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Data Article

Comprehensive smart smartphone image dataset for plant leaf disease detection and freshness assessment from Bangladesh vegetable fields

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ABSTRACT

Bangladesh's agricultural landscape is significantly influenced by vegetable cultivation, which substantially enhances nutrition, the economy, and food security in the nation. Millions of people rely on vegetable production for their daily sustenance, generating considerable income for numerous farmers. However, leaf diseases frequently compromise the yield and quality of vegetable crops. Plant diseases are a common impediment to global agricultural productivity, adversely affecting crop quality and yield, leading to substantial economic losses for farmers. Early detection of plant leaf diseases is crucial for improving cultivation and vegetable production. Common diseases such as Bacterial Spot, Mosaic Virus, and Downy Mildew often reduce vegetable plant cultivation and severely impact vegetable production and the food economy. Consequently, many farmers in Bangladesh struggle to identify the specific diseases, incurring significant losses. This dataset contains 12,643 images of widely grown crops in Bangladesh, facilitating the identification of unhealthy leaves compared to healthy ones. The dataset includes images of vegetable leaves such as Bitter Gourd (2223

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images), Bottle Gourd (1803 images), Eggplants (2944 images), Cauliflowers (1598 images), Cucumbers (1626 images), and Tomatoes (2449 images). Each vegetable class encompasses several common diseases that affect cultivation. By identifying early leaf diseases, this dataset will be invaluable for farmers and agricultural researchers alike.

Specifications Table

Subject	Plant Pathology Branch of Agriculture
Specific subject area	Different Plant Disease Identification and Classification.
Type of data	Raw Images Dataset in 700×700 jpg format.
Data collection	To distinguish different vegetable leaves, images of six types of plant leaves—Bitter Gourd, Bottle Gourd, Cauliflower, Eggplant, Cucumber, and Tomato—were collected using a Realme 9 5G Android smartphone from vegetable fields in Bangladesh. After identifying the disease of each plant, images were captured from various angles to ensure a comprehensive view of a single leaf for each class. To avoid oversaturation and over lighting effects, the images were taken in a well-organized laboratory room with a black background. The dataset comprises approximately 12,643 images, which will have a significant impact on the agricultural field.
Data source location	1. Vegetable field of Kathalkandi, Nasirnagar, Brahmanbaria, Bangladesh (latitude: 24.1915°, longitude: 91.1826°)
Data accessibility	Repository name: Mendeley Data Data identification number: DOI: 10.17632/n67gctmjyj.3 Direct URL to data: https://data.mendeley.com/datasets/n67gctmjyj/3

1. Value of the Data

- The dataset provides detailed information on leaf diseases for six types of vegetable leaves, supporting various research endeavors, including the development of algorithms for automated disease detection, classification of leaf conditions, and yield prediction models[1].
- Advanced applications of this dataset include training machine learning or deep learning models for leaf disease detection, supporting agricultural practices and food growth, and aiding in the development of decision support systems for farmers [2,5].
- Developing advanced deep learning models using this dataset and integrating them into mobile devices will significantly enhance the early detection of leaf diseases with high accuracy, eliminating the need for agricultural experts in rural areas for traditional guidelines.
- As the dataset is open to everyone, it encourages collaboration among researchers, agronomists, and technology developers, further contributing to sustainable agricultural [5] practices and enhanced food security.
- Bangladesh and other agro-ecological regions could greatly benefit from this dataset by promoting agricultural research and innovation.

2. Background

Farmers typically identify vegetable leaf diseases by traditional ways. However, this is not a good practice as today's farmers are cultivating diverse set of plants in a single field. Thus, it is very complex for the farmers to monitor each plant leaves throughout their eyes vision and marking the affected leaves. Unfortunately, due to the lack of technology, many farmers are undermining advance techniques to identify the unhealthy leaves and save their crops from many worst cases. Creating a computer vision-based model is essential to solve this issue as it can

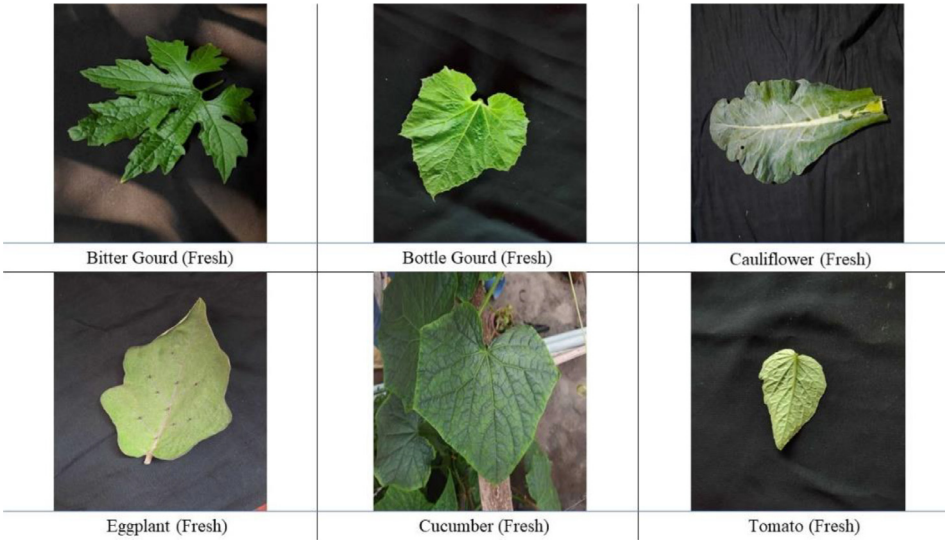


Fig. 1. Healthy leaves from every plant.

identify multiple vegetable leaf diseases and cut down the human labor, expenses, and production times in the agriculture industry. A large volume of data can be useful for deep learning models that are acquired through image augmentation training. As the dataset is categorized perfectly, in this case many deep learning models can be trained without any error. Furthermore, using this classification models, farmers can easily hunt down unhealthy leaves. Some researchers [1] already introduces a dataset aimed at the detection and classification of diseases in papaya plants which will help the researchers to develop advance models to identify the healthy and 5 types of diseases of papaya leaf. The paper [2] proposes 2721 tobacco leaf images dataset where baseline experiments using YOLO-v3 and Mask-RCNN for leaf detection are proposed. Moreover, In the dataset [3] DiaMOS plant with 3505 images of pear leaf diseases enables researchers to develop further model and supports agricultural stakeholders in diagnosing and monitoring plant diseases. In addition, deep learning models plays crucial role in identifying leaf disease [4]. Therefore, it is clear that the dataset will enhance the further research and help to prevent leaf damages and increase the vegetables productivity.

3. Data Description

A large collection of high-quality 12,643 images has been assembled to aid in the creation of sophisticated agricultural image analysis models. To support applications for advanced technology such as deep learning and machine learning models, the dataset is carefully organized. All the images are categorized according to the plant types and class types; as it is necessary to have a better understanding between the healthy and unhealthy leaves. In this dataset [5] we are identifying six different plants along with different classes and diseases shown in Fig. 1 and which are: Bitter Gourd (Downy mildew, Mosaic virus, Fusarium wilt, fresh leaf), Bottle Gourd (Anthracnose, Downy mildew, fresh leaf), Cauliflower (Black rot, Downy mildew, fresh leaf), Eggplant (Verticillium wilt, Cercospora leaf spot, Begomovirus, fresh leaf), Cucumber (Downy mildew, Anthracnose lesions, fresh leaf), and Tomato (Bacterial spot, Tomato leaf curl virus, Tomato spotted wilt, fresh leaf).

Fig. 2. Bitter Gourd leaf with Downy Mildew disease.

Fig. 3. Bitter Gourd leaf with Mosaic Virus disease.

3.1. Bitter gourd

Fig. 2 shows the Bitter Gourd Downy mildew disease where the disease's symptoms are yellow and angular in appearance, and they first occur on the upper portion of leaves. Parts of the plant that have been damaged by the disease eventually turn yellow, with the center remaining brown. In high-humidity environments, the symptoms show up as a gray powder on the underside of the leaves [6].

Fig. 3 shows the Bitter Gourd Mosaic Virus Disease where the tomato leaf curl New Delhi virus (ToLCNDV) and the bitter gourd yellow mosaic virus (BgYMV) are the two begomoviruses that produce yellow mosaic disease, which has a severe effect on bitter gourd. This disease's symptoms include leaf yellowing, alterations to the form of leaves, and puckering [7].

Fig. 4 shows the Bitter Gourd leaf with Fusarium Wilt disease where the mature plants usually exhibit symptoms during fruit set. These symptoms can include dull, grey-green leaves that eventually become yellow, crown foliage that wilts during the day, and finally, death. On the stems and branches of diseased plants, brown stripes will appear. Inside the stem, there is vascular deterioration, and the stem collars frequently turn dark brown [8].

Bitter Gourd is also known as bitter melon. Fig. 5 shows Bitter Gourd Fresh leaves which are typically green in color, heart-shaped with a little wrinkled texture.

Fig. 4. Bitter Gourd leaf with Fusarium Wilt disease.

Fig. 5. Bitter Gourd Fresh leaf.

3.2. Bottle gourd

Fig. 6 shows the Bottle Gourd Leaf with Anthracnose disease where it is characterized by small, sunken, circular patches that are yellowish to brown in the early stages of the illness and big, brown to black aggregated areas with cracked, dead centers that are covered in masses of pink spores in the later stages of the disease [9] (Fig. 6).

Fig. 7 shows Bottle Gourd with Downy Mildew disease where plants exhibiting characteristic downy mildew signs were discovered in the field. On the upper leaf surfaces, the infection caused yellowish or pale green lesions, and on the lower surfaces, a dark grey fungal growth appeared. Leaf veins defined the angular shape of the lesions.

Fig. 8 shows the fresh leaf of the Bottle Gourd which is healthy-looking, broad, and vivid green. It has clean edges and veins that are clearly apparent. It is sturdy and feels smooth to the touch.

3.3. Cauliflower

Fig. 9 shows Cauliflower leaf Black Rot disease where this disease causes tan-colored spots on leaves that eventually darken to gray and then develop into black color dots. Dark black to

Fig. 6. Bottle Gourd leaf with Anthracnose disease.

Fig. 7. Bottle Gourd leaf with Downy Mildew disease.

purple margins can also develop in stems. Sometimes this disease can spread from stems to roots [10].

Fig. 10 shows the Cauliflower leaf with Downy mildew disease which is one of the most harmful and frequent diseases affecting cauliflower is downy mildew, which is brought on by the obligatory parasite Hyaloperonospora parasitica Constant (Pers.: Fr) Fr. (previously Peronospora parasitica). The angular translucid patches that exhibit purplish brown on the underside and tan to yellow hue on the upper surface of leaves are the hallmark symptoms of downy mildew. The afflicted curds initially have a brownish appearance before turning dark brown or black. White mycelial development causes discoloration and deformity in cauliflower curd [11].

Fig. 11 shows the Cauliflower Fresh Leaf where it appears healthy, broad, and vivid green. There are lines on it, and its edges are smooth. It feels robust and smooth to the touch (Fig. 11).

3.4. Eggplant

Fig. 12 shows the Eggplant leaf with Verticillium Wilt disease where it is caused by Verticillium dahliae. Wilt, chlorosis, defoliation, tiny leaves, and stunted plants are some of the symptoms [12].

Fig. 8. Bottle Gourd Fresh leaf.

Fig. 9. Cauliflower leaf with Black Rot disease.

Fig. 13 shows the Eggplant leaf with Cercospora leaf spot where necrotic, angular, circular, or oblong lesions up to 7 mm in diameter are the disease's symptoms. occasionally, the lesions have shot holes in the middle [13].

Fig. 14 shows the Eggplant leaf with Begomovirus disease. Under natural circumstances, the diseased eggplants showed signs of leaf curl, little leaf, and a combination of little leaf and mosaics. Wilt, chlorosis, defoliation, tiny leaves, and stunted plants are some of the symptoms [14].

Fig. 15 shows Eggplant Fresh Leaf. The broad, vibrant green leaf of the fresh eggplant appears healthy. It is veined and has smooth edges. It feels robust and smooth to the touch.

3.5. Cucumber

Fig. 16 shows the Cucumber leaf with Downy mildew disease where a common fungal disease called downy mildew can affect cucumber plants, particularly in damp or moist settings. These sick cucumbers have patches or blotches that are pale green or yellow on their upper leaf surface. a white or grayish-purple, downy-looking growth on the underside of the leaves. The leaves that are harmed may get lesions that coalesce and spread, rendering the leaves brown or necrotic. Eventually, twisted or curled leaves may dry out and fall off the plant [15].

Fig. 10. Cauliflower leaf with Downy Mildew disease.

Fig. 11. Cauliflower Fresh leaf.

Fig. 12. Eggplant leaf with Verticillium Wilt disease.

Fig. 13. Eggplant leaf with Cercospora Leaf Spot disease.

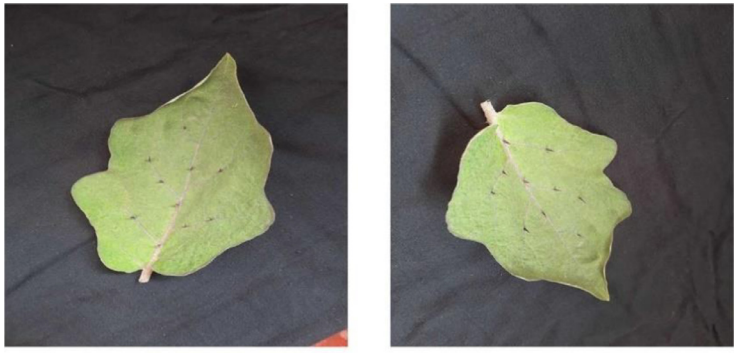
Fig. 14. Eggplant leaf with Begomovirus Wilt disease.

Fig. 17 shows the Cucumber leaf with Anthracnose lesions disease. Cucumbers are frequently affected by the fungus anthracnose. A fungal infection called Colletotrichum orbicular is the cause of anthracnose. The disease can cause blight on all above-ground cucumber parts, fruit rot, stem canker, and leaf spots during the growing season. High disease infection rates in warm, muggy summers can result in early defoliation, decreased yields, and lower-quality fruit. Leaf spots are the most common symptoms in fields; they begin as little, round yellow dots and later spread to damp areas.

Fig. 18 shows the Cucumber Fresh leaf. The leaf of the fresh cucumber is large, green, and healthy. There are tiny cuts all around it. It is crossed by lines. touching it gives a smooth feeling.

3.6. Tomato

Fig. 19 shows the Tomato leaf with Bacterial spot disease. The symptoms start with tiny, greasy, circular to irregular that are mostly visible on the underside of the leaflets. The hues of these water-soaked areas shift from dark green to purplish-gray as they grow, with a contrasting black core. The impacted tissue thins and may break. The areas that are affected could have a white-to-yellowish halo surrounding them. Infected leaves seem burned in damp weather. Defoliation is the result of large lesions [16].



Eggplant (fresh leaf)

Fig. 15. Eggplant Fresh leaf.

Cucumber (Downy mildew)

Fig. 16. Cucumber leaf with Downy Mildew disease.

Cucumber (Anthracnose lesions)

Fig. 17. Cucumber leaf with Anthracnose Lesions disease.

Fig. 20 shows the Tomato leaf with Leaf Curl disease. The following disease appears as stunting, flower abortion, and a more or less noticeable upward curling of the leaflet edges, as well as a reduction in leaflet area and yellowing of the young leaves. Plants infected in their early growth stages lose nearly all of their production, and infections generally result in decreased plant growth and yields [17].

Fig. 18. Cucumber Fresh leaf.

Fig. 19. Tomato leaf with Bacterial Spot disease.

Fig. 21 shows the Tomato Leaf with spotted wilt disease. When it comes to tomatoes, the initial signs are typically tiny, orange-colored spots on the calyx, middle, or lower leaves. Older leaves droop, turn brown, and die as fresh spots form. On the stems and petioles, there are corresponding dots or streaks. The entire plant shrinks, and its drooping leaves give it the appearance of a wilted plant [18].

Fig. 22 shows the Tomato Fresh leaf. A leaf of tomato that is in good health has a vivid green color, a smooth texture, and no apparent lesions, stains, or discoloration. Strong photosynthesis is demonstrated by these leaves, which promotes overall plant vitality and ideal crop development.

3.7. Work comparison, dataset structure and distribution

In order to compare the dataset and enhancing the following study value, a comparative work of previous research is shown in Table 1.

Table 1 indicates that the authors of paper [19] identified only 10 classes of plant leaves with 14,531 images. Moreover, the dataset only focuses on the tomato leave. On the other hand, other authors [20], discover 17 classes of different leaf plants, however the number of images is minimum which is only 2598 images. Lastly, our dataset [5] contains 21 classes with a good number of images which is 12,643. In order to work on the vegetable plants, it can be said that our dataset will provide more efficiency and reliability.

Fig. 20. Tomato leaf with Leaf Curl disease.

Fig. 21. Tomato leaf with Spotted Wilt disease.

Fig. 22. Tomato Fresh leaf.

Table 1
Previous data collection comparison.

Cite	Class	Number of Images
Huang, Mei-Ling; Chang, Ya-Ha [19]	10	14,531
Singh, D., Jain, N., Jain, P., Kayal, P., Kumawat, S., & Batra, N [20]	17	2598
Our dataset [5]	21	12,643

Table 2
Dataset sample distribution.

Original Dataset				
Name of the vegetables	Class	Category	No of images	Folder Name
Bitter Gourd	1	Downy Mildew	570	Downy Mildew
	2	Mosaic Virus	600	Mosaic Virus
	3	Fusarium Wilt	502	Fusarium Wilt
	4	Fresh Leaf	551	Fresh Leaf
Bottle Gourd	1	Anthracnose	601	Anthracnose
	2	Downy Mildew	684	Downy Mildew
	3	Fresh Leaf	518	Fresh Leaf
Cauliflower	1	Black Rot	560	Black Rot
	2	Downy Mildew	512	Downy Mildew
	3	Fresh Leaf	526	Fresh Leaf
Eggplant	1	Verticillium Wilt	730	Verticillium Wilt
	2	Cercospors Leaf Spot	723	Cercospors Leaf Spot
	3	Begomovirus	720	Begomovirus
	4	Fresh Leaf	771	Fresh Leaf
Cucumber	1	Anthracnose Lesions	535	Anthracnose Lesions
	2	Downy Mildew	564	Downy Mildew
	3	Fresh Leaf	527	Fresh Leaf
Tomato	1	Bacterial Spot	589	Bacterial Spot
	2	Tomato Leaf Curl Virus	612	Tomato Leaf Curl Virus
	3	Tomato Spotted Wilt	654	Tomato Spotted Wilt
	4	Fresh Leaf	594	Fresh Leaf

Table 2 shows the information regarding the dataset sample distribution which is necessary to identify the volume of each class of a particular plant. Moreover, there is no minority group (consisting of a smaller number of images) in the overall dataset. Thus, it can be said that the dataset is well distributed. Furthermore, in order to use this dataset for computer vision models then researchers do not need to use random over sampling method to adjust the dataset size. Moreover, while training the deep learning models, there won't be any bias for a particular class. In addition, the trainable model would provide much more accurate results. On the other hand, the dataset consists of 21 classes and six types of plant leaves thus it will be more difficult to navigate to the desired class images. Fig. 23 illustrates the folder structure which will help the researchers to find the particular class of a plant and easy to use the appropriate plant leaves images.

4. Experimental Design, Materials and Methods

4.1. Dataset collection

One of the most important steps in the process of identifying plant diseases is data collection. To achieve a high-quality dataset, we visited different plant fields in Kathalkandi, Nasirnagar, and Brahmanbaria, Bangladesh, and analyzed various plant leaf diseases to understand each disease in depth. In Bangladesh, vegetable leaf diseases like Downy mildew and Mosaic virus are commonly found in most plants. These diseases are well-known. However, to ensure careful inspection and precise diagnosis, we expanded the scope of our investigation to include less well-known illnesses such as Black Rot disease of cauliflower. This method ensures a comprehensive and knowledgeable data collection process by conducting a thorough search for precise information on these conditions. Before collecting the leaf images, we communicated with local farmers in Brahmanbaria, Bangladesh, to identify the vegetable yards. Additionally, we gathered detailed knowledge about each plant disease, which helped us determine whether a plant leaf was unhealthy and, if so, to which class it belonged.

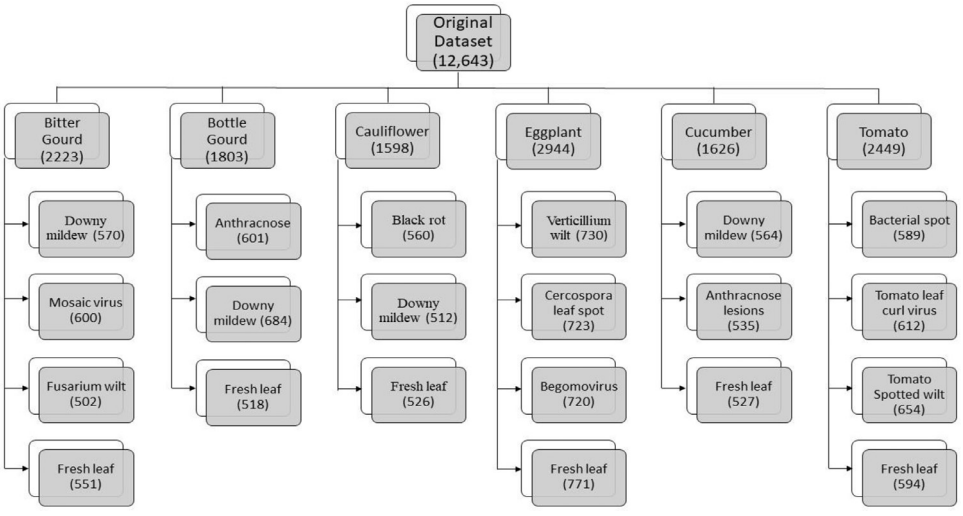


Fig. 23. Dataset Folder Structure.

Table 3
Image captured device specification.

Device Name	Camera Resolution
Realme 9 5G	48MP AI Triple Camera, 48MP UHD Main Camera, Aperture F1.8, FOV 79.8°, Equivalent focal length 25.4 mm, 6P lens, Sensor dimensions 1/2′, 4 cm Macro lens, 2 million pixels, Aperture F2.4, FOV 88.8°, Focus distance 4 cm, Portrait lens, 2 million pixels, Aperture F2.4, FOV 88.8°, Equivalent focal length 21.8 mm, 3P lens

For image collection, we used a Realme 9 5 G smartphone as our main image-capturing device. The camera specifications of this device are shown in Table 3. We captured images of a single leaf from six different angles to ensure a clear view of each leaf. Leaves of the same labels can exhibit intrinsic differences such as variations in size, shape, and the appearance of disease symptoms. To account for these differences and ensure comprehensive representation of each leaf's characteristics, images were taken under consistent lighting conditions from multiple angles. Additionally, a special laboratory area was created to prevent oversaturation due to sunlight and other natural variables. This controlled setting involved adjusting the white balance to maintain true color representation, controlling brightness to avoid shadows and glare, and using artificial lighting to mitigate other environmental factors. These measures were crucial to preserve the originality of the leaves, maintaining the actual color gradient and avoiding oversaturation, which typically refers to excessive brightness and color intensity that can obscure important details and lead to inaccurate identification of disease spots. This step aimed to capture clear, detailed images that reflect the true condition of the leaves without interference from natural light variations.

4.2. Dataset preparation

We collected all possible leaves from the vegetable yards and then began marking down the collected leaves. The working procedure can be broken down into several steps. First, we separated all the plant leaves according to their type. Since our dataset concerns six vegetable plant types, all the plant leaves were divided into six categories. During this process, we took great care to avoid any mismatches (e.g., ensuring that tomato plant leaves were placed only with other tomato leaves) when setting up the classes for each plant, as any errors could have caused

significant issues. Second, we classified the unhealthy leaves of each particular plant type. Third, after sorting all the plant leaves into their correct segments, we began capturing the leaf images. While capturing the images, we ensured that no leaf was selected multiple times, all images were clear and of high quality, and there was no extraneous noise. To reduce picture noise, we used a black background material so that our camera could focus precisely on the leaf, capturing detailed disease spots.

Limitations

While collecting the dataset, we encountered several issues that might have affected its quality. The following are the limitations of this dataset and their potential solutions:

- **Data Augmentation:** We are providing only the raw, captured data, so researchers can apply augmentation techniques as needed. This will enable them to prepare a dataset ready for use in machine learning or deep learning models without needing further augmentation, saving valuable time and reducing dataset complexity. However, before using this dataset, it is advisable for researchers to resize the images from 700×700 pixels to their desired dimensions, based on the specifications of the model they are applying.
- **Image Quality and Environmental Variables**: While capturing the images, sunlight posed a significant challenge, affecting image quality. Issues such as image blurriness and inappropriate capturing angles also arose. To address these problems, we set up a laboratory area where sunlight was controlled by installing light barriers. We placed each leaf in a specific position and moved the camera relative to that position to achieve better stability and accurate color representation. This setup ensured that the images were clear and detailed, capturing the true condition of the leaves without the interference of natural light variations.
- **Data Acknowledgement:** Before capturing the images, acquiring thorough knowledge about each plant disease was mandatory. Therefore, we underwent a dedicated knowledge-gathering period to better understand plant leaf diseases. This involved listing the relevant leaf diseases present in our selected areas and collecting a small sample portion to identify the diseases before collecting the mass dataset. Additionally, face-to-face conversations with local farmers provided valuable insights and helped us locate a significant number of desired vegetable plants in the selected areas.

Ethics Statement

The authors adhere to the journal's ethical guidelines and confirm that this research does not involve humans, animals, or data obtained from social media. The datasets utilized in the study are publicly accessible, and appropriate citation protocols should be followed when utilizing these datasets.

Data Availability

Plant Leaf Freshness and Disease Detection Dataset From Bangladesh (Original data) (Mendeley Data)

CRediT Author Statement

Mahamudul Hasan: Conceptualization, Methodology, Supervision, Visualization, Project administration, Validation; **Raiyan Gani:** Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing; **Dr. Mohammad Rifat Ahmmad Rashid:** Conceptualization, Methodology, Supervision, Visualization, Project administration, Validation;

Taslima Khan Tarin: Investigation, Writing – original draft, Writing – review & editing; **Raka Kamara:** Investigation, Writing – original draft, Writing – review & editing; **Mahbuba Yasmin Mou:** Investigation, Writing – original draft, Writing – review & editing; **Sheikh Fajlay Rabbi:** Investigation, Writing – original draft, Writing – review & editing.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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