both curves indicates a balanced and reliable training process, where the model is not only fitting the training data well but also performs strongly on validation data.

The confusion matrix shown in Fig. 5 highlights the strong classification performance of the dataset, particularly in accurately identifying Healthy Leaves, Downy Mildew, and Powdery Mildew. The high accuracy across these categories reflects the dataset's effectiveness in supporting reliable machine learning training for plant disease detection.

Although overall results are promising, the classification of *Bacterial leaf Spot* shows comparatively lower accuracy, likely due to its limited sample size. Despite this, the model demonstrates

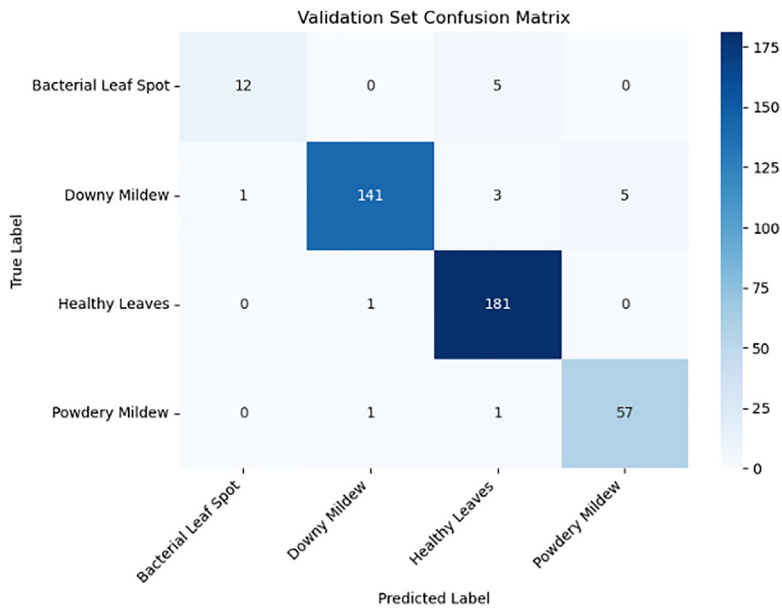


Fig. 5. Confusion matrix for disease classification.

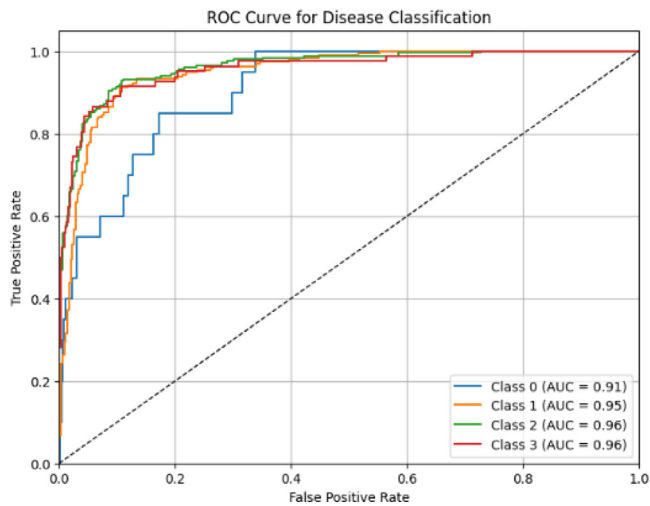


Fig. 6. ROC curve for disease classification.

its ability to capture key distinguishing features across all classes, affirming the dataset’s value for predictive modelling tasks.

The ROC (Receiver Operating Characteristic) curve demonstrates the performance of a multi-class disease classification model as given in Fig. 6. The x-axis is the false positive rate, and the y-axis is the true positive rate. A curve extending further towards the top-left indicates a better classification ability.

The ROC curves indicate that the model properly discriminates among the provided classes, with performance always high across all classes. The fact that the curves show smooth progression indicates an optimal trade-off between sensitivity and specificity. The diagonal dashed line

is the line of random classification, and as all the curves plotted lie well above the baseline, it assures us that the model is much better than random guessing. These results emphasize the robustness and effectiveness of the model in classifying diseases with precision.

These results validate the efficiency of dataset in training deep learning models to accurately classifying disease. Thus, The Niphad Grape Leaf Disease Dataset (NGLD) is a useful dataset for plant pathology studies, especially in the field of AI-based grape leaf disease detection. This further makes it important in precision farming and sustainable grapes crop management.

Limitations

The dataset is collected from a specific region, potentially limiting its applicability to other geographical areas with different disease prevalence or manifestations.

Ethics Statement

Our research aligns with Data in Brief's ethical considerations for datasets, as it does not involve animal or human subjects. Thus, confirm adherence to ethical considerations.

CRediT Author Statement

Madhuri Dharrao: Conceptualization, Methodology, Writing – review & editing; **Nilima Zade:** Writing – review & editing, Data curation, Supervision; **R Kamatchi Iyer:** Writing – review & editing, Data curation **Rakesh Sonawane:** Conceptualization, Data curation, identification, Supervision; **Rabinder Henry:** Writing – review & editing, Data curation; **Deepak Dharrao:** Conceptualization, Data curation, Writing – review & editing.

Data Availability

[Niphad Grape Leaf Disease Dataset \(NGLD\) \(Original data\)](#) (Mendeley Data)

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Declaration of Competing Interest

The authors declare that no known challenges in economic welfare or personal relationships could have appeared to influence the work reported in this paper.

References

- [1] Madhuri Dharrao, Deepak Dharrao, Rakesh Sonawane, Nilima Zade, Niphad Grape Leaf Disease Dataset (NGLD), Mendeley Data V5 (2025), doi:[10.17632/8nnd2ypcv3.5](#).
- [2] R. Gani, et al., Smartphone image dataset to distinguish healthy and unhealthy leaves in papaya orchards in Bangladesh, Data Brief. 55 (2024), doi:[10.1016/j.dib.2024.110599](#).

- [3] <https://mpkv.ac.in/Research> Dept, "Recommendation released by mahatma Phule Krishi Vidyapeeth," 2023.
- [4] E.M.B.M. Karunathilake, A.T. Le, S. Heo, Y.S. Chung, S. Mansoor, The Path to Smart Farming: Innovations and Opportunities in Precision Agriculture, Multidisciplinary Digital Publishing Institute (MDPI), 2023, doi:[10.3390/agriculture13081593](https://doi.org/10.3390/agriculture13081593).
- [5] S. Thite, Y. Suryawanshi, K. Patil, P. Chumchu, Sugarcane leaf dataset: a dataset for disease detection and classification for machine learning applications, Data Brief. 53 (2024), doi:[10.1016/j.dib.2024.110268](https://doi.org/10.1016/j.dib.2024.110268).
- [6] A. Medvedev, et al., GRAPE: genomic relatedness detection pipeline, F1000Res. 11 (2022) 589, doi:[10.12688/f1000research.111658.2](https://doi.org/10.12688/f1000research.111658.2).
- [7] Dr. S. S, S. C, R. P, and R. P, A comprehensive survey of grape leaf disease detection and classification using machine learning based models, Int. Res. J. Comput. Sci. 8 (8) (2021) 183–188, doi:[10.26562/irjcs.2021.v0808.005](https://doi.org/10.26562/irjcs.2021.v0808.005).
- [8] P. Deshpande, S. Kore, and S. Kore, "Disease detection for grapes: a review," 2023, pp. 51–61. doi: [10.1007/978-981-99-2854-5_5](https://doi.org/10.1007/978-981-99-2854-5_5).
- [9] Z. Gao, L.R. Khot, R.A. Naidu, Q. Zhang, Early detection of grapevine leafroll disease in a red-berried wine grape cultivar using hyperspectral imaging, Comput. Electron. Agric. 179 (2020) 105807, doi:[10.1016/j.compag.2020.105807](https://doi.org/10.1016/j.compag.2020.105807).
- [10] Y. Liu, Q. Yu, S. Geng, S. Geng, Real-time and lightweight detection of grape diseases based on Fusion Transformer YOLO, Front. Plant Sci. 15 (2024) 1269423, doi:[10.3389/fpls.2024.1269423](https://doi.org/10.3389/fpls.2024.1269423).
- [11] M. Shantkumari, S.V. Uma, S.V. Uma, X. Wang, Machine learning techniques implementation for detection of grape leaf disease, Multimed. Tools. Appl. 82 (20) (2023) 30709–30731, doi:[10.1007/s11042-023-14441-x](https://doi.org/10.1007/s11042-023-14441-x).
- [12] R. Chin, C. Catal, A. Kassahun, A. Kassahun, Plant disease detection using drones in precision agriculture, Precis. Agric. 24 (5) (Oct. 2023) 1663–1682, doi:[10.1007/s11119-023-10014-y](https://doi.org/10.1007/s11119-023-10014-y).
- [13] P. Kaur, et al., Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction, Sensors 22 (2) (2022), doi:[10.3390/s22020575](https://doi.org/10.3390/s22020575).
- [14] X. Xie, Y. Ma, B. Liu, J. He, S. Li, H. Wang, A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks, Front. Plant Sci. 11 (2020) 751, doi:[10.3389/fpls.2020.00751](https://doi.org/10.3389/fpls.2020.00751).
- [15] H.T. Rauf, B.A. Saleem, M.I.U. Lali, M.A. Khan, M. Sharif, S.A.C. Bukhari, A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning, Data Brief. 26 (2019), doi:[10.1016/j.dib.2019.104340](https://doi.org/10.1016/j.dib.2019.104340).
- [16] Z. Alam, et al., Multivariate analysis of yield and quality traits in sweet potato genotypes (*Ipomoea batatas* L.), Sci. Hortic. 328 (2024), doi:[10.1016/j.scienta.2024.112901](https://doi.org/10.1016/j.scienta.2024.112901).
- [17] Y.-T. Guo, Y. Yan, G.-L. Zhang, Specifications table, Plant Cell Environ. 55 (6) (2024) 1935–1945, doi:[10.17632/fmyrz84f65.3](https://doi.org/10.17632/fmyrz84f65.3).