Freshness detection of fruits and vegetables using multi-task convolutional neural network and ResNet-50

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ABSTRACT

Computer vision-based assessment of the freshness of fruits and vegetables is imperative for many agricultural applications, including automated harvesting and oversight of the supply chain. This manuscript investigates the advancement of deep convolutional neural networks (CNNs) aimed at detecting fruit freshness through the implementation of multi-task learning (MTL). The proposed models, MTL_ResNet-50 and MTL_CNN, leverage shared feature extraction to concurrently enhance freshness detection and fruit-type classification tasks. The MTL_ResNet-50 and MTL_CNN architectures attained accuracies of 99.32% and 97.95%, respectively. By exceeding the efficacy of established methodologies such as single-task learning and manual feature extraction techniques and by employing an imbalanced dataset to bolster the robustness of our models, we address significant gaps within the existing literature. Furthermore, we markedly surpassed the performance of prior approaches, such as InceptionV3 and CNN_bidirectional long short-term memory (CNN_BiLSTM), resulting in substantial implications for enhancing food quality and safety within both agricultural and consumer domains. These implications encompass the improvement of automated quality control mechanisms within the food industry, the mitigation of food waste, and the assurance of heightened standards for food safety. Future research initiatives may concentrate on augmenting model scalability, refining computational efficiency, and investigating additional applications within agricultural technology.

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1. INTRODUCTION

Fruits and vegetables significantly impact human nutrition and overall health, as they are packed with vital vitamins, minerals, fiber, and antioxidants. These nutrient-dense meals are essential for strengthening the immune system, avoiding chronic illnesses, and fostering wellbeing [1]. In contemporary agricultural and food supply chains, the capacity to assess the freshness of fruits and vegetables is essential. Maintaining the freshness of produce throughout the supply chain not only increases consumer satisfaction but also helps reduce food wastage [2]. Traditional methods of assessing freshness often involve manual inspection, where individuals rely on their senses of sight, touch, and smell to evaluate various physical attributes like shape, weight, firmness, and color [3]. However, these methods can be time-consuming, subjective, and prone to errors. Operator biases are lessened by non-destructive diagnostic methods offered by mass spectrometry and chromatographic procedures [4]. Additionally, specific chemical reagents, such as fluorescence probes, are used in certain situations to detect the freshness of fruits [5]. Gas detectors have steadily gained popularity for freshness detection due to the expensive cost of chromatographic and mass spectrometry detectors. However, these methods have some common issues, such as low efficiency, high installation cost, difficulty to operate, and many more. Computer vision and deep learning advancements have created new possibilities for automating freshness detection, offering improved accuracy and efficiency [6]. It is important to remember that deep learning models often require large amounts of training data and computer power [7]. Although deep learning excels in predicting unseen data by learning intricate patterns, this advantage comes with a trade-off. Nonetheless, automatic fruit and vegetable freshness detection research predominantly depends on feature engineering [8]. This process entails extracting features from images of produce with different freshness levels, followed by the utilization of machine learning or deep learning algorithms to classify freshness based on these features [9].

Numerous advanced deep learning models have been used in recent research on the detection of fruit and vegetable freshness. Five deep learning models (SqueezeNet, ResNet18, EfficientNet, MobileNet-V2, and ShuffleNet) were used by Abayomi-Alli *et al*. [10] to identify fruit freshness in a particular dataset, these models were retrained to improve accuracy, albeit at the expense of more time. Rahman *et al*. [11] introduced an automated system for fruit recognition using the MobileNet architecture to classify local fruits, emphasizing the significance of classification in freshness evaluation. Hamim *et al*. [12] explored different image processing techniques like convolutional neural network (CNN), k-nearest neighbors, and support vector machine (SVM) for categorizing rottenness in fruits and vegetables, encountering challenges related to low model performance and accuracy. In order to forecast fruit shelf life, Reka *et al*. [13] explored into machine learning models such gaussian Naïve Bayes, random forest, and visual geometry group 16 (VGG16). However, they fail to consider a number of crucial factors and simply use hue value to estimate the shelf life. Yuan and Chen [14] proposed a novel approach for objective, accurate, and efficient freshness detection by utilizing pre-trained models like GoogLeNet, ResNeXt-101, and DenseNet-201for deep feature extraction from resized images of fruits and vegetables, consolidating the features and reducing their dimensionality with principal component analysis (PCA), although this reduction of deep features may result in the loss of significant features.

In contemporary times, multi-task learning (MTL) has demonstrated its promise in several applications in the modern era, to simultaneously teach numerous related tasks to improve performance. Past research has shown the effectiveness of MTL in diverse image classification tasks, such as pose-invariant face recognition [15], automated breast cancer detection [16], and food safety [17]. In the domain of fruit freshness classification, Göksu *et al*. [18] employed a deep CNN based on ResNet-50 to classify fruit images as fresh or rotten, incorporating data augmentation techniques to improve the dataset diversity; however, the model exhibited overfitting, resulting in a noticeable gap between training and testing performance. Additionally, Zhang *et al*. [19] illustrated that employing MTL for fruit freshness detection via deep CNNs can enhance accuracy compared to single-task learning (STL) models, highlighting the effectiveness of leveraging shared feature extraction processes for multiple related tasks. While MTL has been successful in various image classification domains, its application in fruit freshness detection remains unexplored mainly, presenting an exciting avenue for research and innovation. This study explores deep learning techniques, specifically multi-task learning CNN (MTL_CNN) and ResNet-50, for freshness detection in fruits and vegetables. Through a comprehensive analysis of how advanced machine-learning approaches can revolutionise the way we ensure food quality and safety in both agricultural and consumer contexts. Key contributions of this study include: i) the exploration of deep CNN development for fruit and vegetable freshness detection using MTL; ii) the proposal of two image processing-based MTL models: MTL_RestNet-50 and MTL_CNN; iii) achieving exceptionally high accuracies: 99.32% for MTL_ResNet-50 and 97.95% for MTL_CNN in detecting the freshness of three common fruits and six vegetables; and iv) demonstrating this technique's adaptability opens up vast opportunities for future applications.

2. MATERIALS AND METHODS

2.1. Dataset

The dataset used in this research includes pictures of three common fruits (apples, bananas, and oranges) and six vegetables (bitter gourd, capsicum, cucumber, okra, potato, and tomato). Each fruit or vegetable type is divided into fresh and spoiled categories. Examples of these pictures can be seen in Table 1. The dataset is available to the public at https://www.kaggle.com/datasets/swoyam2609/fresh-and-stale-classification. As per the dataset creator, the images were gathered from three different datasets on Kaggle. This dataset plays a vital role in our study due to the significant imbalance in sample data among categories. For example, the 'fresh apple' category has 3215 images, while the 'fresh bitter gourd' category only has 327 images. To address this imbalance, we limited the number of images in categories with over 2000 samples to 2000 each. Despite these efforts, some imbalance still exists, as depicted in Table 1. The dataset now consists of 23,423 images split into training, testing, and validation sets.

Table 1. Image distribution of fresh and spoiled fruits and vegetables in the dataset

Name	Image distribution in the dataset		Sample images		Custom balanced dataset	
	Fresh	Spoiled	Fresh	Spoiled	Fresh	Spoiled
Apples	3215	4236			2000	2000
Banana	3360	3832			2000	2000
Bitter gourd	327	357			327	357
Capsicum	990	901			990	901
Cucumber	775	676			775	676
Okra	100	562			1005	562
Orange	1854	1998			1854	1998
Potato	806	1172			806	1172
Tomato	2113	2178			2000	2000

2.2. Data preprocessing

To prepare the dataset for training, validation, and testing, we implemented various transformations to enhance the robustness and performance of our deep learning models. For the training dataset, we applied random horizontal flips for augmentation, introduced Gaussian blur for slight blurriness, and randomly adjusted image sharpness to cater to different image qualities. These transformations ensure the model can generalize well under various visual conditions. Also, preprocessing steps are crucial for improving the model's accuracy in classifying fruit and vegetable freshness, making the dataset more reflective of real-world scenarios, and reducing biases stemming from data imbalances. In contrast, the validation and test dataset underwent more straightforward transformations to guarantee consistent evaluation metrics.

2.3. Deep learning models

MTL has demonstrated significant advantages in image classification, proving its effectiveness over STL approaches [19]. CNNs can learn hierarchical representations of visual input, and they are effective tools for feature extraction and image classification. Given these strengths, this study employs an MTL_CNN model to both classify the type of fruit or vegetable and detect their freshness. We also integrate MTL with the ResNet-50 architecture, a highly regarded pre-trained model known for its robust performance in various image classification tasks [20]. Similar to the MTL_CNN model, the MTL_ResNet-50 is used to classify fruit and vegetable types and detect freshness at the same time, as illustrates in Figure 1.

2.3.1. Multi-task learning convolutional neural network

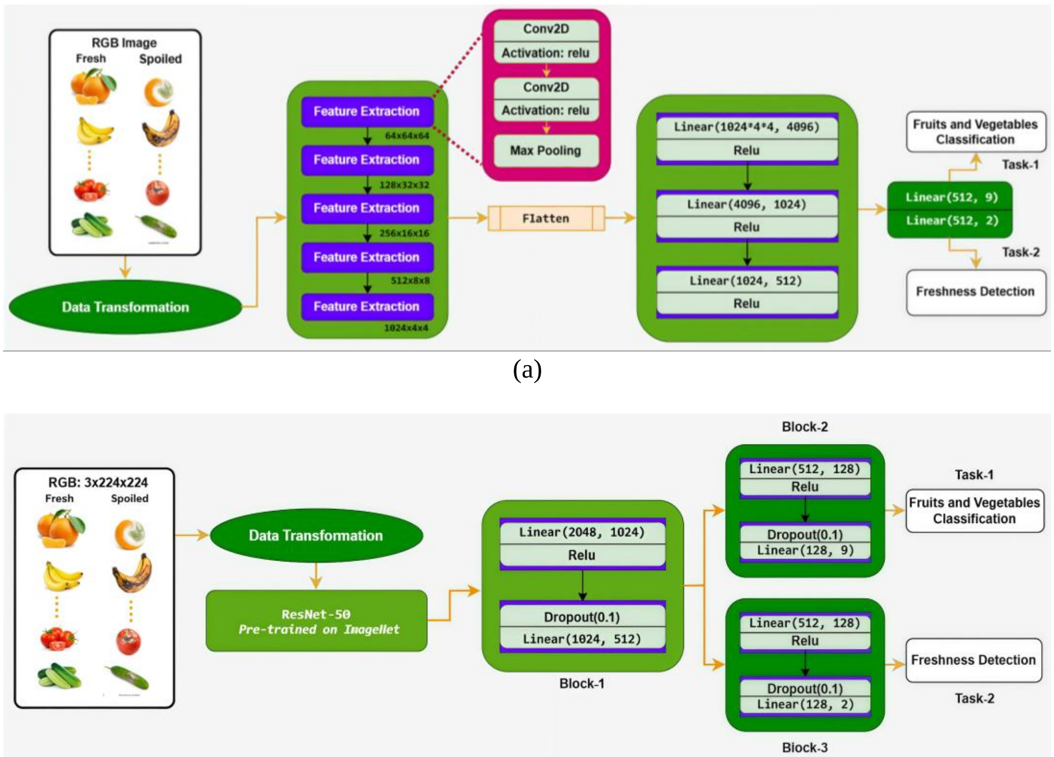
MTL_CNN utilized in this investigation is intended to accomplish two functions: identifying the type of fruit and vegetable and determining its freshness. In order to capture hierarchical characteristics, the core network is made up of many convolutional layers with max-pooling and rectified linear unit (ReLU) activations. As shown in Figure 1(a), the suggested CNN is built as a common feature extractor followed by two task-specific classification heads for MTL. Each of the five convolutional blocks that make up the backbone has two convolutional layers with ReLU activation, followed by a max-pooling layer for spatial downsampling. In order to enable hierarchical feature extraction from low-level textural information to high-level semantic data pertinent to fruit kind and freshness, the network gradually expands the number of feature channels from 32 to 1024. Following feature extraction, three fully connected layers (4096, 1024, and 512 neurons) are applied to the flattened feature map in order to learn compact high-level representations. Finally, two independent output layers are used for the two tasks: fruit category classification (9 classes) and freshness classification (2 classes). The input image resolution used in the implementation results in a final feature map of 1024×4×4 before flattening. The entire model contains 90,662,603 trainable parameters (layer configurations detailed in Table 2).

2.3.2. Multi-task learning ResNet-50

The model's block diagram, displayed in Figure 1(b), starts with a ResNet-50 network previously trained on a large set of images, such as ImageNet. All layers are frozen aside from the final 15, preserving learned features and enabling fine-tuning on the current job. The output layer of ResNet-50 is eliminated and substituted with a unique layer sequence designed for the particular multi-task categorisation issue at hand. The three significant blocks comprise the custom layers of the model: Block-1, which processes the 2048-dimensional output of ResNet-50, consists of two fully connected layers and a dropout layer to minimise overfitting. Block-2 is the second block in which fruits and vegetables are classified, with predictions made for one of nine classes; Block-3, on the other hand, is the block that deals with freshness detection, with predictions made for one of two classes. Because of its modular architecture, the model can efficiently handle complicated tasks with shared and task-specific layers. The MTL_ResNet-50 model was implemented using a transfer learning strategy in which a pretrained ResNet-50 network serves as the shared feature extractor.

Table 2. Layer configuration and parameter distribution of the proposed CNN architecture

Stage	Layer type	Configuration	Output size	Parameters
Input	Image	RGB image	3×128×128	–
Block 1	Conv1	3→32, kernel=3, padding=1	32×128×128	896
	Conv2	32→64, kernel=3, padding=1	64×128×128	18,496
	MaxPool	2×2	64×64×64	0
Block 2	Conv3	64→128, kernel=3, padding=1	128×64×64	73,856
	Conv4	128→128, kernel=3, padding=1	128×64×64	147,584
	MaxPool	2×2	128×32×32	0
Block 3	Conv5	128→256, kernel=3, padding=1	256×32×32	295,168
	Conv6	256→256, kernel=3, padding=1	256×32×32	590,080
	MaxPool	2×2	256×16×16	0
Block 4	Conv7	256→512, kernel=3, padding=1	512×16×16	1,180,160
	Conv8	512→512, kernel=3, padding=1	512×16×16	2,359,808
	MaxPool	2×2	512×8×8	0
Block 5	Conv9	512→1024, kernel=3, padding=1	1024×8×8	4,719,616
	Conv10	1024→1024, kernel=3, padding=1	1024×8×8	9,438,208
	MaxPool	2×2	1024×4×4	0
Feature projection	Flatten	1024×4×4→16384	16384	0
	FC1	16384→4096	4096	67,112,960
	FC2	4096→1024	1024	4,195,328
	FC3	1024→512	512	524,800
Task-1	Fruit classifier	512→9	9	4,617
Task-2	Freshness detector	512→2	2	1,026
Total trainable parameters				90,662,603



(a)

(b)

Figure 1. Block diagram of proposed architectures that can classify fruits and vegetables and detect their freshness; (a) MTL_CNN and (b) MTL_ResNet-50

2.4. Training

The MTL_CNN model was trained using a set of empirically selected hyperparameters to ensure stable convergence and effective learning of both tasks. During training, the dataset was loaded using a batch size of 64 for the training set, while larger batches were used for validation and testing to improve evaluation efficiency. The Adam optimizer was used to train the model for 50 epochs with a learning rate of 0.0001. Because of its capacity for adaptive learning, which speeds up convergence in deep convolutional architectures, this optimizer was chosen.

Within the MTL framework, the CNN backbone acts as a shared feature extractor, producing a common feature representation $f(x;\, \theta_s)$, where x denotes the input image and θ_s represents the shared network parameters. Two task-specific classifiers operate on this shared representation: one for fruit category prediction and another for freshness classification, with parameters θ_f and θ_r, respectively. Each task is optimized using the cross-entropy loss, defined as (1) and (2):

$$L_{fruit} = -\sum_{i=1}^{C} y_i^{(f)} \log\left(\hat{y}_i^{(f)}\right) \quad (1)$$

$$L_{fruit} = -\sum_{i=1}^{C} y_i^{(f)} \log\left(\hat{y}_i^{(f)}\right) \quad (2)$$

where $\hat{y}$ denotes the ground-truth labels and represents the predicted probabilities for each task. The overall training objective combines the two task losses using a joint optimization function.

$$L_{Total} = L_{fruit} + L_{fresh} \quad (3)$$

During backpropagation, gradients from both tasks contribute to updating the shared parameters θ_s:

$$V_{\theta_s} L_{Total} = V_{\theta_s} L_{fruit} + V_{\theta_s} L_{fresh} \quad (4)$$

This joint gradient update encourages the shared convolutional layers to learn representations that are simultaneously informative for both fruit identification and freshness estimation. Since both tasks rely on related visual cues such as color distribution, texture degradation, and structural patterns, the shared learning process promotes more generalized feature representations and reduces the risk of overfitting compared to optimizing each task independently. During MTL_ResNet-50 training, the dataset was processed using a batch size of 64 for training, validation, and testing. The Adam optimizer was used with different learning rates for different network parts. The pretrained ResNet-50 backbone used a smaller learning rate of 1×10^{-5}, while the newly added fully connected layers used 3×10^{-4}. This approach helps preserve pretrained knowledge while allowing the new layers to adapt faster to the target tasks. The model was trained for 20 epochs. The loss functions for the individual tasks follow the same cross-entropy formulation defined for the MTL_CNN model, and therefore are not repeated here. However, unlike the MTL_CNN approach where both tasks are equally weighted, the MTL_ResNet-50 implementation introduces a weighted loss formulation controlled by the coefficient $\alpha = 0.7$:

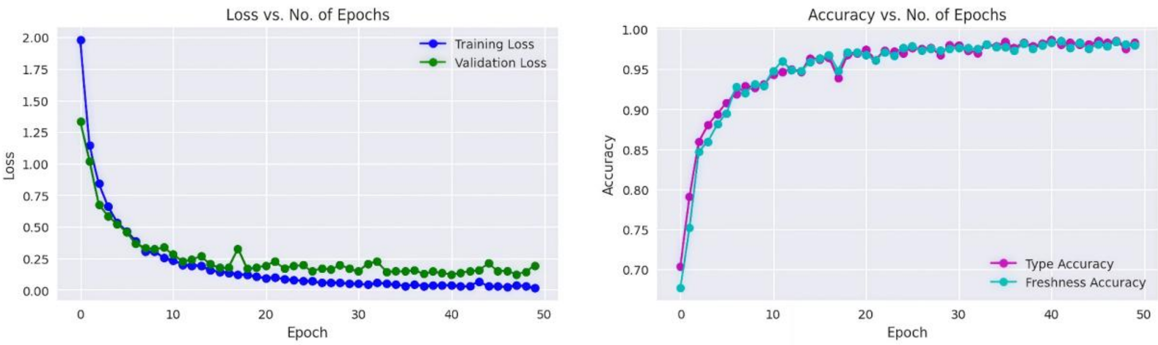
$$L_{Total} = \alpha L_{fruit} + (1-\alpha) L_{fresh} \quad (5)$$

During backpropagation, the gradients applied to the shared parameters become:

$$V_{\theta_s} L_{Total} = \alpha V_{\theta_s} L_{fruit} + (1-\alpha) V_{\theta_s} L_{fresh} \quad (6)$$

This weighting mechanism gives greater emphasis to the fruit and vegetable classification task, which provides strong semantic cues about object identity, while still incorporating freshness information during optimization. Since the visual characteristics related to freshness (such as color degradation, texture changes, and structural variations) are often dependent on its type, prioritizing the fruit and vegetable classification loss helps guide the shared feature extractor toward more discriminative representations. The freshness classifier then benefits from these enriched representations, enabling more reliable freshness prediction within the MTL framework.

Figure 2 shows the training and validation loss and accuracy curves of the proposed models across different epochs. These graphs show how the models improved during training for both classification and freshness detection tasks. Figure 2(a) presents the results of the MTL_CNN model. At the beginning, both training and validation losses were high because the model weights were randomly initialized. As training continued, the losses decreased quickly, showing that the model was learning important visual features from the images. After around 10–15 epochs, the loss curves became stable at low values. The validation loss stayed close to the training loss with only small fluctuations, which suggests good generalization and limited overfitting. The accuracy curves increased rapidly during the early epochs and later stabilized around 98–99% for both tasks. This indicates that the shared convolutional layers were effective for MTL. Figure 2(b) shows the performance of the MTL_ResNet-50 model. The initial loss values were lower than those of MTL_CNN because ResNet-50 used pre-trained ImageNet features. Both training and validation losses decreased rapidly and gradually converged to very small values. Although slight fluctuations appeared in the validation loss, the curve closely followed the training loss, indicating stable learning behavior. The accuracy curves also improved quickly and stabilized near 99% for both tasks. The small gap between training and validation accuracy suggests that the model generalized well without significant overfitting.



(a)

(b)

Figure 2. Loss and accuracy visualization over training epochs; (a) MTL_CNN and (b) MTL_ResNet-50

2.4.1. Stochastic gradient descent

Stochastic gradient descent (SGD) is a widely used optimization method for training machine learning models, particularly deep neural networks. Unlike traditional gradient descent, which computes the gradient of the loss function using the full dataset, SGD modifies the model parameters using only one data point (or a small batch) at each iteration. It can handle big datasets with ease because of its processing efficiency. The parameter update rule in SGD is given by (7):

$$\theta_{(t+1)} = \theta_t + \eta \nabla_\theta L(\theta_t; x_i, y_i) \tag{7}$$

where the model parameters are represented by θ_t at iteration t.

The learning rate is denoted by η, and the gradient of the loss function L in relation to the parameters θ_t obtained from the i^{th} training sample (x_i, y_i) is represented by $\nabla_\theta L(\theta_t; x_i, y_i)$. By repeatedly adjusting the parameters, SGD aims to minimize the loss function, improving the model's performance.

2.5. Performance evaluation

To make sure the trained models are effective in classifying fruit/vegetable types (task-1) and detecting freshness (task-2) their performance is evaluated using a variety of indicators. The main measures that are employed in the evaluation process are described in this section.

- Accuracy: the percentage of accurate predictions the model produces out of all forecasts is known as accuracy. It offers a simple yet thorough statistic for evaluating the performance of the model in both classification tasks.
- F1-score: calculated as the harmonic mean of accuracy and recall, the F1-score is a statistic that strikes a balance between the two. When assessing models on unbalanced datasets, when accuracy and recall by themselves might not give a clear picture, it is very helpful.
- Precision: precision shows the proportion of correct positive predictions among all the positive predictions made by the model. It shows how well the model predicts a certain class.
- Recall: recall, also known as sensitivity or true positive rate, is the proportion of accurate positive predictions among all actual positive cases. It shows how well the model can find all relevant examples of a class.

The performance of the models is carefully evaluated using a range of indicators, ensuring accurate classification for task-1 and effective detection for task-2. Since freshness detection is our primary objective, we focus on task-2 to assess the model's performance. To ensure robust results and minimize randomness in accuracy measurements, we test the model with various train-test-validation splits. Table 3 presents the evaluation metrics from the model's training for freshness detection.

Table 3. Evaluation metrics from the model's training for freshness detection

Model	Train (%)	Validation (%)	Test (%)	Freshness	F1-score	Precision	Recall
MTL_CNN	70	15	15	Fresh	0.98	0.98	0.98
				Spoiled	0.98	0.98	0.98
	75	10	15	Fresh	0.98	0.98	0.98
				Spoiled	0.98	0.98	0.98
	80	10	10	Fresh	0.98	0.97	0.99
				Spoiled	0.98	0.99	0.97
MTL_ResNet-50	70	15	15	Fresh	0.99	0.99	0.98
				Spoiled	0.99	0.98	0.99
	75	10	15	Fresh	0.99	0.99	0.99
				Spoiled	0.99	0.99	0.99
	80	10	10	Fresh	0.99	0.99	0.99
				Spoiled	0.99	0.99	0.99

3. RESULTS AND DISCUSSION

This study demonstrates that the proposed MTL_ResNet-50 and MTL_CNN models outperform several state-of-the-art techniques in detecting the freshness of fruits and vegetables. The MTL_ResNet-50 achieved an accuracy of 99.32%, while the MTL_CNN reached 97.95%. In addition to the freshness detection task, the proposed multi-task framework simultaneously performs fruit and vegetable type classification, achieving 99.72% accuracy with MTL_ResNet-50 and 98.15% with MTL_CNN. To evaluate the contribution of task interaction, we compared the MTL models with corresponding STL models trained under the same experimental setup for the freshness detection task only. The STL models achieved lower accuracies of 95.78% using ResNet-50 and 89.08% using the CNN architecture. The noticeable improvement obtained by the MTL models indicates that fruit-type classification provides complementary information that benefits freshness detection. In the MTL framework, both tasks share a common feature extraction backbone, allowing the model to learn more discriminative representations that capture both category-specific visual characteristics (e.g., texture, shape, and color patterns of different fruits) and freshness-related degradation cues. This shared representation enables knowledge transfer between tasks, which improves feature generalization and reduces misclassification. These results suggest that joint optimization of fruit-type recognition and freshness detection allows the network to leverage inter-task correlations, leading to more robust parameter optimization and improved overall performance. Furthermore, the confusion matrix results shown in Table 4 highlight the superior performance of the MTL_ResNet-50 model, which correctly classified a higher number of fresh and spoiled samples compared with MTL_CNN.

Table 4. Confusion matrices comparing MTL_CNN and MTL_ResNet-50 models

Model	True labels	Predicted label: Fresh	Predicted label: Spoiled
MTL_CNN	Fresh	1122	15
	Spoiled	33	1173
MTL_ResNet-50	Fresh	1175	5
	Spoiled	11	1152

The results of MTL_ResNet-50 outperform several models, including GoogLeNet, ResNeXt-101, and DenseNet-201, and surpass the accuracies reported in previous studies. A thorough comparison of our suggested method's performance with other models is given in Table 5. For instance, Zhang *et al*. [19] reported an accuracy of 93.24% using the MTL-CNN model for eight types of fruits and vegetables, which is significantly lower than our MTL_CNN model's accuracy of 97.95% on nine types. Similarly, Karakaya *et al*. [21] employed an SVM-based approach for three types of fruits and vegetables and achieved an accuracy of 96.8%. Yogesh *et al*. [22] also used an SVM model for five types and reported 95.9% accuracy. Bhargava and Bansal [23] obtained 95.3% accuracy using SVM for six types, while Khoje *et al*. [24] achieved 91.6% for two types. Moreover, Fahad *et al*. [25] reported a lower accuracy of 82.2% using VGG-16 for the classification of 11 types of fruits and vegetables. Similarly, Yuan *et al*. [26] achieved 97.76% accuracy with their CNN_BiLSTM model on six types, which is also lower than the performance of our proposed models. Chandini and B. [27] reported an accuracy of 85.6% using an SVM-based method for a single fruit type, whereas Kulkarni *et al*. [28] achieved 95.7% using a CNN model on three types. Likewise, Miah *et al*. [29] reported 97.34% using InceptionV3 for five types, while Palakodati *et al*. [30] achieved 97.82% with their CNN model on three types. Overall, our proposed MTL_ResNet-50 model demonstrates a remarkable improvement, achieving an accuracy of 99.32%, highlighting the effectiveness of MTL frameworks in enhancing classification accuracy and reliability in freshness detection systems.

Table 5. An analysis contrasting the suggested approach with current cutting-edge research techniques

Reference	Model	Type of fruits and/or vegetables	Accuracy (%)
Hamim *et al.* [12]	CNN	11	78
Yuan and Chen [14]	GoogLeNet, DenseNet-201 and ResNeXt-101	10	96.98
Göksu *et al*. [18]	ResNet-50	32	90.8
Zhang *et al.* [19]	MTL-CNN	8	93.24
Karakaya *et al*. [21]	SVM	3	96.8
Yogesh *et al*. [22]	SVM	5	95.9
Bhargava and Bansal [23]	SVM	6	95.3
Khoje *et al*. [24]	SVM	2	91.6
Fahad *et al.* [25]	VGG-16	11	82.2
Yuan *et al.* [26]	CNN_BiLSTM	6	97.76
Chandini and B [27]	SVM	1	85.6
Kulkarni *et al*. [28]	CNN	3	95.7
Miah *et al.* [29]	InceptionV3	5	97.34
Palakodati *et al.* [30]	CNN	3	97.82
Proposed methods	MTL_CNN	9	97.95
	MTL_ResNet-50	**9**	**99.32**

Note: this comparison table does not include details regarding the datasets or the total number of images used in these studies because we can't find these for all studies.

Despite promising outcomes, this study has several limitations. The dataset used in the experiments contains up to 2000 images per category, which may not fully capture the variability found in real-world agricultural environments. Therefore, a larger range of fruits and vegetables as well as photos taken with varying lighting, backdrops, and freshness levels should be included to the dataset in future studies. The model would be able to learn more resilient traits and enhance its generalization to real-world situations with such variety. Additionally, training deep learning models, particularly MTL architectures, requires considerable computational resources. Future work should also evaluate the scalability and robustness of the proposed models using larger and more diverse datasets collected from different sources and environments.

More concrete research directions can further enhance the applicability of the proposed system. In order to minimize model size and computational complexity without sacrificing performance, model compression methods including pruning, quantization, and knowledge distillation might be studied. These methods would improve the system's suitability for real-time applications. Second, domain adaptation methods can be explored to improve model generalization when applied to images obtained from different farms, markets, or imaging conditions. Third, incorporating multi-view image fusion, where images of fruits and vegetables are captured from multiple perspectives, may provide richer visual information and improve freshness detection accuracy. Another promising direction is the deployment of the proposed models on embedded or edge devices, such as smartphones, internet of things (IoT)-based agricultural sensors, or low-power computing platforms. This would enable real-time freshness monitoring directly within agricultural supply chains, storage facilities, and marketplaces. Furthermore, integrating additional modalities, such as texture analysis, hyperspectral imaging, or sensor-based fragrance indicators, could further enhance the robustness of freshness prediction systems. Finally, our results strongly support the idea that MTL models, specifically MTL_ResNet-50 and MTL_CNN, significantly enhance the precision and effectiveness of detecting fruit and vegetable freshness. These models surpass conventional single-task methods by utilising shared representations, offering a reliable solution for practical applications. This research adds to the expanding collection of works on food quality and safety, illustrating the potential of advanced deep-learning techniques to transform agricultural and consumer domains.

4. CONCLUSION

This study introduces novel uses of MTL with MTL_ResNet-50 and MTL_CNN to detect freshness in fruits and vegetables, outperforming existing methods. It highlights MTL's potential to improve classification accuracy by leveraging shared features across tasks. The research findings are significant for computer vision and agriculture, enhancing freshness detection for quality control, reducing waste, and ensuring food safety. MTL's success here suggests its applicability in sorting, grading, and real-time monitoring of produce quality. Future studies can expand on this work by testing scalability with larger datasets and optimizing computational efficiency for practical use in industries. This study advances freshness detection understanding and provides a foundation for future innovations in the field.

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Naima Islam		✓			✓			✓	✓	✓	✓			
Md. Mynoddin					✓	✓				✓			✓	
Md. Manik Ahmed					✓	✓				✓			✓	
Md. Anwar Hossain		✓		✓		✓	✓			✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/swoyam2609/fresh-and-stale-classification.

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