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Early Detection of Bruises in Khasi mandarin (*Citrus reticulata Blanco*) for the Assessment of Post Harvesting Losses: A Machine Learning Approach

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Abstract: This paper explores the application of machine learning (ML) and thermal imaging (TI) for early detection of bruises in Khasi mandarin (*Citrus reticulata Blanco*), aiming to reduce supply chain losses by identifying damaged fruit before deterioration becomes visually apparent. Leveraging the principle that materials emit distinct infrared radiation based on their physicochemical properties, thermal imaging is used to differentiate bruise from unbruise Khasi mandarins. A machine learning model is applied for classification, successfully analyzing thermal images to identify subtle variations indicating early damage. The thermal images showed that a temperature difference of more than 0.5°C between the bruise and unbruise areas enhanced the detection process. The results demonstrate the possibilities of combining thermal imaging and ML for non-destructive and efficient fruit quality monitoring. This approach offers a reliable method for early identification of fruit damage, enabling timely interventions that prevent further deterioration and minimize post-harvest losses. The study underscores the possibilities for integrating advanced imaging and machine learning techniques in agricultural quality control. Future research with larger datasets can improve model accuracy, benefiting stakeholders across the fruit supply chain and supporting industry sustainability.

Keywords: Khasi mandarin; bruise; unbruise; thermal imaging; machine learning model

1. Introduction

According to study 30-40% production of vegetables and fruits suffer from bruises and additional mechanical injury, which are unavoidable in the postharvest chain, with bruises being the most frequent type of damage during harvesting, sorting, packing, storing, transporting, and retailing [1]. After bananas and mangoes, citrus, a fruit belonging to the *Rutaceae* family, is the third most significant crop in India [2, 3]. Its diverse forms are believed to have originated and been distributed in Northeastern India [4, 5]. Among citrus varieties, the Khasi mandarin holds significant popularity and economic importance, being widely recognized and accepted globally [6]. India ranks ninth in global mandarin orange production, contributing to a worldwide output of 47.8 million metric tons in 2017–2018 and covering 3.11 lakh hectares of cultivated land [7]. Mandarin cultivation in India, in the year 2021-22, resulted in a total production of 6219.38 thousand metric tonnes, grown across 476 thousand hectares [8]. Khasi mandarin produces over 38.2% of India's total citrus-growing land and 43.6% of its total citrus production [9]. Due to its high commercial value, this variety dominates the Northeastern region of India in terms of export and production potential [10]. Khasi mandarins are known for their ease of peeling, when ripe it has a deep orange color, and exceptional nutritional and dietary properties [4]. These fruits are commonly eaten fresh or used for juice, while the peel is frequently discarded as waste [11]. The significance of Khasi mandarin extends beyond economic value to include nutritional and medicinal benefits that contribute to human and animal health [11]. However, the fruit's fragile nature and short shelf life of just 1–2 weeks at ambient temperature pose challenges for postharvest management, resulting in significant losses for farmers and the economy [12]. During a recent field visit, insights were gathered from a local farmer and exporter. In the village named Jimbrigoan, located in Ri-Bhoi, Meghalaya, a traditional method is predominantly used for fruit harvesting. A farmer detailed their approach, which involves twisting fruits from the tree using a bamboo stick as shown in Figure 1. The harvesting season runs from November to the first week of January. Approximately 40-50% of the fruit is lost between the flowering and plucking stages. These losses stem from factors, like insect damage, environmental stress, etc. as stated by the farmers.

Figure 1. Plucking Khasi mandarin using bamboo stick: Photograph captured by the investigator in Jimbrigoan, Ri-Bhoi, Meghalaya

After harvesting, fruits are transported via a reefer van from the field to the processing unit and then to Guwahati airport. Air India Cargo then handles the international shipment to the UAE (United Arab Emirates). The exporter stated that the spoilage is approximately 30% without pre-processing from the field to the plate of the consumer, attributed to inadequate handling and manual quality control methods. Now the exporter used the pre-processing unit, which has some of the advanced pre-processing units, like waxing and sorting and grading systems based on colour and size, so the spoilage is reduced, but there is still room for research for the automated detection of early bruises, which will reduce the post-harvest loss in the supply chain. Thermal imaging (TI) is a valuable non-invasive technique that transforms an object's radiation into a surface temperature map. With its non-invasive nature, high accuracy, excellent repeatability, lack of demand for an external light source, operational simplicity, and fast processing, TI has found extensive applications in the fields of civil engineering, maintenance of industrial production, aerospace, medicine, agriculture and pharmaceuticals [13]. The foundation of TI lies in observations that the infrared radiation is emitted by all materials, with TI measuring this radiation rather than the reflected light. Thermal diffusivity and other physicochemical characteristics vary among materials, highlighting the ability of TI to effectively identify deep and small-area bruises. This also addresses the challenges of detecting bruises in vegetables and fruits exhibiting dark colours [1]. Many algorithms, including backpropagation neural networks (BPNN), linear discriminant analysis (LDA), support vector machines (SVM), artificial neural networks (ANNs), decision trees, Bayesian classifiers and k-nearest neighbour, have been widely used for the classification of fruit bruises. Machine vision is a new technology that enables computer systems to "see" objects. It has been employed in numerous applications., including self-driving car, packaging of product, detection of safety, and Sorting in the food and agricultural sectors [13]. Convolutional neural network (CNN) is among the most widely used deep learning architectures [14]. Ünal *et al.*, [15] collected NIR datasets, which were used to train and test the AlexNet, Inception V3, and VGG16 network architectures. The testing results showed that AlexNet achieved a test accuracy of 99.33%, while both InceptionV3 and VGG16 achieved a perfect accuracy of 100%. Similarly, several studies have shown the application of deep learning for the quality assessment of vegetables and fruits [1, 14,16,17, 18, 19, 20, 21, 22, 23, 24]. Therefore, this study aims to detect early bruise in Khasi mandarin using a TI-based method combined with a machine learning approach to reduce supply chain losses and minimize waste.

2. Materials and Methods

2.1. Thermal Images Acquisition

The system is set up by interfacing the Topdon TC001 thermal camera with a PC (Personal computer), ensuring secure connections. An TC001 app is used to capture and display images. The camera is placed inside a box (image processing unit) made of plywood, as shown in Figure 2. This setup enables the detection of bruises in fruits, facilitating the classification of Khasi mandarin based on their thermal images. The approach leverages the thermal camera's ability to detect subtle temperature variations, allowing for precise and effective sorting of fruits into unbruise and bruise categories using machine learning. Khasi mandarin samples are collected from a village named Jimbrigoan, located in Ri-Bhoi, Meghalaya. Each fruit is dropped from a height of 150 cm to produce artificial bruises on one side. This technique results in mild, superficial skin bruises that are not initially noticeable to the naked eye. Hot air is blown using a hot air blower (BLAZE Neo, Gestor) to raise the temperature inside the image processing unit to 35°C to obtain clear images, and the temperature is maintained throughout the experiment. The distance between the sample under test (SUT) and the thermal camera is kept at 20 cm, and an image is captured 1 to 60 seconds after the sample is placed in the processing unit. Each bruise Khasi mandarin (SUT) is then positioned with its bruised side facing the camera. For consistent data collection, the same process is applied to every Khasi mandarin sample. For unbruise fruits, healthy Khasi mandarin without any natural or artificial bruises are selected, and their images are also captured.

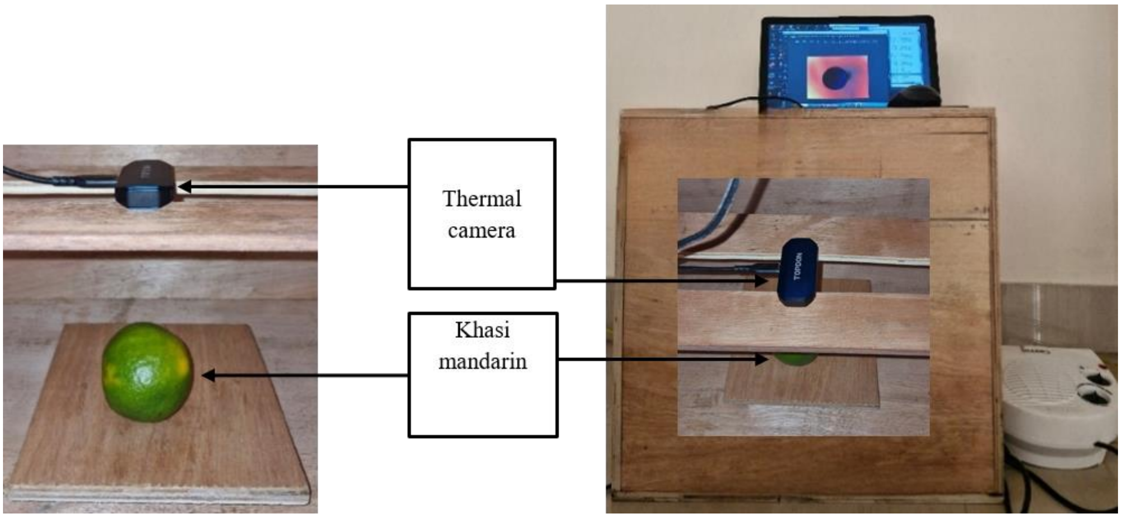


Figure 2. Experimental setup for thermal imaging and image processing unit

2.2. Data Preprocessing

Data preprocessing includes resizing or cropping images to 224 x 224 pixels for region of interests (RoIs) selection, brightness adjustments, and data augmentation using random flips, image rotations, and scaling. The preprocessed images (RoIs) are then divided into train, validation and test sets as illustrated in Figure 3. It includes bruise and unbruise images which are divided as follows: 70% for training, 20% and 10% for validation and testing sets respectively. Finally, the images are classified as bruise or unbruise using the proposed classification model.

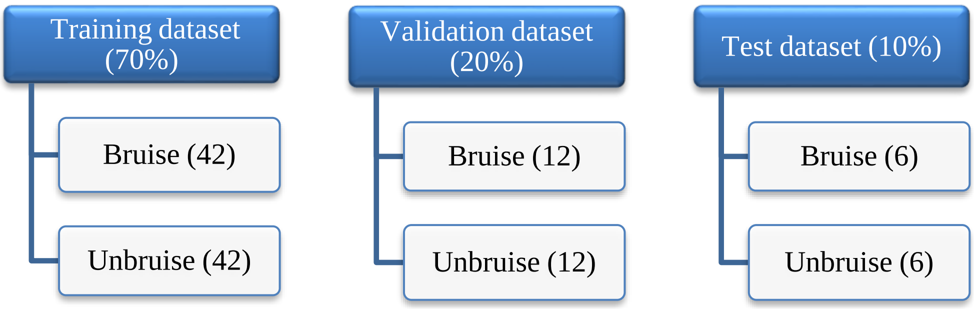


Figure 3. Data structure: the numbers indicated in brackets represent the actual number of thermal images for experimentation

2.3. Model Selection for Deep Learning

DenseNet121 is preferred because its dense connections offer better classification compared to a traditional CNN by avoiding the learning of redundant feature maps. Additionally, some ResNet variations have shown that many layers can be removed because they only contribute minimally. ResNets is the basic architecture of residual network which is best work with simple unstructured data. DenseNet layers, on the other hand, is a deeper network with added new feature maps for better classification. Another problem with very deep networks is that the gradients and information flow make training the model challenging. DenseNets mitigate this issue by allowing each layer to calculate the gradients directly from the input image and the loss function. The complete architecture of DenseNet121 is shown in the Figure 4. In this study, Convolutional Neural Network models like Residual Network (ResNet50) [25], DenseNet121 [26], Visual Geometry Group (VGG16) [27], and VGG19 [28] are used.

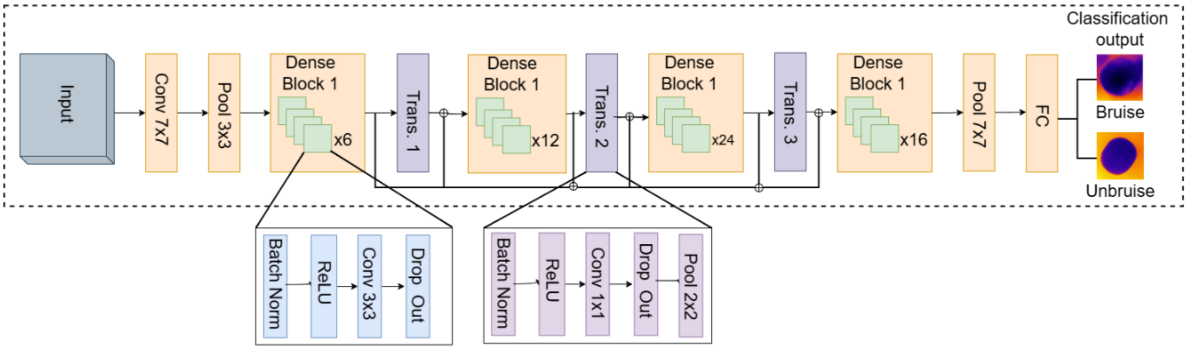
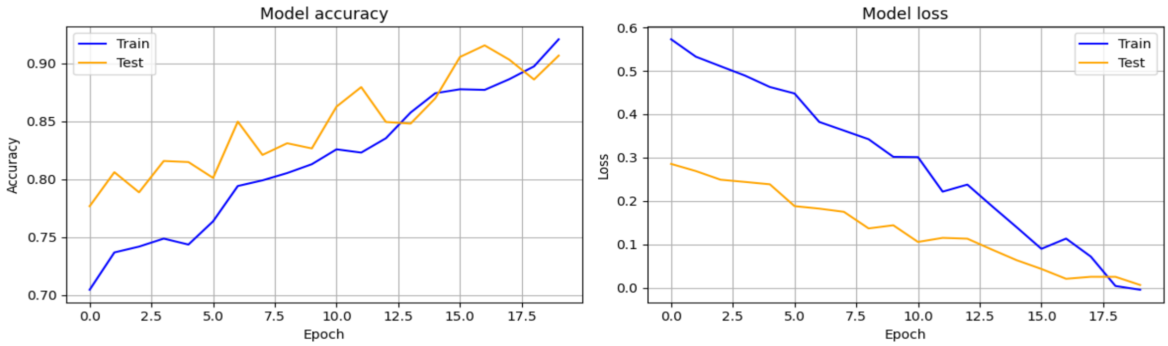


Figure 4. A simple representation of the DenseNet121 model

3. Results and Discussion

3.1. Detection of Bruises in Khasi Mandarin

The simulations were performed using the Spyder IDE with Python 3.7.12 on a GPGPU server featuring a Tesla V100 GPU with 32GB RAM and 1TB of drive storage. The thermal images of the Khasi mandarin show that the noticeable difference is seen when the temperature difference between the unbruise and bruise area is more than 0.5°C, as also stated by [13]. Among the four models used, viz ResNet, DenseNet121, VGG16, and VGG19, DenseNet121 achieves the best accuracy compared to the others. Although it does not achieve very high accuracy, it demonstrates that reasonable accuracy can be obtained even with a small dataset. This suggests that, in future studies, using a larger dataset could lead to even higher accuracy.



(a) (b)

Figure 5. (**a**) Training vs Test accuracy plot (**b**) Training vs Test loss for DeseNet121 model

The training vs test accuracy plot and the training vs test loss for the DenseNet121 model is shown in Figure 5. The comparison of the selected model with state-of-the-art (SOTA) models in terms of accuracy is presented in Table 1. The DenseNet121 model gives the highest accuracy, 88.63%, compared to the other models. Figure 6 shows the test accuracy of the model. From the results, we can infer that the model can classify the bruise and unbruise categories of the data with high accuracy.

3.2. Performance Evaluation Metrics

We evaluated the classification model using state-of-the-art evaluation metrics commonly used for classification. This include accuracy, recall, and the F1_Score, for better understanding of the model's performance. Below, we define each metric along with the relevant formulas and the terms used such as

(a) Accuracy: The proportion of cases (both positive and negative) that were correctly classified out of all the instances is defined as accuracy [Eq. (1)].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

(b) Recall or Sensitivity: It evaluates the model's ability to correctly identify all positive instances [Eq. (2)].

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

(c) F1-Score: The F1-score represents the harmonic mean of precision and recall, balancing the trade-off between the two [Eq. (3)].

$$F1\_Score = \frac{2TP}{2TP+FP+FN} \tag{3}$$

The key definitions of the terms TP, FP, FN and TN are given below:

- True Positive (TP): Prediction of positive instances correctly
- True Negative (TN): Prediction of negative instances correctly
- False Positive (FP): Prediction of negative instances incorrectly as positive
- False Negative (FN): Prediction of positive instances incorrectly as negative

Table 1. Comparison of selected model vs SOTA models in terms of accuracy models

Sl.	Deep learning models	Training accuracy (%)	Test accuracy (%)	Recall (%)	F1_Score (%)
1	ResNet50	86.21	84.70	83.91	84.09
2	VGG16	80.54	78.23	75.71	77.24
3	VGG19	85.32	83.14	85.32	84.63
4	DenseNet121 (selected model)	90.34	88.63	87.41	86.11

3.3. Quantitative and Qualitative Analysis of Classification Model

The confusion matrix shown in Figure 7, provides a detailed analysis of the classification model performance by showing how well it distinguishes between the two classes, "Bruise" and "Unbruise" From the confusion matrix, we can infer that TP count as "Bruise" is 12, while TN count as "Unbruise," is 13. FP and FN counts are 9 and 10 respectively. This analysis allows for a comprehensive understanding of the model's performance, offering insights into areas where the model needs improvement, such as addressing imbalances in misclassifications or improving the detection of specific classes.

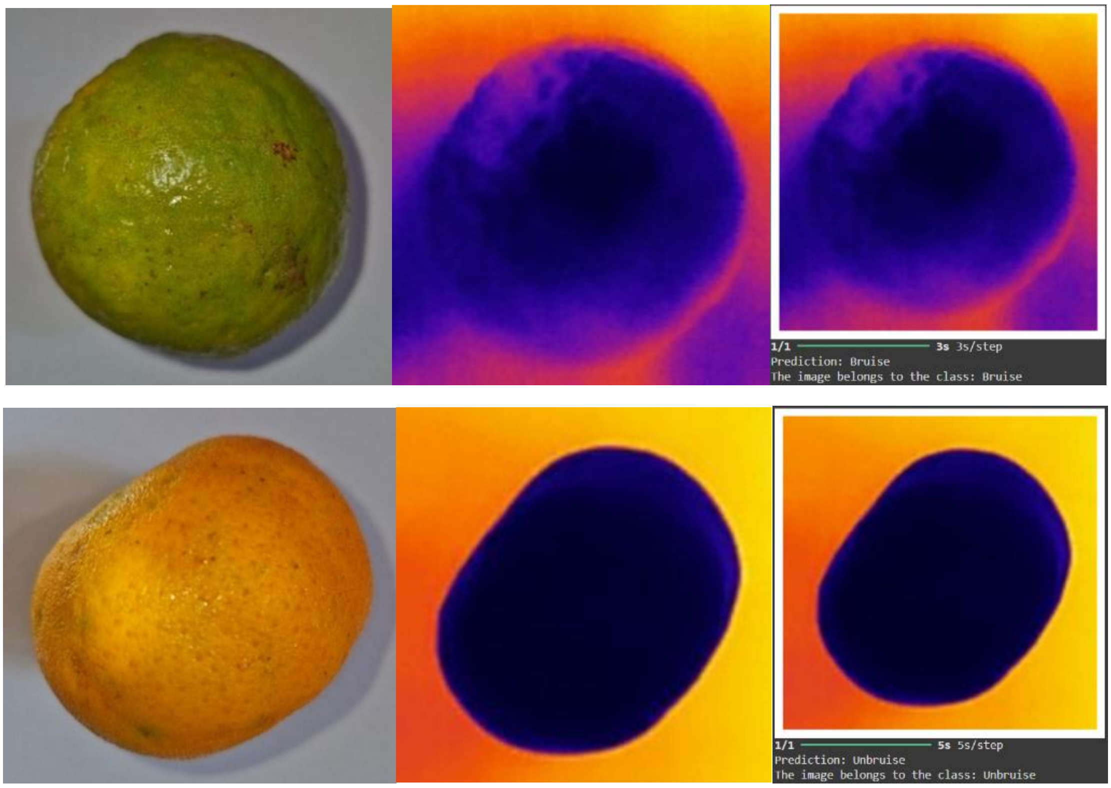


Figure 6. Bruise and unbruise images of RGB, test and prediction image

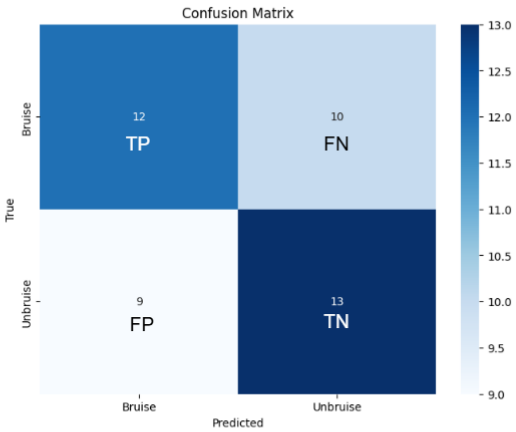


Figure 7. Confusion matrix of the trained classification model.

Further, we conducted 5-fold cross-validation to assess the performance of the classification model. We created a dataset, comprising 100 images with data augmentation using image rotation and flipping (50 Bruise and 50 Unbruise). Next the dataset was separated into 5 equal subsets, with individually subsets containing 20 images. In each fold, the test set consists of one subset, and the training set consists of the remaining 80 images. This process was repeated five times, ensuring that each image was used for testing exactly once. The metrics used for evaluation are accuracy, recall, precision, and F1_Score, which were computed for each fold, and the final results were reported as the average across all five folds as shown in Table 2.

Table 2. 5-fold cross-validation for the classification model

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1_Score (%)
Fold 1	84.4	86.0	84.2	85.1
Fold 2	88.3	87.9	88.5	88.2
Fold 3	86.7	85.8	87.3	86.7
Fold 4	84.9	86.6	84.0	84.7
Fold 5	87.3	88.0	86.5	87.2
Average	86.3	86.8	86.1	86.4

The distribution of entropy plot as shown in Figure 8, suggest that the model is highly confident in the majority of its classifications. However, there are a smaller number of predictions of FP with higher entropy, reflecting instances where the model is less certain, likely due to ambiguous or challenging samples. This overall pattern highlights that while the model performs confidently in most cases, further analysis of high-entropy predictions TP and TN will help identify areas for improvement or better understand the sources of uncertainty in future work.

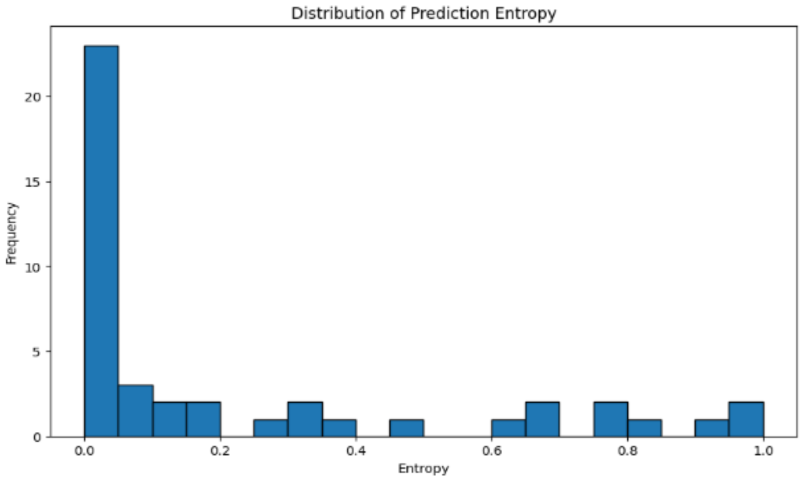


Figure 8. The distribution of entropy plot

3.4. Assessment of Post Harvesting Losses

As the detection of bruises has shown potential results, the assessment of post-harvest losses can be predicted by computing the number of pixels in the bruised area of the thermal images. Additionally, the prediction of the fruit's shelf life can be studied in the future by studying the percentage of bruise pixels in the thermal images with passing days. In such cases, fruits intended for export or long-term storage can be carefully selected, while mildly fresh bruised fruits can be sold in the local market within one or two days.

4. Conclusions

Thermal imaging combined with convolutional neural networks provides a promising non-destructive method for early detection of damage in Khasi mandarin, effectively distinguishing between bruise and unbruise fruit even when defects are not visually apparent. The DenseNet121 model demonstrated superior performance, achieving reasonable accuracy even with a small dataset, showcasing its potential to reduce post-harvest losses, enhance quality control, and promote sustainability in the fruit industry. Future studies with larger datasets could further improve accuracy, enabling more efficient agricultural quality assessment. This technology can make the fruit supply chain more sustainable by reducing waste, increasing profitability, and benefiting both small-scale farmers and large-scale enterprises. Additionally, the detection of bruises offers potential for predicting of shelf life, allowing careful selection of fruits for export or long-term storage, while mildly bruised fruits can be sold in local markets within one or two days, further minimizing waste and supporting economic sustainability. Some of the future scopes of this study are:

1. Improvement of classification model for bruises detection in the Khasi mandarin using deep learning-based attention mechanism.
2. A thermal imaging system with preprocessing to enable early detection of bruises for efficient industrial fruit sorting.
3. A portable hardware prototype for monitoring and early assessment of bruises.
4. Integration of the prototype thermal imaging system with mobile apps for internet of things (IoT)-based end-user quality checks.

Multidisciplinary Domains

This research covers the domains: (a) Imaging and computer vision, (b) Food engineering, (c) Transport processes, (d) Deep learning.

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Conflicts of Interest

The authors declare no conflict of interest.

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