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Corresponding Author	Family Name	**Koneti**
	Particle	
	Given Name	**Prakash**
	Prefix	
	Suffix	
	Role	
	Division	
	Organization	REVA Academy for Corporate Excellence, REVA University
	Address	Bangalore, India
	Email	prakash.ai05@race.reva.edu.in
	ORCID	http://orcid.org/0009-0000-3931-2229
Author	Family Name	**Simha**
	Particle	
	Given Name	**J. B.**
	Prefix	
	Suffix	
	Role	
	Division	
	Organization	REVA Academy for Corporate Excellence, REVA University
	Address	Bangalore, India
	Email	jb.simha@reva.edu.in
	ORCID	http://orcid.org/0000-0002-6733-7535
Author	Family Name	**Agarwal**
	Particle	
	Given Name	**Rashmi**
	Prefix	
	Suffix	
	Role	
	Division	
	Organization	REVA Academy for Corporate Excellence, REVA University
	Address	Bangalore, India
	Email	rashmi.agarwal@reva.edu.in
	ORCID	http://orcid.org/0000-0003-1778-7519

Abstract

Consuming fresh Leafy Vegetables (LVs) offers numerous health benefits due to their essential vitamins, minerals, and fiber content. However, accurately identifying freshness can be difficult, leading to post-purchase spoilage and waste. This research addresses the challenge of manually classifying the freshness of LVs. The agricultural industry faces numerous challenges throughout the production cycle. When it comes to LVs they have short self-life and their quality deteriorates rapidly over time. Distinguishing between Day01 and Day02 freshness can be particularly tricky, but beyond Day02, wilting accelerates, causing significant losses for consumers, retailers, exporters, and restaurant owners. A model capable of classifying LVs into multiple freshness categories would enable informed inventory management, timely buying and selling decisions, and optimized sales and profits. Fresh LVs were obtained directly from a vendor who supplied directly from farm. Captured images from Day01 to Day03 and saved images under freshness category. This research investigates the use of deep learning pre-trained models using transfer learning for LVs freshness classification. Experimented *VGG-16, ResNet50, DenseNet201* architectures. The *DenseNet* architecture, known for its dense connectivity, feature propagation, reduced parameter count, and strong feature extraction capabilities, was chosen for its effectiveness in vegetable and LV classification. *DenseNet* with *unfrozen denseblock3* and *denseblock4* layers, were explored using transfer learning. The proposed *DenseNet201* model achieved the highest test accuracy 96.46% with unfreezing *denseblock3* and *denseblock4*. It is accurately classifying the LVs into multiple categories Day01, Day02, Day03.

Keywords (separated by '-')	Convolution neural network - Deep learning - Transfer learning - Freshness classification - Leafy vegetables - Densenet201

Chapter 49
Leafy Vegetable Freshness Classification Using Transfer Learning

Prakash Koneti, J. B. Simha, and Rashmi Agarwal

Abstract Consuming fresh Leafy Vegetables (LVs) offers numerous health benefits due to their essential vitamins, minerals, and fiber content. However, accurately identifying freshness can be difficult, leading to post-purchase spoilage and waste. This research addresses the challenge of manually classifying the freshness of LVs. The agricultural industry faces numerous challenges throughout the production cycle. When it comes to LVs they have short self-life and their quality deteriorates rapidly over time. Distinguishing between Day01 and Day02 freshness can be particularly tricky, but beyond Day02, wilting accelerates, causing significant losses for consumers, retailers, exporters, and restaurant owners. A model capable of classifying LVs into multiple freshness categories would enable informed inventory management, timely buying and selling decisions, and optimized sales and profits. Fresh LVs were obtained directly from a vendor who supplied directly from farm. Captured images from Day01 to Day03 and saved images under freshness category. This research investigates the use of deep learning pre-trained models using transfer learning for LVs freshness classification. Experimented *VGG-16, ResNet50, DenseNet201* architectures. The *DenseNet* architecture, known for its dense connectivity, feature propagation, reduced parameter count, and strong feature extraction capabilities, was chosen for its effectiveness in vegetable and LV classification. *DenseNet* with *unfrozen denseblock3* and *denseblock4* layers, were explored using transfer learning. The proposed *DenseNet201* model achieved the highest test accuracy 96.46% with unfreezing *denseblock3* and *denseblock4*. It is accurately classifying the LVs into multiple categories Day01, Day02, Day03.

Keywords Convolution neural network · Deep learning · Transfer learning · Freshness classification · Leafy vegetables · Densenet201

P. Koneti (✉) · J. B. Simha · R. Agarwal
REVA Academy for Corporate Excellence, REVA University, Bangalore, India
e-mail: prakash.ai05@race.reva.edu.in

J. B. Simha
e-mail: jb.simha@reva.edu.in

R. Agarwal
e-mail: rashmi.agarwal@reva.edu.in

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49.1 Introduction

Fresh LVs as shown in Fig. 49.1 are very important for keeping people healthy. They contain many nutrients that our bodies need. These vegetables have things like fiber, vitamins, healthy fats, minerals, and proteins that are good for us. LVs are a cheap way to get these important nutrients. Many people do not get enough of these nutrients in their regular diet, so eating LVs can help fix that problem. In addition to being healthy food, many cultures use LVs as medicine. People have used these plants for a long time to treat different health problems. They are part of traditional healing practices in many parts of the world [1].

LVs are important to eat every day to stay healthy. They can be consumed in different ways like Fresh in salads, Cooked in meals. More and more people are choosing to eat LVs because they are learning about how good natural and organic foods are for them. These vegetables are a big part of eating a balanced diet and they are at the top of the food pyramid. This makes them perfect for people who want to watch their weight or lose some pounds. So, eating LVs is an easy way to get lots of good nutrients without eating too many calories [2].

Freshness is a key indicator of LVs quality and safety. Consumers and retailers often rely on visual cues like color to assess freshness, but this method can be unreliable. Some suppliers may use deceptive practices to enhance the apparent freshness of LVs, leading to rapid spoilage. Consuming older LVs may offer lower nutritional value, and retailers risk financial losses due to spoilage of less-than-fresh produce. Exporters face similar challenges due to misclassification of LV freshness.

Fig. 49.1 Leafy vegetable produce

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This study focuses on eight commonly available LVs (1) Amaranthus Green, (2) Amaranthus Virdis, (3) Coriander, (4) Malabar Spinach, (5) Moringa, (6) Mustard Greens, (7) Red Amaranth, (8) Sorrel Leaves.

This study aims to develop system for classifying LV freshness into multiple categories. Deep learning-based system has been proposed which utilizes computer vision techniques to analyze vegetable images and determine their age category. The system is designed to classify vegetables into the following categories: (a) One day old (b) Two days old (c) Three days old.

This paper is organized as follows. Section 49.2 provides a review of the relevant literature. Section 49.3 presents the proposed methodology which covers business understanding and data acquisition methods, and exploration of various models. Section 49.4 discusses the detailed implementation steps, data acquisition, image pre-processing, and training the model. Section 49.5 focuses on analysis and results, detailing the dataset, preprocessing, various models performance and key findings of the overall study. Finally, Sect. 49.6 concludes the paper with conclusion, scope for future enhancements.

49.2 Literature Review

Existing research on leafy greens, especially regarding classification and disease identification, is limited compared to other crops. This study addresses this gap by employing CNN models to classify seven types of LVs and identify seven types of diseases affecting them. Using datasets of 3306 and 4493 images respectively, the research achieved impressive classification and segmentation accuracies. The methodology involved image preprocessing followed by model application, with YOLOv8 and YOLOv7 demonstrating the best performance for classification and segmentation, respectively [3]. YANLEI XU et al. developed a new method to classify lettuce freshness using an improved ResNet-50 architecture called Im-ResNet. The original ResNet-50 was modified by adding a convolutional layer, a pooling layer, and two fully connected layers to enhance feature extraction and classification. The model was trained on a dataset of 1939 lettuce images and achieved a test accuracy of 95.60%, surpassing other models like VGG16, AlexNet, GoogleNet, and the original ResNet-50 [4].

The freshness of picked lettuce declines rapidly due to physiological deterioration and microbial degradation. Particularly, the nitrate naturally present in lettuce can convert into nitrite during storage, which poses health risks. Consequently, the classification of lettuce freshness is highly significant for consumers [5]. To classify locally available spinach varieties in Bangladesh, the authors [6] developed a deep learning model and identified five spinach types: jute spinach, Malabar spinach, red spinach, taro spinach, and water spinach. They used 3,785 images of fresh spinach leaves to train four CNN models InceptionV3, Xception, VGG19, and VGG16. The highest accuracy 99.79% achieved for VGG16.

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In a separate study, Sennan et al. [7] created a new *CNN* model to detect four spinach varieties: amaranth leaves, black nightshade, curry leaves, and drumstick leaves. The performance of different models was as follows: *SVM* at 83%, *Random Forest* at 85%, *VGG16* at 93%, *VGG19* at 94.5%, *ResNet50* at 95%, and the proposed *CNN* model achieved the highest accuracy of 97.5%. Akter et al. introduced automated system to classify vegetable freshness into multiple categories. They used five types of vegetables: Capsicum, Chilli, Coriander, Cucumber, and Lemon. Model was trained to classify the vegetables into multiple classes, namely fresh, aged, and rotten. Multiple pretrained models, including *Xception*, *InceptionV3*, *DenseNet121*, and *DenseNet201*, were trained. *DenseNet201* achieved the best test accuracy of 98.56% [8].

New custom *CNN* model called *FreshDNN* was developed by Ahmed et al. to classify the freshness of images collected from various online sources. The dataset contains a total of 36,800 images spanning 16 classes, comprising eight types of fruits and vegetables in both fresh and stale conditions. The model achieved high accuracy (97.8% validation) and efficiency compared to other existing models [9]. Salim et al. evaluated four pre-trained deep learning models *DenseNet201*, *Xception*, *MobileNetV3-Small*, and *ResNet50* for fruit classification using Fruits-360 and the Fruit Recognition dataset. All models performed well on Fruits-360, achieving 98% accuracy. *DenseNet201* and *Xception* excelled on both datasets, with *DenseNet201* achieving up to 99.87% accuracy and *Xception* reaching 98.94%. These results suggest strong potential for these models in real-world fruit recognition [10].

A comparative study has been conducted to determine the most effective deep *CNN* model for detecting plant leaf diseases. Four deep *CNN* models *DenseNet201*, VGG16, *Inception V3*, and *ResNet152 V2* were evaluated using a plant leaf disease dataset for training and testing. The dataset, which comprised images of tomato, potato, and pepper leaves, was divided into three parts: training, validation, and testing, with each part representing 25% of the dataset. In the proposed model, *DenseNet201* is used for feature extraction, followed by a *CNN* classifier. The results show that the proposed model achieves the highest accuracy among the tested models [11].

Research on LVs, particularly in disease detection and classification, is relatively rare compared to studies on other crops. Recent investigations employing deep learning techniques have shown promising results in this area. These studies successfully classified various LV types, identified diseases, and assessed lettuce freshness with high accuracy. Although past research has focused on individual vegetables or specific freshness-related issues, there is now growing interest in developing an integrated system for comprehensive quality assessment of leafy greens. The accurate classification of LV freshness is crucial for several reasons. It enables consumers to make informed decisions when purchasing produce, ensuring they obtain the most nutritious options. Additionally, it allows farmers and retailers to optimize inventory management, reducing waste and increasing profitability.

49.3 Proposed Methodology

Team Data Science Process (TDSP) method as shown in the Fig. 49.2 is used in this study, which is a systematic approach for solving data science problems. This methodology is used for acquiring the dataset, performing pre-image processing, feed the data into model and evaluate the performance of the model.

49.3.1 Business Understanding

Consumers require a reliable method to identify LVs freshness, ensuring they purchase vegetables with optimal nutritional value. Retailers benefit from accurate classification by selecting fresh produce with a longer shelf life, minimizing waste and maximizing sales. Traditional methods based on visual inspection are subjective and prone to manipulation. This study aims to develop a more objective and reliable system for LV freshness classification, empowering stakeholders to make informed decisions and potentially reducing food waste.

49.3.2 Data Acquisition and Understanding

This study focuses on eight commonly available LVs (Amaranthus Green, Amaranthus Virdis, Coriander, Malabar Spinach, Moringa, Mustard Greens, Red Amaranth, Sorrel Leaves) due to their prevalence in the market. A total of 8 types of LVs were

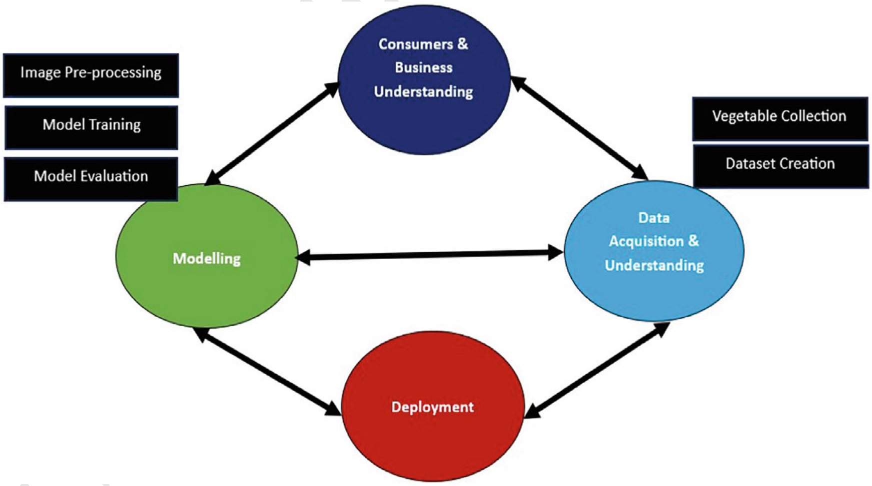

Fig. 49.2 Proposed methodology

collected directly from a vendor who supplied them directly from the farm. To simulate real-world conditions, the vegetables were stored outside a refrigerator in bags at home, mimicking the farm-to-vendor supply chain. However, this approach does not account for the influence of temperature and humidity on freshness degradation. Future studies could explore the impact of controlled environments.

49.3.3 Modelling

To leverage pre-trained CNN architectures for image recognition, employed transfer learning approaches. This technique utilizes pre-trained models on large datasets and fine-tunes them for our specific task of LV freshness classification. Various transfer learning approaches were explored, including VGG-16, ResNet50, DenseNet201, and DenseNet with unfrozen denseblock3 and denseblock4 layers. The model selection was based on performance metrics such as accuracy, precision, and recall. DenseNet201 achieved the best results on these metrics.

49.4 Implementation

This study was implemented using the Python programming language. It leveraged the PyTorch framework to incorporate and train several pre-existing network architectures and codebase encompasses various stages, including data collection and analysis, the construction and assessment of models.

49.4.1 Data Acquisition and Understanding

Eight types of LVs were collected from a vendor who sourced them from a farm. In total 2532 Photos have been captured and stored with labels assigned accordingly. To simulate real-world conditions, the vegetables were stored outside of a refrigerator, acknowledging the limitations in temperature and humidity control. A detailed list of images under each label for each vegetable is provided in Table 49.1.

Figures 49.3, 49.4, 49.5, 49.6, 49.7, 49.8, 49.9, and 49.10 illustrates the appearance of the LVs over three days. The images reveal no noticeable change between Day01 and Day02. However, by Day03, a slight decay is evident in most of the LVs.

Total images have been divided into training, validation, testing as mentioned in the Table 49.2.

Table 49.1 Leafy vegetables with number of images used in this study

Vegetables	Day01	Day02	Day03	Grand total
Amaranthus green	117	95	84	296
Amaranthus virdi’s	133	136	103	372
Coriander	109	109	108	326
Malabar spinach	96	92	117	305
Moringa	109	99	85	293
Mustard greens	120	141	77	338
Red amaranth	110	103	93	306
Sorrel leaves	85	75	136	296
Grand total	879	850	803	2532

Fig. 49.3 Amaranthus green

Fig. 49.4 Amaranthus virdis

49.4.2 Image Pre-Processing

Different data augmentation techniques applied to the LVs dataset before training. Image preprocessing is a crucial step in preparing images for deep learning models. It enhances the quality of image data for classification tasks by applying various

Fig. 49.5 Coriande

Fig. 49.6 Malabar spinach

Fig. 49.7 Moringa

Fig. 49.8 Mustard greens

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Fig. 49.9 Red amaranth

Fig. 49.10 Sorrel leaves

Table 49.2 Train, test, validation split

Phase	Number of images	Percentage
Training	1822	71.96
Validation	456	18.01
Testing	254	10.03
Total	2532	100.00

techniques. These techniques ultimately lead to cleaner images that improve feature extraction capabilities of the model.

49.4.3 Model Training

Experimented with multiple pretrained models VGG-16, ResNet50, DenseNet201 initially. DenseNet201 given good performance hence experimented this model by unfreezing the layers one by one. Finally trained the model by unfreezing the denseblock3, denseblock4.

49.5 Analysis and Results

49.5.1 Dataset and Preprocessing

This study investigated the freshness classification of eight LV types (Amaranthus green, Amaranthus viridis, Coriander, Malabar spinach, Moringa, Mustard greens, Red amaranth, Sorrel leaves) across three categories: Day01, Day02, and Day03. The LVs were sourced directly from a vendor who obtained them fresh from a farm. To simulate real-world conditions experienced by retailers who might not refrigerate vegetables, the LVs were stored using damp cloths instead of refrigeration.

Images of LVs were captured under natural, uncontrolled lighting conditions to simulate real-world scenarios often encountered by retailers and consumers. While this approach adds realism to the dataset, it also introduces variability in lighting, which may affect the model's consistency and accuracy. Variations in lighting can influence the visual appearance of LVs, potentially altering the perceived color, texture, and other freshness indicators that the model relies on for classification. Acknowledge that controlled lighting could help standardize these visual cues and reduce noise in the data. Future work could explore one or more of the following approaches to mitigate this limitation: (1) Controlled lighting conditions. (2) Various data augmentation techniques introducing brightness and contrast adjustments through data augmentation techniques. (3) Lighting-Invariant feature extraction by exploring preprocessing techniques.

49.5.2 Model Performance

Employed transfer learning with multiple pre-trained models, including VGG-16, ResNet50, DenseNet201, and DenseNet with unfrozen denseblock3 and denseblock4 layers. The DenseNet model with unfrozen denseblock3 and denseblock4 delivered the highest performance across all evaluation metrics, including accuracy, precision, recall, and F1-score. This model was followed by VGG-16, then the standard DenseNet and lastly, ResNet50. Train and validation scores are detailed in Table. 49.3, and Test scores are presented in Table. 49.4.

49.5.3 Key Findings

Unfreezing the denseblock3 and denseblock4 layers in the DenseNet architecture significantly improved training, validation, and test performance. This resulted in a test accuracy improvement from 77.95% to 96.46%. Interestingly, the standard VGG-16 outperformed the standard DenseNet for LV freshness classification, despite DenseNet being considered a more advanced architecture.

Table 49.3 Summary of performance of the different models (train, validation)

Model	Train loss	Train accuracy (%)	Validation loss	Validation accuracy (%)
VGG-16	0.2913	88.42	0.4795	82.46
ResNet50	0.8097	63.17	0.687	66.89
DenseNet201	0.5569	76.13	0.4497	81.36
DenseNet201 (Unfrozen, denseblock3, denseblock4)	0.0646	97.64	0.0695	97.37

Table 49.4 Summary of performance of the different models(test)

Model	Accuracy (%)	Loss	Precision	Recall
VGG-16	79.92	0.4938	0.8017	0.7992
ResNet50	63.39	0.7634	0.6423	0.6339
DenseNet 201	77.95	0.5194	0.7797	0.7795
DenseNet201 (Unfrozen, denseblock3, denseblock4)	96.46	0.1084	0.9656	0.9646

The unfrozen *DenseNet* model exhibited very good classification with minimal misclassifications as shown in the Table. 49.5. Day01 had strong overall accuracy with few errors, only 4 samples were misclassified (3 as Day03, 1 as Day02), likely due to minor visual variations. Day02 showed the confusion, with 4 misclassifications split between Day03 (3 samples) and Day01 (1 sample). This suggests Day02's visual characteristics overlap with both other days due to gradual degradation. Day03 performed well with only 1 misclassification (as Day01) and none as Day02, indicating clearer visual markers of degradation by this stage.

These misclassification patterns suggest that Day02 and Day03 categories display subtle differences that may be harder for the model to detect reliably. To address this, future work could involve enhanced image preprocessing and targeted data augmentation focusing on degradation transitions.

Table 49.5 Confusion matrices

	Day 01	Day 02	Day 03
Day 01	84	1	3
Day 02	1	81	3
Day 03	1	0	80

49.6 Conclusion and Future Scope

This study successfully investigated the feasibility of employing a deep learning approach for LVs freshness classification. Transfer learning has been leveraged with a DenseNet201 architecture to develop a model capable of distinguishing between various freshness levels (Day01, Day02, and Day03) by unfreezing denseblock3 and denseblock4. The model achieved a commendable accuracy of 96.46% on the test dataset, demonstrating its potential for real-world applications.

In the future scope please include environment factors like light, temperature, humidity into training data to improve real-world generalization. Expand the dataset to broader variety of other leafy vegetables. Explore alternative deep learning architectures to enhance classification accuracy and efficiency. Develop a mobile application for real-time leafy vegetable freshness assessment which helps consumers and retailers. Optimize hyperparameters such as learning rate, optimizer to achieve further performance.

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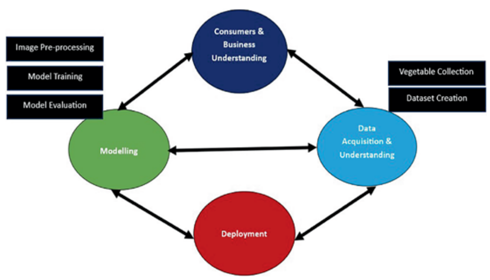
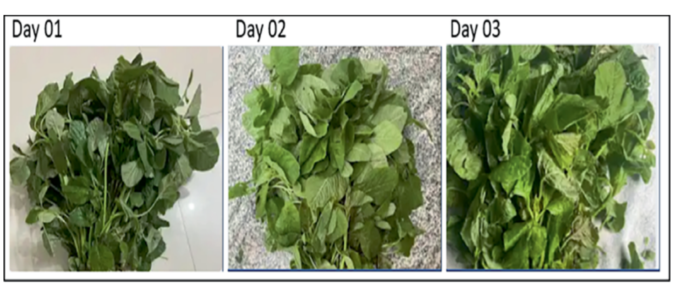
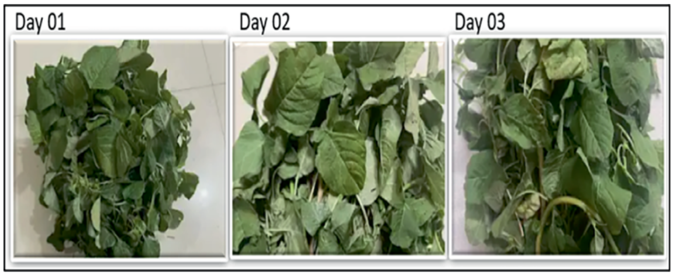
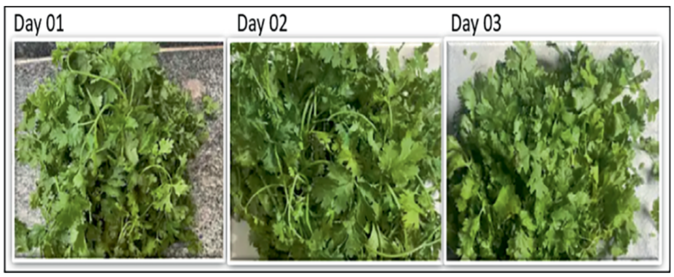
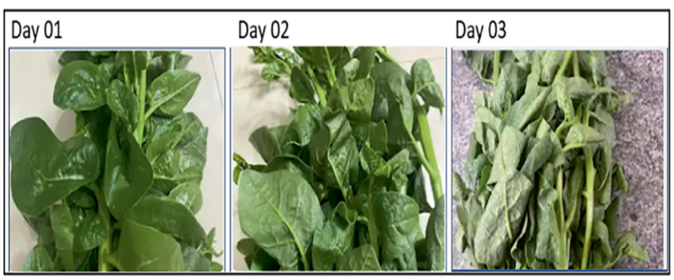
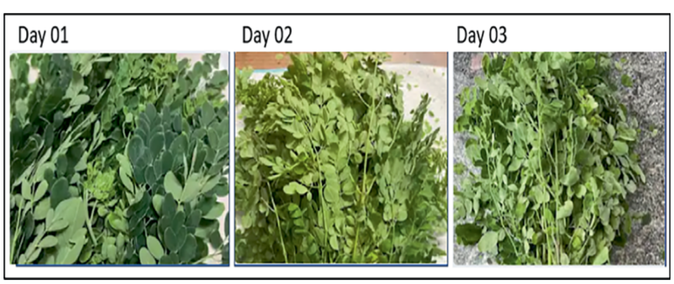
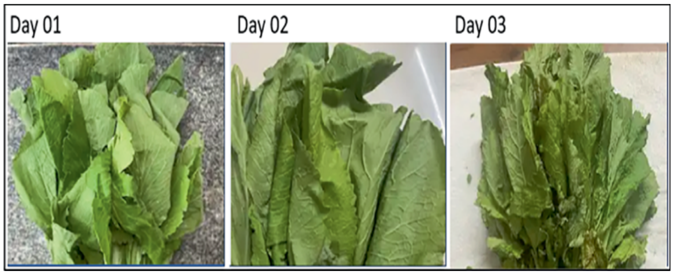
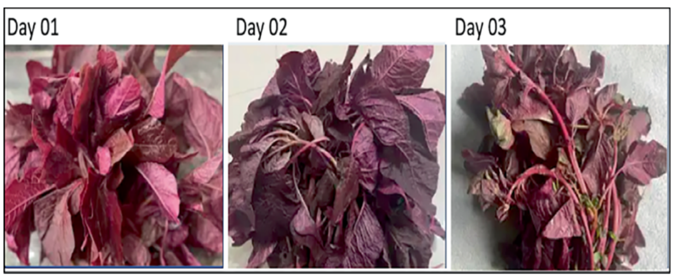
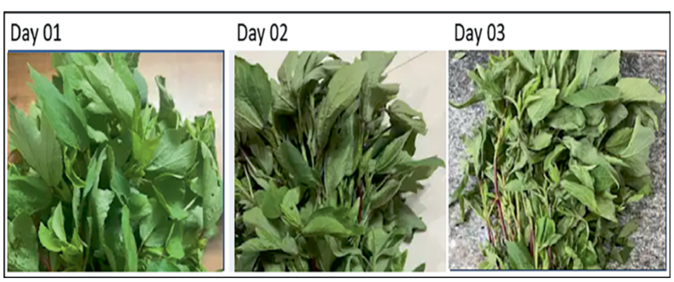
Alternative Texts for Your Images, Please Check and Correct them if Required

Page no	Fig/Photo	Thumbnail	Alt-text Description
2	Fig1		Aerial view of a large, organized array of various leafy greens and red lettuce plants. The plants are arranged in a grid pattern, showcasing different shades of green and red. The image highlights the diversity and uniformity of the plants, likely in a controlled agricultural or hydroponic setting.
5	Fig2		Flow chart illustrating a process with four main stages: "Consumers & Business Understanding" in a dark blue oval, "Data Acquisition & Understanding" in a light blue oval, "Modelling" in a green oval, and "Deployment" in a red oval. Arrows indicate the flow between stages, forming a cycle. Additional steps include "Image Pre-processing," "Model Training," and "Model Evaluation" linked to "Modelling," and "Vegetable Collection" and "Dataset Creation" linked to "Data Acquisition & Understanding."
7	Fig3		Three-panel image showing a bunch of green leaves over three days. Panel one, labeled "Day 01," shows fresh, vibrant green leaves. Panel two, labeled "Day 02," displays slightly wilted leaves with a duller green color. Panel three, labeled "Day 03," shows further wilting and discoloration, with leaves appearing more shriveled and less vibrant. The background changes from a white surface on Day 01 to a speckled surface on Day 02 and Day 03.

Page no	Fig/Photo	Thumbnail	Alt-text Description
7	Fig4		Three-panel image showing the progression of leafy greens over three days. The first panel, labeled "Day 01," shows fresh, vibrant green leaves. The second panel, "Day 02," displays slightly wilted leaves with some discoloration. The third panel, "Day 03," shows further wilting and browning of the leaves, indicating deterioration over time.
8	Fig5		Three photos showing the progression of cilantro leaves over three days. Each image is labeled: "Day 01," "Day 02," and "Day 03." The cilantro appears fresh and vibrant, with slight changes in leaf arrangement and brightness over the days. The background is a neutral surface.
8	Fig6		Three side-by-side photos showing the progression of spinach leaves over three days. Day 01: Fresh, vibrant green leaves. Day 02: Leaves appear slightly wilted but still green. Day 03: Leaves are visibly wilted and dull in color. The images are labeled "Day 01," "Day 02," and "Day 03" at the top.
8	Fig7		Three side-by-side photos of leafy greens labeled "Day 01," "Day 02," and "Day 03." Each image shows a bunch of green leaves, with slight variations in color and freshness over the days. The leaves appear vibrant and healthy, illustrating changes over time.

Page no	Fig/Photo	Thumbnail	Alt-text Description
8	Fig8		Three images of green leafy vegetables labeled "Day 01," "Day 02," and "Day 03." Each image shows the leaves on different days, highlighting changes in appearance over time. The leaves appear fresh and vibrant on Day 01, slightly wilted on Day 02, and more wilted on Day 03. The background changes from a textured surface to a smooth one.
9	Fig9		A series of three photos showing the progression of red leaves over three days. The first image, labeled "Day 01," shows vibrant, fresh red leaves. The second image, "Day 02," displays the leaves slightly wilted. The third image, "Day 03," shows the leaves more wilted and less vibrant. Each photo captures the changes in leaf texture and color over time.
9	Fig10		Three photos of green leafy plants labeled "Day 01," "Day 02," and "Day 03." Each image shows the progression of the plant's appearance over three days. The leaves appear vibrant and fresh on Day 01, slightly wilted on Day 02, and more wilted with some browning on Day 03. The background is a neutral surface.