SeasVeg: An Image Dataset of Bangladeshi Seasonal Vegetables

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Data Article

SeasVeg: An image dataset of Bangladeshi seasonal vegetables

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ABSTRACT

Seasonal vegetables play a crucial role in both nutrition and commerce in Bangladesh. Recognizing this significance, our research introduces the 'SeasVeg' dataset, comprising images of ten varieties of seasonal vegetables sourced from Dhaka and Pabna regions. These include *Carica papaya, Momordica dioica, Abelmoschus esculentus, Lablab purpureus, Trichosanthes cucumerina, Trichosanthes dioica, Solanum lycopersicum, Brassica oleracea, Momordica charantia, and Raphanus sativus*. Our dataset encompasses 4500 images, 1500 original and 3000 augmented, meticulously captured under natural light conditions to ensure authenticity. While our primary focus lies in leveraging machine learning and deep learning techniques for advancements in agriculture science, particularly in aiding healthcare aspects with seasonal vegetables and nutrition's, we acknowledge the versatile utility of our dataset. Beyond healthcare, it serves as a valuable educational resource, facilitating children's and toddlers' learning to identify these vital vegetables. This dual functionality broadens the dataset's appeal and underscores its societal impact beyond the realm of healthcare. Besides, the research culmi-

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nates in the implementation of machine learning models, achieving noteworthy accuracy. We get the highest 99 % accuracy with the ResNet50 pre-trained CNN model and a good 94 % accuracy with the InceptionV3 pre-trained CNN model when it comes to the computer-aided vegetable classification. However, the 'SeasVeg' dataset represents not only a significant stride in healthcare innovation but also a promising tool for educational endeavors, catering to diverse stakeholders and fostering interdisciplinary collaboration.

Specification Table

Subject	Computer Science, Agricultural Science
Specific subject area	Machine Learning, Deep Learning, Image Classification, Image Processing
Data format	The images are in 2D RGB format, both original and augmented by (.jpg format).
Type of data	Image
Data collection	In August and September of 2023, we collected high-quality pictures of seasonal vegetables in natural settings from various areas in Dhaka and Pabna cities. We used Vivo-2116 and Realmex2-pro cameras in Dhaka and Redmi-11, Oppo A-95, and iPhone 13 Pro-Max cameras in Pabna. Afterward, we removed low-resolution images and left 1500 vegetables categorized into ten groups with 150 pictures per category. Additionally, we included 3000 augmented ima- ges. We ensured adequate lighting and avoided capturing noticeable shadows (less than 0 % shadow capture) during the process. The resulting image was 3024×4032 pixels.
Data source location	We have collected images from five different locations– 1. Azompur Kacha Bazar, Uttara, Dhaka 2. Sector 11 Kacha Bazar, Uttara, Dhaka 3. Baipail, Savar, Dhaka 4. Savar Bus Stand, Dhaka 5. Kodomdanga Bazar, Atgharia, Pabna 6. City/ Town/Region: Dhaka, Pabna 7. Country: Bangladesh
Data accessibility	Repository: Mendeley Data DOI: 10.17632/s6gyxb2cg9.1 URL: https://data.mendeley.com/datasets/s6gyxb2cg9/1

1. Value of Data

- The dataset "SeasVeg" provides valuable information on seasonal vegetables from Bangladesh, including their scientific classifications. This data can benefit farmers and consumers alike. With the help of a machine vision-based model, the production rate of seasonal vegetables can be increased while minimizing human effort and expenses. To achieve this, a reliable classification model has been developed to create an effective dataset.
- The "SeasVeg" dataset assists novice nutritionists and researchers in determining which seasonal vegetables are optimal for computer-assisted solution classification. This application will promote the health benefits of seasonal vegetables, inform individuals, and encourage consumers and students, in particular, to try and rate them.
- This dataset, called ''SeasVeg'', can be used to develop algorithmic models based on machine and deep learning, image processing and analysis, and pattern recognition. These models can help determine different categories of seasonal vegetables and their optimal use.

- “SeasVeg” is a dataset that is built with a variety of vegetable images both indoors and outdoors. The images are collected and analyzed using different image processing tools to identify and categorize the diversity of different types of vegetables. It will be effective for the agriculturists to identify and categorize each vegetable properly with an agricultural automation system that enables the best evaluative mechanism.
- The collected images in the “SeasVeg” dataset have enriched the database, making it easier for researchers to determine their effectiveness, usefulness, and health benefits for future investigations and confirm their practical use on humans.

2. Background

Seasonal vegetables in Bangladesh, often referred to as seasonal produce or seasonal crops, are a fundamental component of Bangladeshi agriculture and the foundation of countless diets for Bangladeshi people [1]. These vegetables are grown and harvested when temperature, daylight, and rainfall are optimal. Seasonality in agriculture has a deep basis in nature and particular agricultural practices. The significance of seasonal vegetables transcends their role as mere staples in our diets. They contribute substantially to the economic, nutritional, and ecological aspects of agriculture. Seasonal vegetables not only provide essential nutrients to communities but also sustain the livelihoods of countless farmers and contribute to local and global food security [2]. Aligning crop production with natural cycles promotes sustainable farming and reduces the environmental impact of agriculture. In recent years, the study of seasonal vegetables has gained increased attention, primarily due to shifting climatic patterns, changing consumer preferences, and the need to optimize agricultural practices for greater sustainability [3]. As Bangladeshi populations continue to grow, the demand for nutritious, locally sourced, and environmentally friendly food has become a central concern. Thus, this research explores seasonal vegetables’ botanical diversity, cultivation methods, nutritional profiles, economic impacts, and ecological value in Bangladesh. The study also explores the role of vegetables in computer vision and production precision to create a more sustainable and nutritional future.

3. Data Description

Seasonal vegetables are recognized as the most plentiful and resourceful source of vitamins, fiber, nutrients, and so on [4]. Besides, the usage and consumption of these seasonal vegetables should be accomplished in an appropriate way. For this reason, the main objectives of this article are to provide a dataset of images of Bangladeshi seasonal vegetables that are identified and categorized into ten different categories, which are: ‘*Carica papaya, Momordica dioica, Abelmoschus esculentus, Lablab purpureus, Trichosanthes cucumerina, Trichosanthes dioica, Solanum iycopersicum, Brassica oleracea, Momordica charantia, Raphanus sativus*’. Fig. 1 shows the classification of the vegetables in our dataset according to the names and shapes of the images. Besides, the study consists of a deep/machine vision-based recognition model that helps us to automatically recognize these different categories of seasonal vegetables, their benefits, and their healthier effects on humans. The research also leads to an increase in the order of farmers or harvesters to grow more seasonal vegetables for increasing agricultural efficiency, boosting production, and ensuring food security and healthier benefits. Furthermore, this dataset holds certain attention and raises awareness among people to evaluate and educate themselves for the in-field and out-field working capabilities as required. Again, it should encourage people to make the best effects on growing seasonal vegetables more and more, which fulfills the needs of our vegetable demands and ensures much productivity and safety for the environment as well.

As a team, we plan to create a dataset of seasonal vegetables. As per the plan, we decided to take photos in two steps: indoors and outdoors. We captured 80 indoor and 70 outdoor vegetable images. First, we went to different markets and took pictures. Our members captured

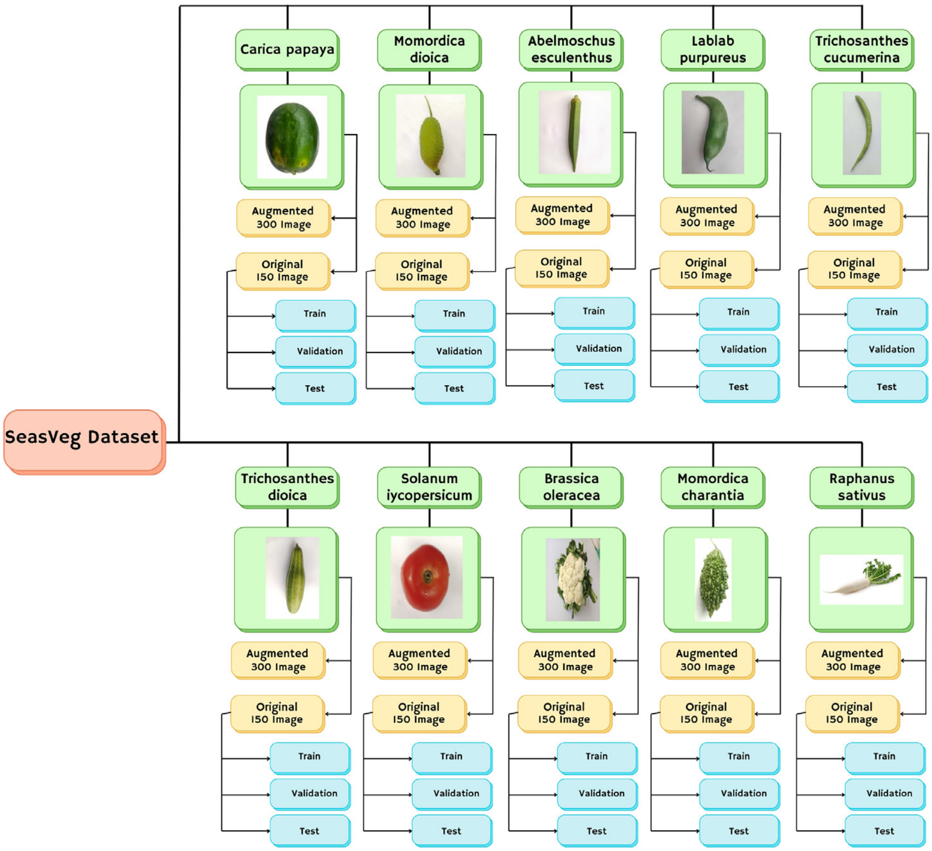


Fig. 1. Directory tree of the proposed SeasVeg dataset.

the image of *Carica papaya* (Date: 07 August 2023, Location: Azampur Kacha Bazar, Uttara, Dhaka), *Momordica diocia* (Date: 08 August 2023, Location: Azampur Kacha Bazar, Uttara, Dhaka), *Abelmoschus esculenthus* (Date: 10 August 2023, Location: Sector 11 Kacha Bazar, Uttara, Dhaka), *Lablab purpureus* (Date: 11 August 2023, Location: Sector 11 Kacha Bazar, Uttara, Dhaka), *Trichosanthes cucumerina* (Date: 12 August 2023, Location: Sector 11 Kacha Bazar, Uttara, Dhaka), *Trichosanthes dioica* (Date: 14 August 2023, Location: Baipail Wholesale Kacha Bazar, Savar, Dhaka), *Solanum iycopersicum* (Date: 14 August 2023, Location: Baipail Wholesale Kacha Bazar, Savar, Dhaka), *Brassica oleracea* (Date: 14 August 2023, Location: Baipail Wholesale Kacha Bazar, Savar, Dhaka), *Momordica charantia* (Date: 16 August 2023, Location: Savar Bus Stand Kacha Bazar, Savar, Dhaka) and *Raphanus sativus* (Date: 18 August 2023, Location: Kodomdanga Bazar, Atgharia, Pabna) these ten vegetables. From August 21 to 25, we captured indoor images of ten vegetables in our university lab. Fig. 2 shows an overview of the collected regions of our dataset. After the image-capturing step, we created indoor and outdoor data sets of images. Later, we increased the dataset using the augmentation method from 1500 images to 3000 more images. Then, we uploaded the entire dataset to Mendeley by reducing the storage size of the image while maintaining the image quality using the compress method [5]. Table 1 shows the summary of the collected dataset with the number of collected images, their local and scientific names, short descriptions and sample images.

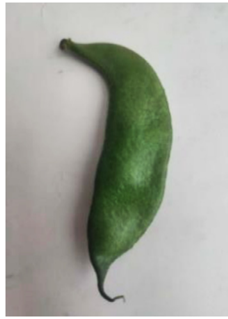
This category contains 150 original images in this dataset. Fig. 3 Presents the number of original images in each class. Table 2 presents the number of training, validation, and test images on the original images and the total number of augmented images from each class [6].

Table 1
The summary of the “SeasVeg” Dataset.

Serial No	Scientific Name	English Name	No. of Image	Data Description	Simple Images
01	*Carica papaya*	Papaya	150	*Carica papaya* is an herbaceous vegetable and belongs to the *Caricaceae* family. It is regularly known as “Papaya” in some English-speaking countries and familiar as“Pepe” in Bangladesh. This vegetable is green in color and usually round to cylindrical, usually 7.3–48.0 cm (2.8–19 in) or more in length and sometimes weighing 8 to 10 kg (17.64–22.0 pounds). On the walls of the central area, there are numerous rounds of black seeds attached to a cavity.	
02	*Momordica dioica*	Spiny gourd	150	*Momordica dioica* belongs to the Cucurbitaceae family and is a seasonal vegetable. It is known as a Spiny gourd or Thorned gourd in English-speaking countries and is called "Kakrol" in Bangladesh. This particular vegetable is generally small to medium-sized, measuring around 1–3 cm in diameter and 2–7 cm in length. The shape is oblong and oval.	
03	*Abelmoschus esculenthus*	Lady finger	150	*Abelmoschus esculenthus* is a seasonal vegetable and belongs to the Malvaceae family. It is commonly known in some English-speaking countries as a lady-finger and is called “Derosh” in Bangladesh. This vegetable is typically growing 3–5 in. tall. It has edible green seed pods.	

(*continued on next page*)

Table 1 (*continued*)

Serial No	Scientific Name	English Name	No. of Image	Data Description	Simple Images
04	*Lablab purpureus*	Hyacinth bean	150	*Lablab purpureus* is a seasonal vegetable and belongs to the Fabaceae family. It is commonly known in some English-speaking countries as Hyacinth bean and known as “Chim” in Bangladesh. These vegetable pods are oblong, flattened, flat, and elongated with a prominent beak, about 7–12 cm long and 2 cm wide, containing 3–4 seeds.	
05	*Trichosanthes cucumerina*	Snake gourd	150	*Trichosanthes cucumerina* is a seasonal vegetable and belongs to the Cucurbitaceae family. It is commonly known in some English-speaking countries as Snake gourd and known as “Ushi” in Bangladesh. This vegetable is characterized by its waxy green skin, often speckled or striped with a lighter shade of green. This vegetable comes in longer and shorter varieties, with lengths averaging 40–45 cm and 15–20 cm, respectively.	

(*continued on next page*)

Table 1 (*continued*)

Serial No	Scientific Name	English Name	No. of Image	Data Description	Simple Images
06	*Trichosanthes dioica*	Pointed gourd	150	*Trichosanthes dioica* is a seasonal vegetable and belongs to the Cucurbitaceae family. In some English-speaking countries, it is referred to as Pointed Gourd, while in Bangladesh, it is known as Potol. This vegetable is green, white, or unstriped with unpotable seeds. On average, it grows between 5 and 15 cm (equivalent to 2 to 6 in.).	
07	*Solanum iycopersicum*	Tomato	150	*Solanum icopersicum* is a seasonal vegetable and belongs to the Solanaceae family. It is commonly known in some English-speaking countries as Tomato and known as ''Tomato" in Bangladesh. This vegetable is green. Its size ranges from 2 to 3 in.. Once it ripens, the fruit turns from green to red. Fruit contains numerous kidney-shaped seeds covered in pulp. The Seeds are covered in long, soft hairs measuring between 0.2 and 0.3 mm in length and have a yellow-grey color.	
08	*Brassica oleracea*	Cauliflower	150	*Brassica oleracea* is a seasonal vegetable and belongs to the Brassicaceae family. It is commonly known in some English-speaking countries as Cauliflower and known as "Fullcopy" in Bangladesh. Although usually white, cauliflower does come in other colors, including purple, yellow, and orange. Cauliflower heads typically measure between 5 and 8 in. (13 to 20 cm) in diameter, with size varying depending on the variety and the time of harvest. Occasionally, certain types of cauliflower can produce heads as big as 9 inches (23 cm) in diameter.	

(*continued on next page*)

Table 1 (*continued*)

Serial No	Scientific Name	English Name	No. of Image	Data Description	Simple Images
09	*Momordica charantia*	Bitter gourd	150	*Momordica charantia* is a seasonal vegetable and belongs to the Cucurbitaceae family. It is commonly known in some English-speaking countries as Bitter melon and called a “Korola” in Bangladesh. This vegetable comes in a variety of shapes and sizes. Its vegetable is oblong and narrow, averaging 7–10 cm in length. The skin is thick, waxy, and rough, and has small bumps called “teeth” knobs and vertical ridges.	
10	*Raphanus sativus*	White radish	150	*Raphanus sativus* is a seasonal vegetable and belongs to the Brassicaceae family. It is commonly known in some English-speaking countries as Dikon and known as “White Mula” in Bangladesh. The vegetable can grow up to 6–15 in. long and has an average diameter on 2–3 in.. The skin is usually white.	

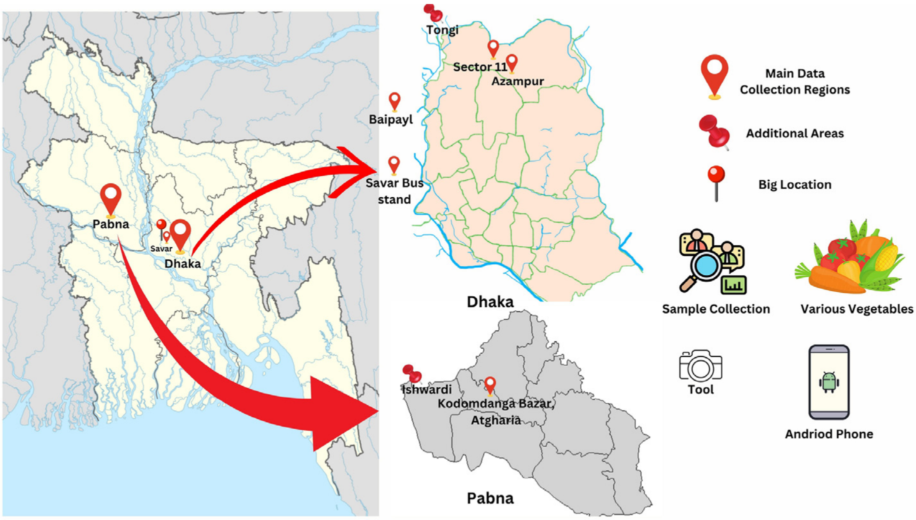


Fig. 2. 'SeasVeg' dataset collection in different regions.

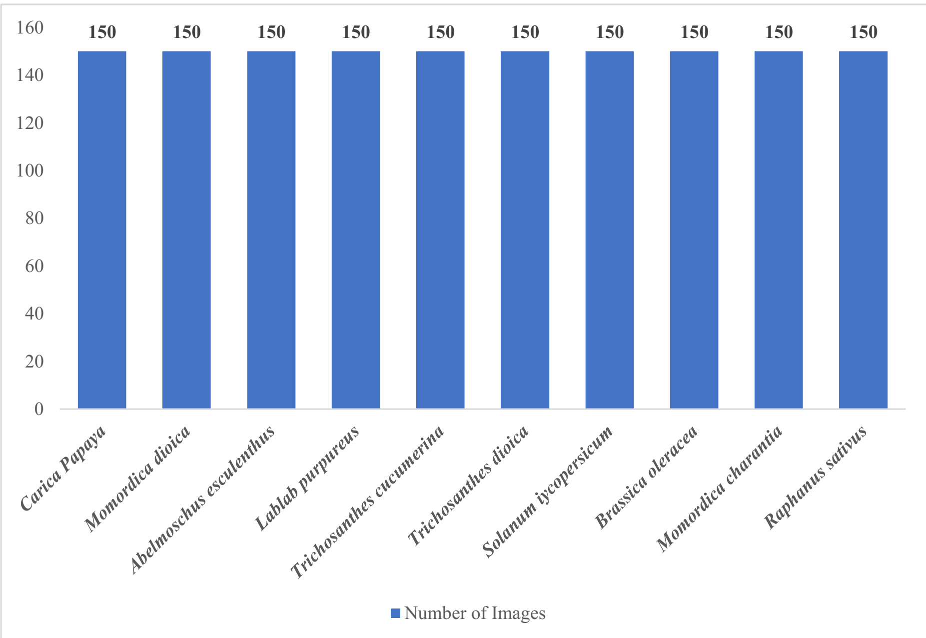


Fig. 3. Class-wise image distribution in the ''SeasVeg'' Dataset.

4. Experimental Design, Materials, and Methods

The five processes in the generating of the ''SeasVeg'' dataset were the gathering of photos, image preprocessing, and image augmentation. In this section, a description of each of those steps is given.

Table 2
Number of images in each class of the proposed SeasVeg Dataset.

Class Name	Number of original images		Number of augmented		
	Train	*Validation*	*Test*	*Total*	*images*
Carica papaya	120	15	15	150	300
Momordica dioica	120	15	15	150	300
Abelmoschus esculentus	120	15	15	150	300
Lablab purpureus	120	15	15	150	300
Trichosanthes cucumerina	120	15	15	150	300
Trichosanthes dioica	120	15	15	150	300
Solanum iycopersicum	120	15	15	150	300
Brassica oleracea	120	15	15	150	300
Momordica charantia	120	15	15	150	300
Raphanus sativus	120	15	15	150	300
Total images			**1500 (original)**	**3000 (augmented)**	

4.1. Image acquisition system

The collection contains 10 unique seasonal vegetable classifications. All of the images depicting seasonal vegetables were taken at several vegetable markets in Dhaka and Pabna, Bangladesh, using Vivo V23e (with a 64MP AF, 8MP Ultra-wide angle, 2MP macro Aperture: f/1.79 Ultra-wide angle f/2.2 macro f/2.4), Realme X2 Pro (64MP, f/1.8, 26 mm (wide), 1/1.72″, 0.8 µm, PDAF,13 MP, f/2.5, 52 mm (telephoto), 1/3.4″, 1.0 µm, PDAF, 2x optical zoom,8 MP, f/2.2, 16 mm (***ultrawide***),2 MP, f/2.4, (depth)) and iPhone 13 Pro-Max (12 MP, f/1.6, 26 mm (wide), 1.7 µm, sensor-shift OIS, dual pixel PDAF,12 MP, f/2.4, 120˚, 13 mm (***ultrawide***)). All of the images were captured against a background of natural daylight. During the image-collecting process, diffused lighting was used to improve photos of seasonal vegetables and reduce shadows. Throughout the capture, we also kept the background a constant, natural one. During the collection procedure, we made sure to verify the image quality often. This required checking the focus and lighting, and taking photos from different perspectives to allow for shifts in seasonal vegetables. We conducted quality control checks after gathering all the images. Images that had too much brightness, lacking contrast, or unclear sections were marked and removed via the dataset. Remarkably, this action was crucial in ensuring that only images of excellent quality were included for analysis. We have ensured the dataset's integrity and improved the accuracy of subsequent analyses by eliminating these failing images. An initial collection of 1734 vegetable images was made, of which 1500 images were selected as the dataset for this study. The images were then reduced in size to 2448×3264 pixels, and all images with poor resolution were removed. Because of that, we were able to collect 150 images from each of the 10 classes for a total of 1500 seasonal vegetables. 3000 enhanced images are also included in the collection. We made sure to maintain better brightness, an equally distributed light source, and almost 0 % shadow capture throughout the process to take images with no visible shadows [6].

4.2. Image preprocessing

The resolution of 72 dots per inch (DPI) on both the horizontal and vertical axes is used for all of the original images, which have a size of 3024 × 4032. The resolution of the image files that were processed to generate the augmented images was 2448 by 3264 pixels. The image class of the Python Imaging Library (PIL), additionally known as the Python Imaging Library, was used for adjusting the image's dimensions. PIL provides several industry-standard techniques for manipulating images. Among them are per-pixel alterations covering up and transparency handling, image filtering (such as reducing, contouring, smoothing techniques, or edge detection), image modifying (things like sharpening, adjusting contrast, saturation, or color), and adding text to photographs, among many more. The Image module provides a class with a name such

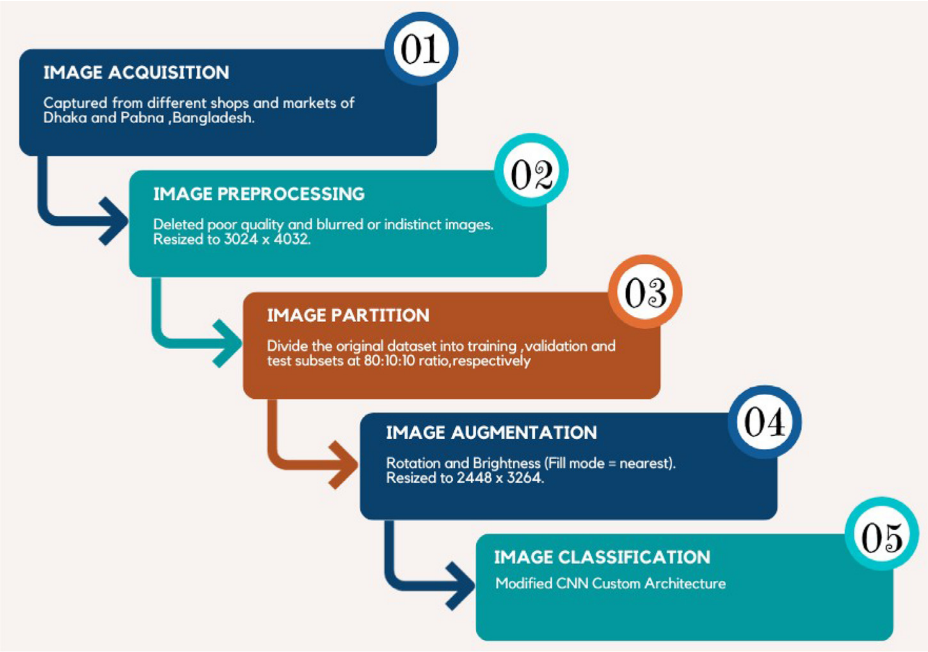


Fig. 4. The development process of the ''SeasVeg'' dataset.

as ''Image to represent an image in the PIL''. A variety of factory features are also provided by the module, which may involve the capacity to create fresh images and import images from files.

4.3. Image partition

We have showcased a total of 1500 original photos of 10 different vegetables, captured both indoors and outdoors. To train and evaluate both the Machine Learning-based and Deep Learning-based models, the original raw vegetable images were randomly divided into training, validation, and test subsets at an 80:10:10 ratio for each category.

4.4. Image augmentation

We can improve the image information by utilizing several methods. The following are examples of geometric transformations that are capable of being used for improving image data: flipping, cropping, rotating, zooming, etc.; employing color modifications to enhance picture data by changing its brightness, darkness, sharpness, saturation, etc.; improving images by random erasure, image mixing, etc. Images are given an additional variety through the process of image augmentation, which improves the ability to generalize and the effectiveness of machine-learning and deep-learning-based classification models. We used the Keras Image Data Generator class to increase the number of images. The aforementioned class was used in combination with several image enhancement methods, including 20 ˚rotation and brightness alteration (ranging from random −0.5 to 60). All of the gathered images were given an image enhancement and organized into folders by class so that researchers were able to interact with them as needed. Each enhanced image was reduced to an approximately average size of 2448 × 3264 pixels (Fig. 4).

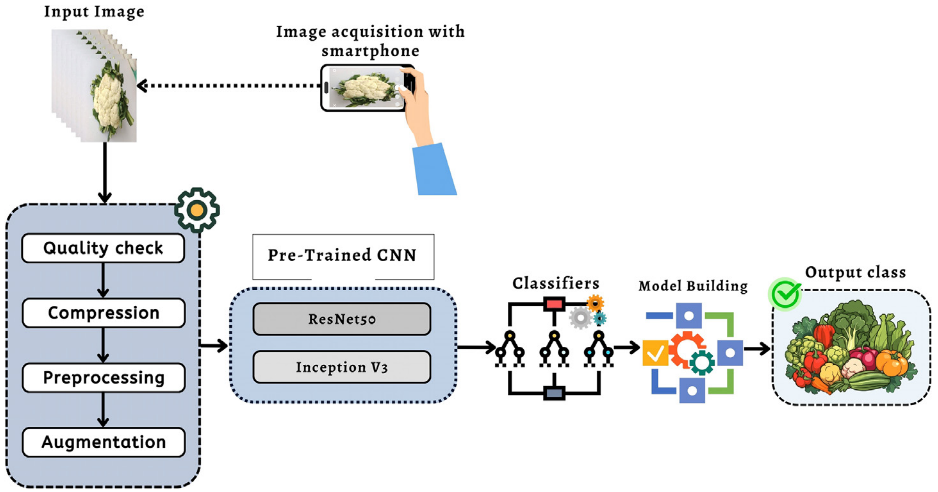


Fig. 5. The graphical abstract for vegetable classification.

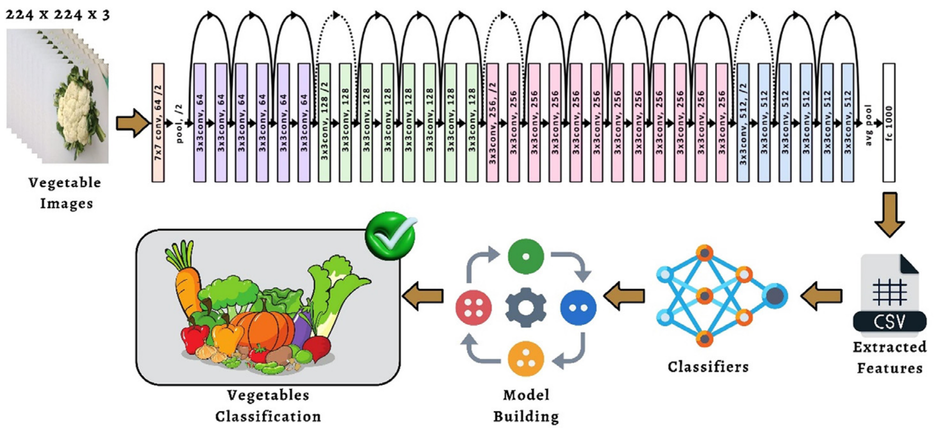


Fig. 6. The proposed architecture of ResNet50 for vegetable classification.

4.5. Vegetable classification with deep learning models

To apply computer-aided classification with machine learning to the “SeasVeg” dataset, we have utilized two well-known convolutional neural network (CNN)-based DL models. These two pre-trained CNN architectures are ResNet50 and InceptionV3. ResNet50 is a CNN architecture that belongs to the Residual Network (ResNet) family. ResNet’s main innovation is the use of residual learning, which involves introducing shortcut connections or skip connections that allow the network to learn residual functions [7]. Fig. 5 shows the graphical abstract of the proposed computer-aided vegetable classifications, and Fig. 6 shows the architecture of Resnet50 pre-trained CNN. Here are the ResNet50 architecture key features and components:

Basic Building Block (Residual Block): The basic building block of ResNet50 is the residual block; it uses a jam design. Each block consists of three convolutional layers: 1×1, 3×3, and 1×1 convolutions. This design helps to reduce the computational complexity while maintaining the representative power of the network.

Table 3
Experimental Data analysis with performance of evaluation matrices from ResNet50 model.

Serial	Vegetables Name	Precision	Recall	F1-score	Support
1	*Carica papaya*	0.95	1.00	0.98	21
2	*Raphanus sativus*	1.00	1.00	1.00	16
3	*Momordica dioica*	0.95	1.00	0.98	21
4	*Abelmoschus esculentus*	1.00	1.00	1.00	24
5	*Lablab purpureus*	1.00	0.95	0.98	21
6	*Trichosanthes cucumerina*	0.95	1.00	0.98	20
7	*Trichosanthes dioica*	1.00	0.93	0.97	15
8	*Solanum iycopersicum*	1.00	1.00	1.00	16
9	*Brassica oleracea*	1.00	1.00	1.00	15
10	*Momordica charantia*	1.00	1.00	1.00	23
	accuracy			**0.99**	192
	macro avg	0.99	0.99	0.99	192
	weighted avg	0.99	0.99	0.99	192

Bottleneck Design: ResNet50 uses a bottleneck design in its residual blocks. A bottleneck block consists of three convolutional layers: 1 × 1, 3 × 3, and 1 × 1 convolutions. The 1 × 1 convolutions are responsible for reducing and then increasing the dimensionality, while the 3 × 3 convolution performs the actual feature learning.

Skip Connections: Skip connections, also known as identity shortcuts, allow the gradient to bypass one or more layers. This helps train deep networks by ensuring that the information from earlier layers can be easily propagated through the network.

Global Average Pooling (GAP): Instead of using fully connected layers at the end of the network, ResNet50 employs global average pooling. This reduces the spatial dimensions of the feature maps to a 1 × 1 size, leading to a more compact representation.

Output Layer: The final layer of ResNet50 is a fully connected layer with softmax activation; it is commonly used for classification tasks.

ResNet50 refers explicitly to a ResNet with 50 layers, counting all layers, including convolutional layers, batch normalization, and activation layers. There are also variants like ResNet18, ResNet34, ResNet101, ResNet152, etc., which have different depths based on the number of layers. ResNet50 is widely used for various computer vision tasks, including image classification, object detection, and segmentation, due to its excellent performance and ease of training deep networks. Fig. 7 shows the proposed architecture of ResNet50 for vegetable classification. Fig. 7 displays the training versus validation accuracy curves and confusion matrixes for the utilized architectures during the training process and testing process. In Fig. 7(a) the x-axis represents the number of training iterations or epochs and Fig. 7(b), the x-axis represents the number of training and validation losses or epochs, while the y-axis represents the accuracy performance metric for the pre-trained Resnet50 architectures, respectively.

After checking the accuracy curves for training and validation, it is clear that the proposed dataset provides enough examples to smoothly converge the DL-based models. The presented curves illustrate that the integrated DL-based models converge effectively with the given image data at the initial, intermediary, and final stages of training. It illustrates the efficient use of the proposed “SeasVeg” dataset in DL-based models for seasonal vegetation image classification tasks. However, Fig. 7(c) depicts the confusion matrix evaluated on the unknown test dataset on the pre-trained ResNet50, and Fig. 7(d) illustrates the ROC curve for the validation of the models. Besides, Table 3 shows the experimental results from the ReseNet50 pre-trained CNN model. The figures and table show that we have achieved the highest average accuracy of 99 % while performing vegetable classification with the ResNet50 architecture.

The InceptionV3 architecture is a deep convolutional neural network (CNN) designed for image classification tasks [8]. The key innovation in InceptionV3 is the use of inception modules, which are blocks containing multiple parallel convolutional layers with different kernel sizes. These modules allow the network to capture information at various spatial scales and learn a

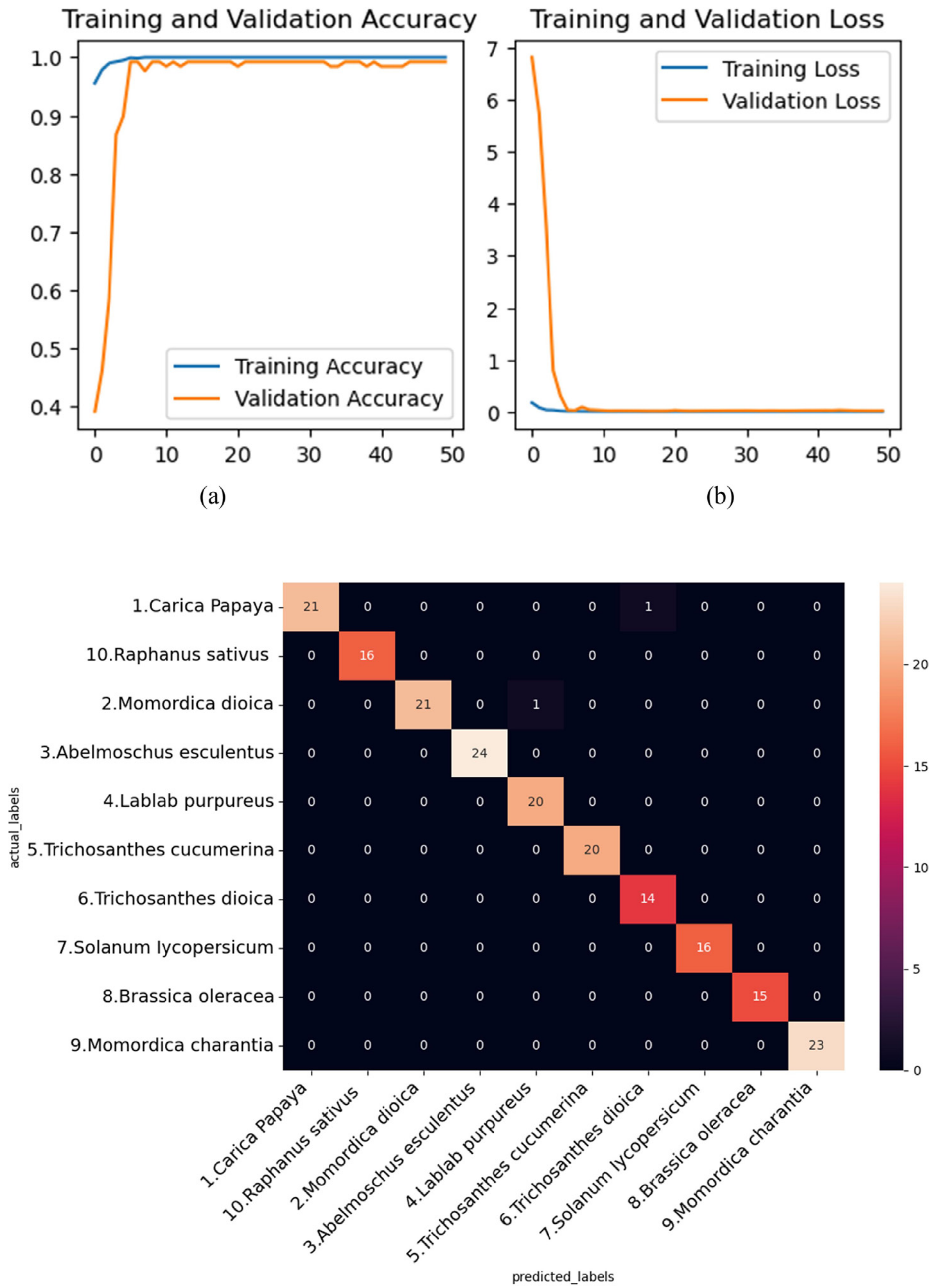
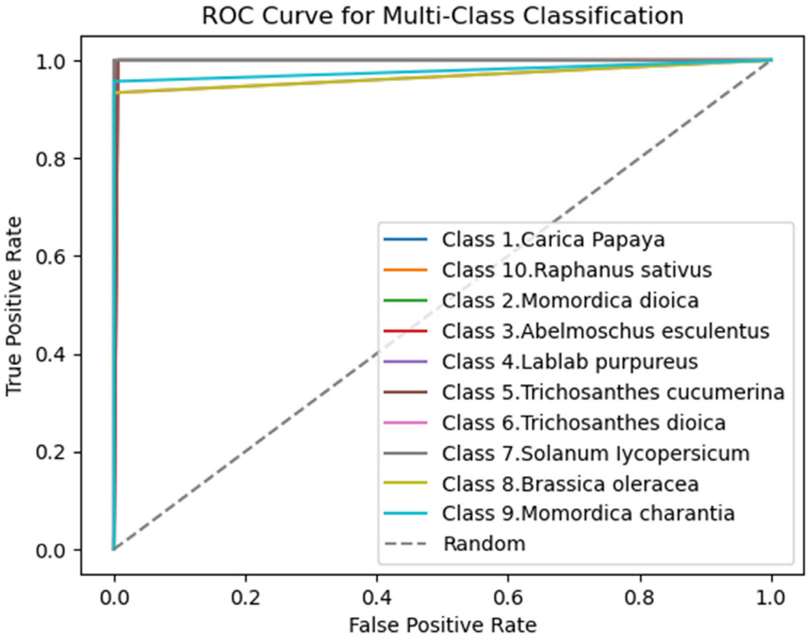


Fig. 7. Experimental data analysis with (a) training vs. validation accuracy (b) training vs. validation loss (c) confusion matrix of the trained model (d) ROC-curve for performance evaluation and validation of the model.



(d)

Fig. 7. Continued

diverse set of features. InceptionV3 also incorporates techniques such as factorized convolutions, batch normalization, and improved dimension reductions to enhance its efficiency. Fig. 8 shows the architecture of the InceptionV3 model and its architecture.

Here is a simplified representation of the InceptionV3 architecture:

Input Layer: The input to InceptionV3 typically consists of RGB images with a size of 299×299 pixels.

Convolutional Layers: The core building blocks of InceptionV3 are the inception modules. Each module consists of parallel convolutional layers with different kernel sizes (1 × 1, 3 × 3, and 5 × 5), pooling layers, and sometimes 1 × 1 convolutions for dimensionality reduction. These parallel branches are concatenated along the depth dimension.

Reduction Blocks: Interspersed between the inception modules, there are reduction blocks that include a mix of convolutional layers, pooling, and dimensionality reduction operations. These blocks help reduce the spatial dimensions of the feature maps.

Fully Connected Layers: Towards the end of the network, global average pooling is applied to reduce the spatial dimensions to a vector, which is then connected to fully connected layers for the final classification.

Output Layer: The output layer produces the final classification predictions. In many cases, softmax activation is used to obtain class probabilities.

Besides, the research also applied the InceptionV3 pre-trained CNN model to the “SeasVeg” dataset to assess the performance of the DL model in vegetable classification. The InceptionV3 architecture is designed to achieve a good balance between computational efficiency and performance, making it suitable for a variety of computer vision tasks. The inceptinV3 pre-trained CNN architecture is very promising, while it works with the target image size of 299 × 299. In Fig. 9(a), the x-axis represents the number of training iterations or epochs, and in Fig. 9(b), the x-axis represents the number of training and validation losses or epochs, while the y-axis

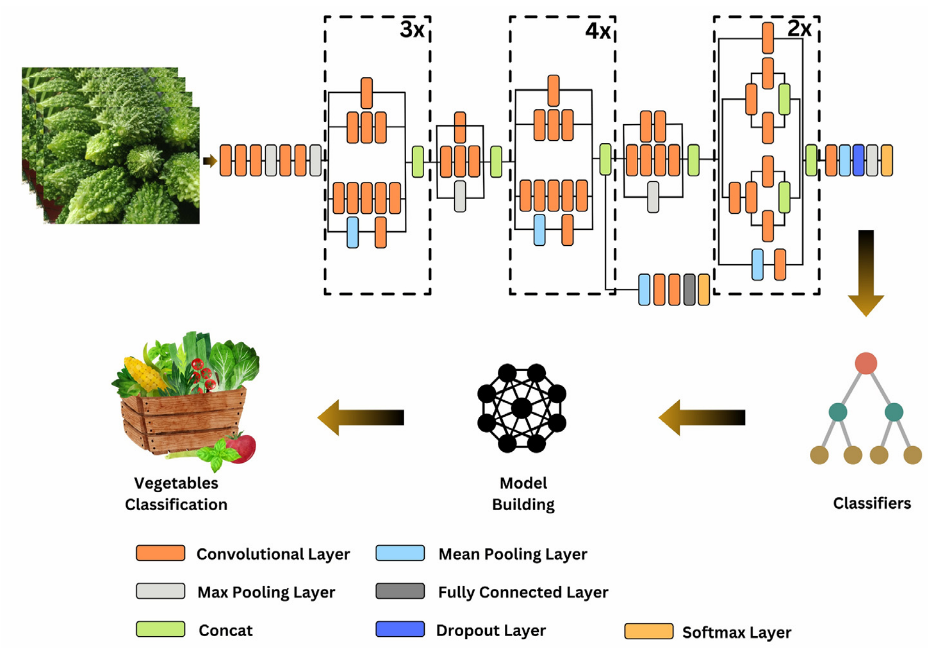
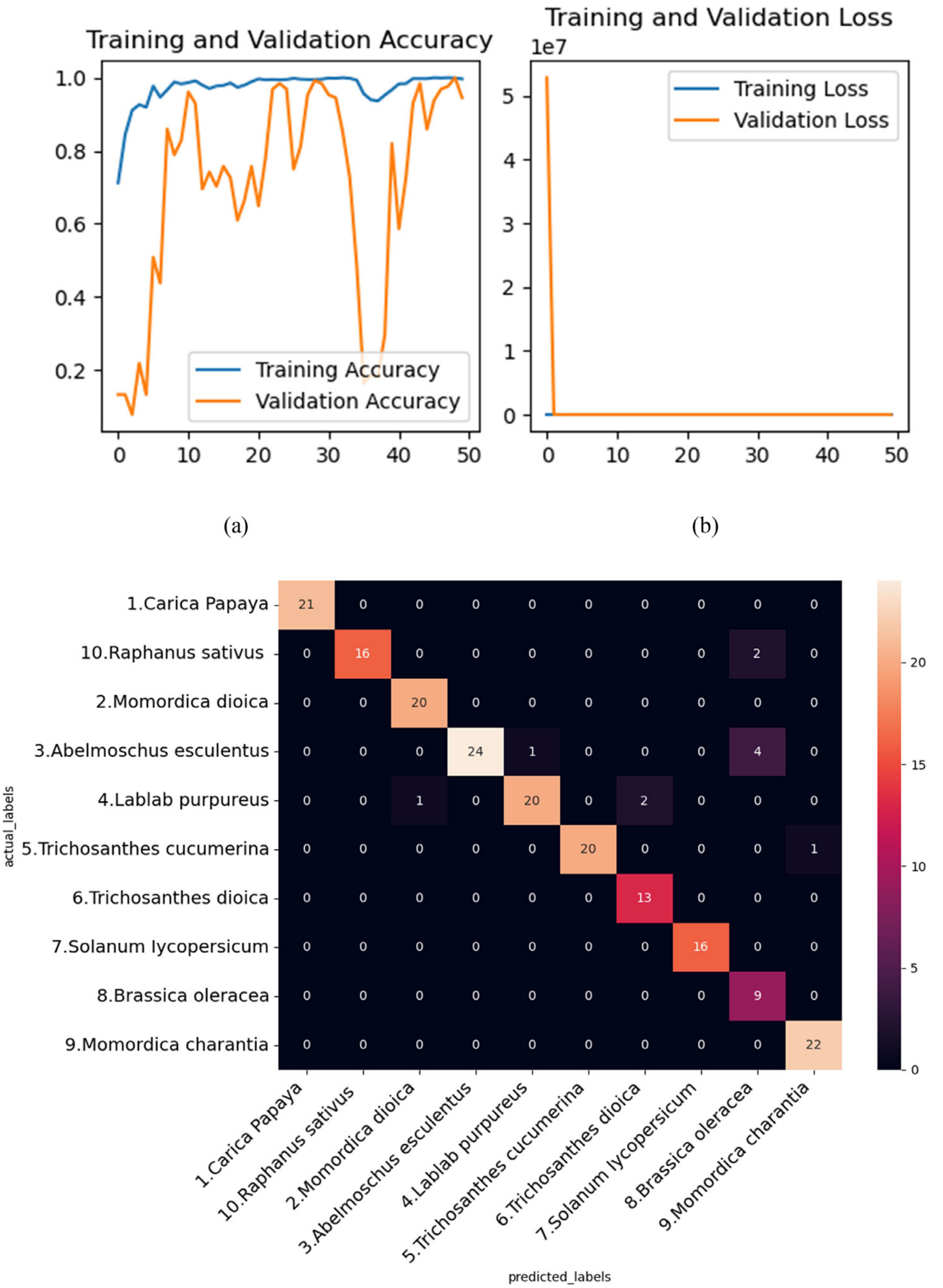


Fig. 8. The proposed architecture of InceptionV3 for vegetable classification.

Table 4
Experimental Data analysis with performance of evaluation matrices from InceptionV3 model.

Serial	Vegetables Name	Precision	Recall	F1-score	Support
1	*Carica papaya*	1.00	1.00	1.00	21
2	*Raphanus sativus*	0.89	1.00	0.94	16
3	*Momordica dioica*	1.00	0.95	0.98	21
4	*Abelmoschus esculentus*	0.83	1.00	0.91	24
5	*Lablab purpureus*	0.87	0.95	0.91	21
6	*Trichosanthes cucumerina*	0.95	1.00	0.98	20
7	*Trichosanthes dioica*	1.00	0.87	0.93	15
8	*Solanum iycopersicum*	1.00	1.00	1.00	16
9	*Brassica oleracea*	1.00	0.60	0.75	15
10	*Momordica charantia*	1.00	0.96	0.98	23
	accuracy			**0.94**	192
	macro avg	0.95	0.93	0.94	192
	weighted avg	0.95	0.94	0.94	192

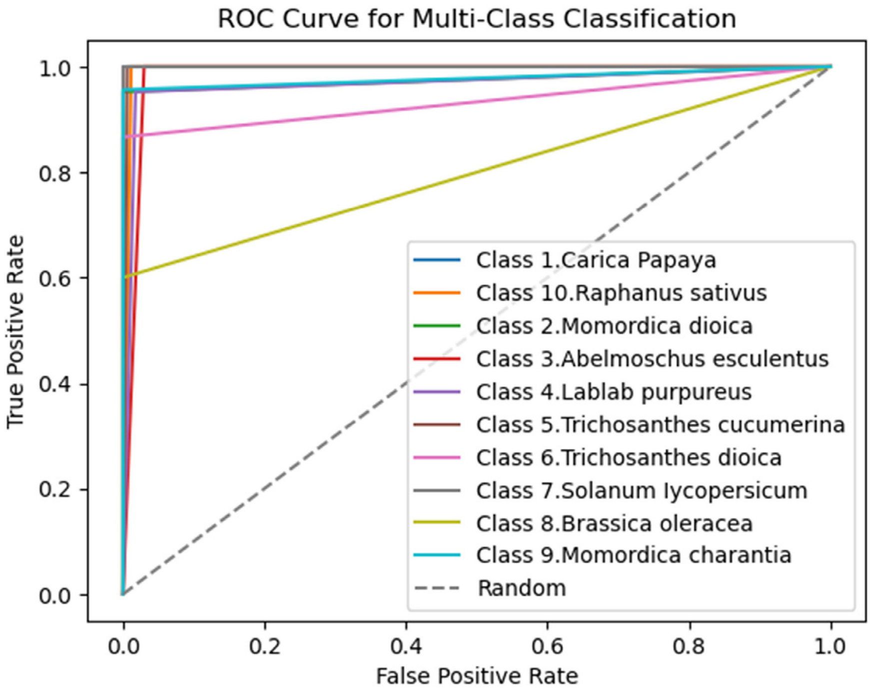
represents the accuracy performance metric for the pre-trained InceptionV3 architectures, respectively. Further, the objective of applying the InceptionV3 model is to check the efficacy of the ResNet50 model. Thus, Fig. 9(c) depicts the confusion matrix evaluated on the unknown test dataset on the pre-trained InceptionV3 and Fig. 9(d) illustrates the ROC curve for the validation of the models. Table 4 shows the experimental results from the pre-trained CNN model from the InceptionV3 model. The figures and table show that we have achieved the highest average accuracy of 94 % while performing the vegetable classification.



(a) (b)

(c)

Fig. 9. Experimental data analysis with (a) training vs. validation accuracy (b) training vs. validation loss (c) confusion matrix of the trained model (d) ROC-curve for performance evaluation and validation of the InceptionV3 model.



(d)

Fig. 9. Continued

4.6. Discussion with the comparison

As we have applied the two pre-trained Convolutional Neural Network (CNN) models namely, ResNet50 and InceptionV3 model, we have identified some crucial observations from these two models. The summary of our observations is depicted in the following:

- ResNet50 is a deeper network with 50 layers, while InceptionV3 has 48. The depth of ResNet50 can be beneficial for learning more complex features, but it may also require more computational resources. Whereas InceptionV3 uses factorized convolutions and Inception modules, which are designed for computational efficiency, making it a good choice when resources are a concern. Thus, while working with the vegetable classification, we found the ResNet50 model very convergent to the higher computational resources.
- In the model training, the target image size of 224 × 224 was for ResNet50, and for InceptionV3, the target image size was 299 × 299.
- We have achieved the highest accuracy of 99 % with the ResNet50 architecture, while accuracy for the InceptionV3 model was 94 %. Figs. 10 & 11 show the comparison among the performance evaluation matrices from the ResNet50 and InceptionV3 models respectively.

The research also performed a comparison among the existing and related research works based on the number of images, the size of the dataset, and the highest accuracy of the different models. Table 5 shows the summary of the comparison among the related and existing works. From this table, most authors worked on vegetable classification with a comparatively small dataset. In the paper [9], Irawati et al. worked on the four classes of vegetable classification, but the number of images was only 600. In the paper [10–12,15], the authors researched the spinach

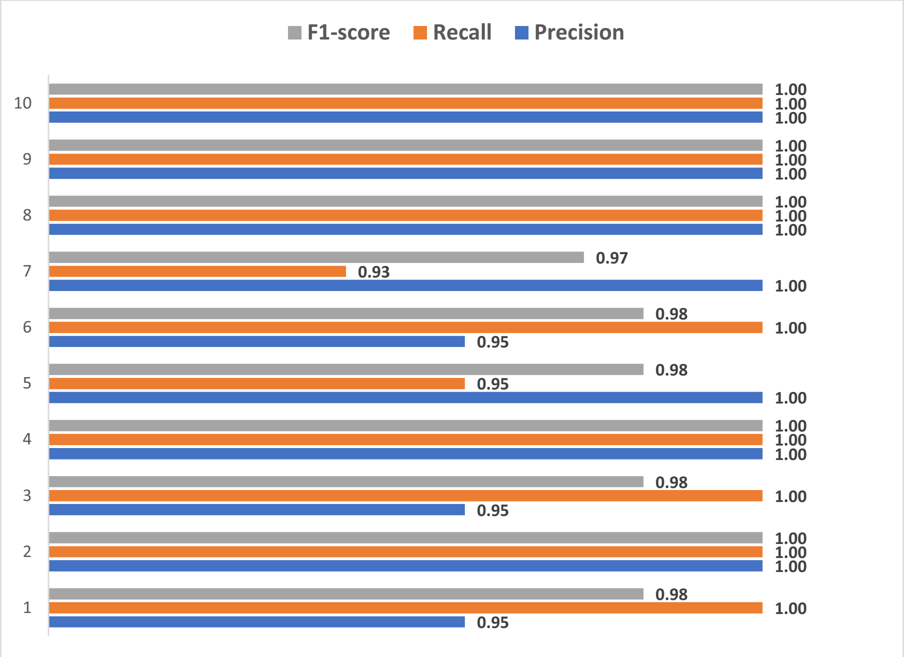


Fig. 10. Comparison among different performance evaluation matrices from Resnet50 model.

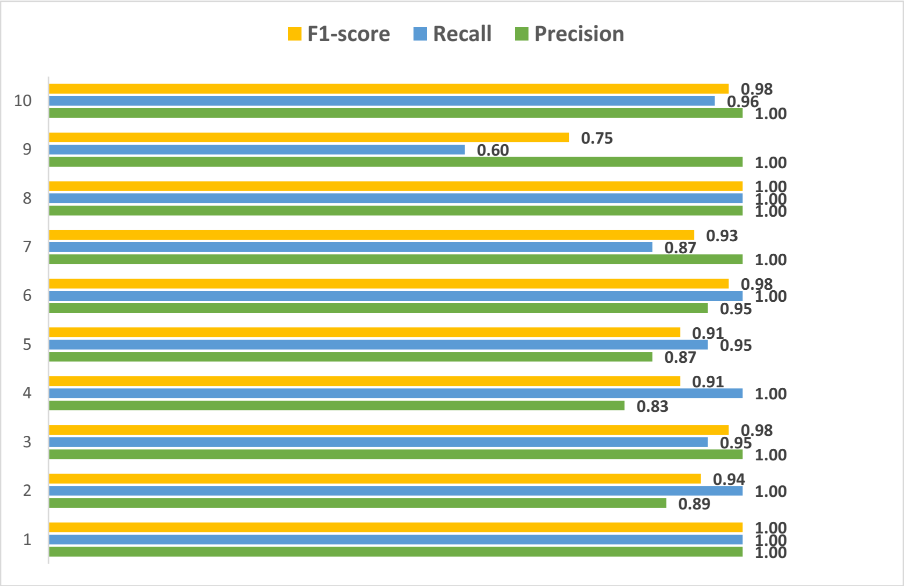


Fig. 11. Comparison among different performance evaluation matrices from InceptionV3 model.

Table 5
The summary of the comparison among the related and existing works.

References	Year	Types of Images	Dataset Type	Number of classes	Dataset Size	Deep Learning Model	Highest Accuracy
Irawati et al. [9]	2023	Vegetables	Not Own	4	600	AlexNet	98 %
Sennan et al. [10]	2022	Spinach	Own	4	400	SVM, Random Forest,VGG16,VGG19, ResNet50, modified CNN	97.5 %
Islam et al. [11]	2022	Spinach	Own	5	3785	InceptionV3, Xception, VGG19, and VGG16	98.68 % - 99.79 %
Koyama et al. [12]	2022	Spinach	Own	4	1045	ResNet	85 %
Ukwuoma et al. [13]	2022	Fruits	Not Own	3	3232 (Orchard Data), 81,226 (Fruit 360), 2633 (Supermarket Produce Dataset), 3139 (InterFruit)	CNN, ResNet50	99 %
Kanda et al. [14]	2021	Plant	Not Own	Not Specified	1360	GAN, CNN, LR	98.5 %
Koyama et al. [15]	2021	Spinach	Own	Not Specified	1045	SVM, ANN	84 %
Wagle et al. [16]	2021	Plant	Not Own	9 (PV), 32 (Flavia)	Not Specified	AlexNet, CNN	99.9 %
Proposed Research	**2023**	**Vegetables**	**Own**	**10**	**4500 (Original 1500 and Augmented 3000)**	**ResNet50, InceptionV3**	**99.00 %**

classification, which is almost related to the vegetable classification. Among these papers, Islam et al. [11] worked on five classes of spinach and achieved the highest accuracy of 99.79 %. But, in our research, we built our dataset with 10 classes of Bangladeshi seasonal vegetables, and a total of 4500 images were included. Also, we have applied two pre-trained CNN models and achieved the highest accuracy of 99.00 % with the Resnet50 pre-trained CNN model.

Limitations

While working with the proposed dataset, the researchers found some drawbacks in model training and dataset collection. We captured vegetable photos using mobile phones, resulting in comparatively lower picture quality compared to high-tech cameras. In the future, we plan to utilize advanced cameras for improved image quality. Our study focused on ten classes of vegetables, and data collection was limited to specific areas in Dhaka and Pabna. It's worth noting that the transferability of pre-trained models, such as ResNet50 and InceptionV3, may be constrained when applied to a specific regional context. These models are typically trained on more generic datasets. In future research, we aim to enhance the diversity of our dataset by including more vegetables. We plan to collect data from various regions across the entire country and build a smartphone application to automatically identify or classify the vegetables in order to create awareness among the younger generations. Additionally, we acknowledge the use of mobile phones for data collection, and we anticipate that the inclusion of high-quality images from advanced cameras will further improve the performance of our classification models.

Ethics Statement

The research conducted followed ethical principles with utmost dedication to high standards. The data collection process did not cause any harm to vegetables. It is worth noting that all images were obtained with explicit consent from the respective owners, including those responsible for different markets in Dhaka and Pabna. It was not required to obtain written consent to capture the images. The authors have confirmed that the current work did not involve human subjects or experiments and have complied with ethical requirements for publication in Data in Brief.

Credit Author Statement

Md. Tusher Ahmad Bappy: Data Collection, Formal analysis, Conceptualization, Methodology, Investigation, Writing – original draft, Visualization, Codding, Data Preprocessing, Augmentation, Data Compression; **Kazi Mehedi Hasan Rabbi**: Writing – original draft, Data Collection, Formal analysis, Conceptualization, Methodology; **Md. Jonayed Ahmed**: Data Collection, Conceptualization, Writing – original draft; **Wahidur Rahman**: Conceptualization, Formal Analysis, Supervision, Project administration, Writing – review and editing, Software, Validation; **Mahin Zeesan**: Data Collection, Conceptualization, Formal analysis, Writing – original draft; **Mohammad Motiur Rahman**: Formal analysis, Conceptualization, Project administration, Supervision, Writing – review and editing; **A. H. M. Saifullah Sadi**: Project administration, Supervision.

Data Availability

SeasVeg: An Image Dataset of Bangladeshi Seasonal Vegetables (Original data) (Mendeley Data).

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Declaration of Competing Interest

The authors certify that they do not currently have any prior financial or interpersonal conflicts that might have affected the findings of this study.

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