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Automated classification of apple bruises from hyperspectral images: an approach for fruit quality assessment

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ABSTRACT

Apple bruise detection plays a crucial role in post-harvest quality control; however, conventional manual inspection remains labor-intensive, subjective, and unsuitable for large-scale industrial deployment. This study proposes an automated classification framework for identifying bruised regions in apples using hyperspectral imaging combined with deep learning and adaptive optimization techniques. The proposed model integrates a long short-term memory (LSTM) network optimized using an adaptive sand cat swarm optimization (ASCSO) algorithm, along with a ResNet-50 feature extraction backbone. The adaptive behavior embedded within ASCSO dynamically adjusts the optimization parameters to enhance convergence and prevent premature stagnation during LSTM hyperparameter tuning. Hyperspectral images were processed to extract relevant spectral–spatial features, which were subsequently fed into the optimized classifier. Experimental evaluations demonstrate that the proposed hybrid model significantly outperforms conventional and baseline deep learning approaches, achieving a classification accuracy of 98.0% while maintaining robustness across varying bruise patterns and intensity levels. The results highlight the effectiveness of combining hyperspectral imaging with adaptive deep learning optimization for high-precision fruit quality assessment. This research contributes a reliable, scalable solution for automated bruise detection and quality grading in the fruit supply chain, offering strong potential to reduce post-harvest losses and improve operational efficiency in the agro-food industry.

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1. INTRODUCTION

Apple bruising is a major post-harvest quality issue caused by mechanical stresses during handling and transportation, leading to tissue damage, microbial susceptibility, reduced shelf life, and economic loss [1]–[3]. Early and accurate bruise detection is essential, yet conventional RGB imaging techniques are limited in identifying subtle or subsurface damage [4]. Hyperspectral imaging offers a powerful non-destructive alternative by capturing detailed spectral information, enabling improved early bruise detection and quality assessment [5]–[7]. This study presents an artificial intelligence (AI)-based framework for apple bruise classification using hyperspectral images to support efficient fruit grading and quality control processes [8]–[11]. The proposed method employs line-scan hyperspectral imaging [12] with Gaussian filtering for preprocessing [13], visual geometry group (VGG)-16 for feature extraction [14], and long short-term memory (LSTM) classifier optimized using adaptive sand cat swarm optimization (ASCSO) [15]–[19]. The optimized model achieves high detection accuracy and rapid classification, demonstrating its effectiveness for real-time apple bruise detection and waste reduction [20].

Early apple bruise detection methods relied on RGB imaging due to low cost, but these techniques are ineffective for detecting subsurface bruises and are highly sensitive to lighting variations, limiting industrial use. Thermal imaging improved internal damage detection but suffered from instability under varying ambient temperatures. To overcome these issues, near-infrared (NIR) and hyperspectral imaging techniques were introduced, offering enhanced spectral sensitivity for non-destructive bruise detection. The studies [21], [22] demonstrated high detection accuracy using hyperspectral data combined with deep learning, though at the expense of increased computational complexity and limited generalization. Other studies using convolutional neural network (CNN) and traditional classifiers achieved promising results but remained dataset-dependent and sensitive to noise [23], [24]. A portable hyperspectral sensing device achieved high accuracy in fruit firmness assessment, but its effectiveness is limited for complex bruise classification involving multiple categories and varying severity levels [25]. Optimization-based methods such as sand cat swarm optimization (SCSO) improved learning efficiency but struggled with high-dimensional deep models [26]. Overall, existing approaches lack effective spectral dependency modeling and robust optimization. These limitations motivate the proposed ASCSO-LSTM framework, which exploits sequential spectral information while enhancing robustness and computational efficiency for apple bruise classification.

2. METHOD

The proposed study focuses on apple bruise classification using hyperspectral imaging, as illustrated in Figure 1. Apple images are acquired using a hyperspectral camera to capture detailed spectral information across multiple wavelengths. The acquired images are preprocessed using a Gaussian filter to reduce noise and enhance image quality. Deep features are then extracted using the VGG-16 CNN [27], which effectively identifies discriminative characteristics of healthy and bruised apple tissues. These features are classified using a LSTM network, which is well suited for modeling the sequential spectral information inherent in hyperspectral data. To improve classification accuracy and computational efficiency, optimization techniques are employed to automatically tune the LSTM hyperparameters. This optimized framework enables accurate and efficient apple bruise detection, supporting improved quality control in apple production and distribution.

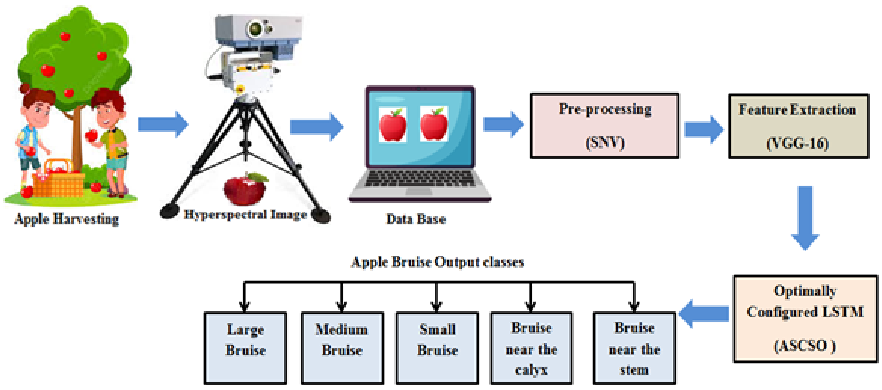

Figure 1. Apple bruise classification from hyperspectral images using an optimally configured LSTM model

2.1. Dataset description

Red fuji apples were collected from a local market in Kashmir, India. Samples (6–8 cm diameter) without visible defects were cleaned and stored at 25 °C and 75% relative humidity. Controlled bruises were induced by dropping a ball from heights of 200–500 mm at equatorial positions. A total of 1,345 hyperspectral samples were categorized into five bruise classes: small (298), medium (285), large (244), stem (270), and calyx (248). The dataset was divided into training, validation, and testing subsets, as detailed in Table 1. The training set was used for model learning, the validation set for hyperparameter tuning and early stopping, and the test set for unbiased performance evaluation. Stratified sampling was applied to preserve class balance across all subsets.

Table 1. Dataset partitioning for training, validation, and testing phases

Dataset partition	Percentage (%)	Number of samples
Training set	70	942
Validation set	15	202
Testing set	15	201
Total	100	1,345

2.1.1. Cross-validation strategy

To enhance model reliability and generalizability, a 5-fold cross-validation was applied in addition to the fixed dataset split. The training set (70%) was partitioned into five folds; in each iteration, four folds were used for training and one for validation. This process was repeated five times, and the final results were obtained by averaging performance across all folds. This strategy improves robustness, reduces overfitting, and provides a reliable estimate of performance on unseen data.

2.2. Hyperspectral imaging system

The graphic shows a hyperspectral imaging system with slit widths of 30 μm and a spectral resolution of about 2.8 nm. An imaging spectrograph (ImSpector VNIR-V10E-EMCCD) with a standard 23 mm C-mount zoom lens, a 150-Watt halogen lamp with two-line lighting fibers to ensure uniform visible near-infrared (Vis-NIR) illumination, an electron-multiplying charge-coupled device (EMCCD) camera (Andor Luca EMCCD DL-604M), a sample displacement platform, and a computer (Dell E6520, Intel Core i5-2520M@2.5 GHz, 8 GB RAM) make up this setup. The resolution of the images that were shot was 1004 by 1002. To enhance image quality, only data in the wavelength range of 450 to 1,000 nm were retained; data outside of this range were removed due to the limits of the charge-coupled device (CCD) detector.

2.3. Pre-processing

Hyperspectral data were preprocessed using standard normal variate (SNV) transformation to reduce illumination and scattering effects. This was followed by vector and min–max normalization to ensure uniform feature scaling. This preprocessing enhanced spectral discrimination, improved training stability, and significantly boosted the classification performance and generalization of the ASCSO-LSTM model.

2.4. Feature extraction

The feature extraction process in apple bruise classification involves utilizing the VGG-16 architecture, a CNN developed by the VGG [28]. VGG-16 is well acclaimed for its versatility in a variety of computer vision tasks, including feature extraction and image categorization. Fundamentally, VGG-16 comprises 16 weight layers, primarily consisting of 13 convolutional layers tasked with extracting detailed patterns and data from input images. By using 3×3 filters with a stride of 1 and "same" padding, these convolutional layers preserve important spatial information across the network. Additionally, VGG-16 incorporates 2×2 max-pooling layers after each block of convolutional layers at a stride of 2. These layers downsample the feature maps, gradually reducing their spatial size while augmenting their depth. This architectural design allows the network to effectively capture hierarchical features, essential for accurate apple bruise classification.

2.5. Long short-term memory

LSTM networks are employed to classify apple bruises into small, medium, large, stem, and calyx categories by modeling sequential dependencies in hyperspectral features extracted using VGG-16. The LSTM network would then learn to analyze these features over time, considering the sequential nature of the data [29]. By learning temporal patterns from labeled data, the LSTM effectively captures bruise-related variations, enabling accurate and robust classification for apple quality assessment. The mathematical representation of the LSTM network is as (1) to (5).

$$f_k = \sigma\left(W_{ix}x_k + W_{ih}h_{k-1} + b_f\right) \tag{1}$$

$$i_t = \sigma\left(W_{fx}x_k + W_{fh}h_{k-1} + b_i\right) \tag{2}$$

$$\tilde{c}_k = tanh(W_{cx}x_k + W_{ch}h_{k-1} + b_c) \quad (3)$$

$$o_k = \sigma(W_{ox}x_k + W_{oh}h_{k-1} + b_o) \quad (4)$$

$$h_k = o_k \cdot tanh(c_k) \quad (5)$$

The input vector at time t is represented by x_k in this equation, the hidden state at time t is denoted by h_k, the input, forget, and output gates are represented by i_t, f_k, and o_k, respectively, and the memory cell is indicated by $\tilde{c}_k$. The model's trainable parameters consist of weights W and biases b. The LSTM cell (along with the equations) with a forget gate are shown in Figure 2. Hyperparameter optimization plays a crucial role in improving LSTM-based apple bruise classification by tuning key parameters such as the number of layers, hidden units, dropout, and learning rate. Automated optimization methods reduce the complexity and time associated with manual tuning, prevent overfitting or underfitting, and enable efficient use of computational resources while enhancing model generalization and performance.

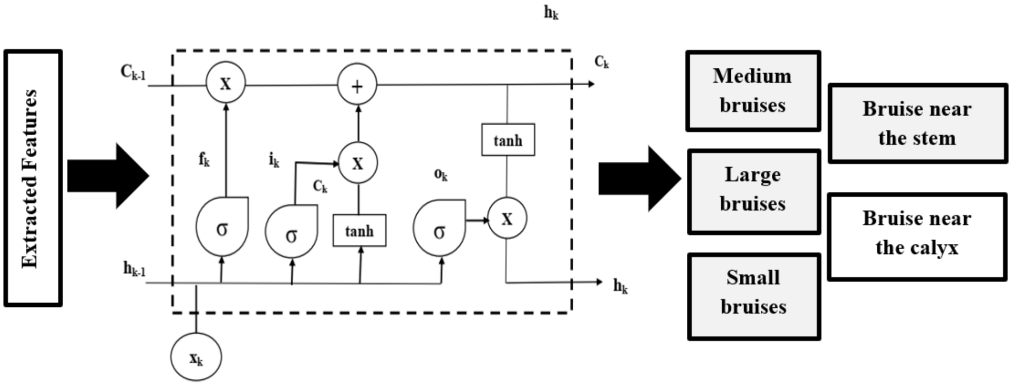

Figure 2. LSTM for apple bruises classification

2.6. Sand cat swarm optimization

The behavior of sand cats in their natural habitat served as the model for the SCSO algorithm as shown in Algorithm 1. The two main behaviors exhibited by these cats are actively searching for prey and successfully obtaining it. The programmed emulates the exceptional low-frequency sound detection capacity of the sand cat, a unique characteristic that makes efficient prey location possible, both above and under the surface. This exceptional skill empowers sand cats to swiftly pinpoint and seize their prey [30].

Algorithm 1. Sand cat swarm optimization algorithm
1: Initialize population using opposition-based learning.
2: Evaluate fitness of each solution.
3: Identify the best solution.
4: For t =1 to maximum iterations do
  a. For each sand cat do
    i. Select movement direction using roulette wheel selection.
    ii. Update position using exploration or exploitation strategy.
    iii. Apply cauchy mutation to enhance diversity.
    iv. Enforce boundary constraints.
  b. End for
  c. Update the global best solution.
5: End for
6: Return the best solution.

2.6.1. Cauchy mutation

A wider mutation scale is introduced utilizing the cauchy distribution. The general formula for its probability density function is given by (6).

$$f(x_v) = \frac{1}{s\pi(1+((x_v-t_i)/s)^2)} \tag{6}$$

The random variable $Oy = F(xv)$ has a uniform distribution in the range [0, 1] when a random variable x_v has a distribution function F. This is the calculation process for a cauchy random variable. In the event when F is reversed, the random variable can thus employ a uniform density to resemble random variable x because $X = F - 1(Oy)$.

3. RESULTS AND DISCUSSION

The proposed model is evaluated using comprehensive performance metrics, including accuracy, precision, recall, F1-score, false discovery rate (FDR), false positive rate (FPR), false negative rate (FNR), Matthews correlation coefficient (MCC), negative predictive value (NPV), and specificity. Receiver operating characteristic (ROC) curves, confusion matrices, and convergence analysis are also used to assess optimization effectiveness. Comparative results across LSTM variants and CNN models (VGG-16 and ResNet-50) are reported using true positive, true negative, false positive, and false negative measures to quantify classification performance in apple bruise detection.

3.1. Performance evaluation matrices

Performance evaluation metrics quantitatively assess the effectiveness of apple bruise classification from hyperspectral images. Together with the confusion matrix, help identify model strengths, weaknesses, and comparative performance, ensuring accurate and reliable detection. The performance results of suggested ASCSO method for designing LSTM for the categorization of apple bruising from hyperspectral images show strong predictive capability, achieving an accuracy of 97.5%, FDR of 2.9%, F1-score of 91.4%, FNR of 2%, FPR of 3%, MCC of 95%, NPV of 98%, precision of 97%, recall of 98%, and specificity of 97%.

Figure 3 shows the performance comparison of the employed models for apple bruise classification. Figure 3(a) presents the accuracy comparison among the models. Figure 3(b) shows the precision performance of the models, while Figure 3(c) illustrates the recall results. The LSTM–ASCSO model consistently outperforms all others, achieving the highest accuracy (0.98), precision (0.97), recall (0.98), specificity (0.97), MCC (0.95), and NPV (0.98), while recording the lowest FDR (0.03), FPR (0.03), and FNR (0.02). These results demonstrate its superior reliability in minimizing false detections and missed bruises. Overall, the adaptive ASCSO-based optimization significantly enhances LSTM performance compared to LSTM-SCSO, LSTM-CSO, baseline LSTM, and CNN-based models (VGG-16 and ResNet-50). Table 2 shows that the proposed ASCSO–LSTM outperforms support vector machine (SVM), random forest (RF), VGG-16, ResNet-50, and EfficientNet-B0, achieving the highest accuracy (0.98), precision (0.97), and recall (0.98), confirming its superior spectral–temporal feature learning and robustness for hyperspectral apple bruise classification.

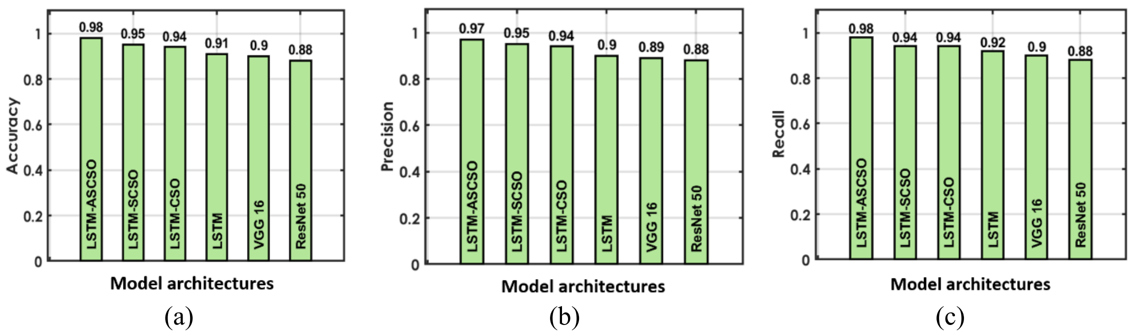

Figure 3. Evaluating the performance of employed models for classifying apple bruises of (a) accuracy, (b) precision, and (c) recall

Table 2. Performance comparison of baseline models and proposed ASCSO–LSTM

Model	LSTM–ASCSO	LSTM–SCSO	LSTM–CSO	LSTM	SVM	RF	VGG-16	EfficientNet-B0	ResNet-50
Accuracy	0.98	0.95	0.94	0.91	0.89	0.90	0.90	0.92	0.88
Precision	0.97	0.95	0.94	0.90	0.88	0.89	0.89	0.91	0.88
Recall	0.98	0.94	0.94	0.92	0.87	0.88	0.90	0.91	0.88

3.2. Confusion matrix

The confusion matrix analysis is presented in Figure 4, showing the performance of different techniques. The proposed LSTM–ASCSO model achieves the best class-wise discrimination with minimal misclassification across all apple bruise categories (Figure 4(a). It outperforms the optimized LSTM variants, including LSTM–SCSO and LSTM–CSO (Figures 4(b) and 4(c)), as well as the baseline LSTM (Figure 4(d)) and CNN-based models, VGG-16 (Figure 4(e)) and ResNet-50 (Figure 4(f)), which exhibit higher cross-class confusion due to weaker spectral–temporal modeling.

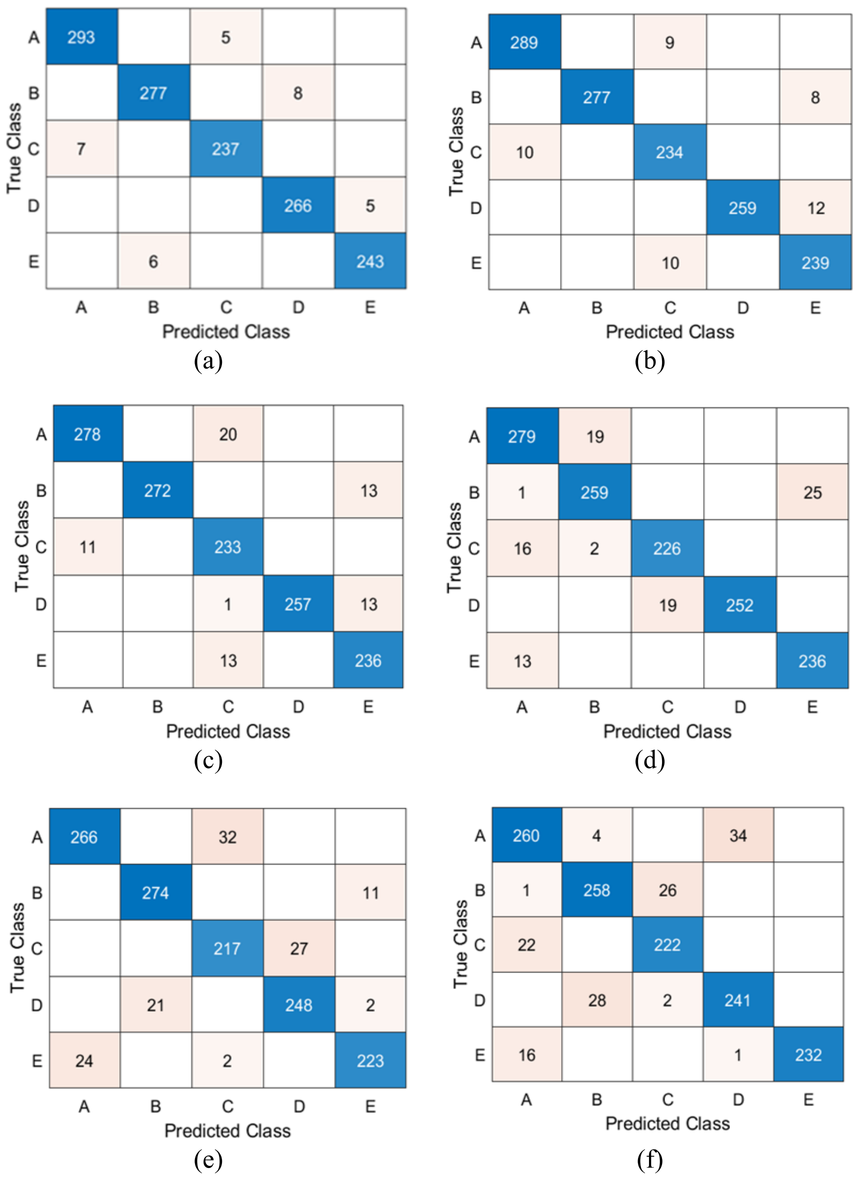

Figure 4. Confusion matrix across different techniques of (a) LSTM-ASCSO, (b) LSTM-SCSO, (c) LSTM-CSO, (d) LSTM, (e) VGG-16, and (f) ResNet-50

3.3. Receiver operating characteristic and convergence graph

Figure 5 presents the ROC curve, illustrating the model's ability to distinguish between bruised and non-bruised apples by plotting the true positive rate against the FPR across different thresholds. This analysis reflects the classification effectiveness and the trade-off between sensitivity and specificity. Figure 6 shows the convergence behavior of the optimization algorithm during LSTM training. The curve illustrates changes in performance across iterations, indicating convergence speed and training stability. A smooth, stable trend for the proposed method confirms effective optimization, while fluctuations may suggest convergence issues.

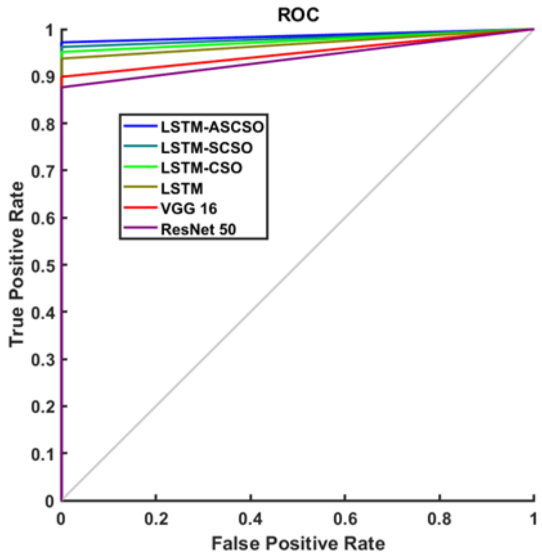

Figure 5. ROC curve

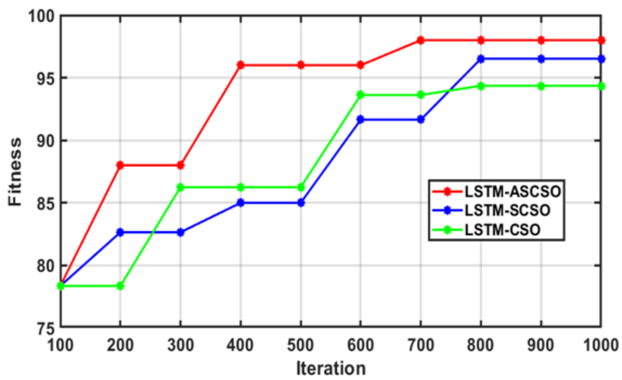

Figure 6. Convergence graph

4. CONCLUSION

This research investigated the automated classification of apple bruises using hyperspectral imaging combined with an adaptively optimized LSTM network. A novel optimization strategy, ASCSO, was introduced to tune the LSTM hyperparameters effectively. Extensive experimental evaluation using statistical and classification metrics such as accuracy, precision, recall, MCC, specificity, and error rates demonstrated that the proposed LSTM-ASCSO framework consistently outperformed traditional LSTM models, conventional optimization approaches, and CNN-based architectures including VGG-16 and ResNet-50. The incorporation of adaptive mechanisms, namely opposition-based learning and Cauchy distribution, enhanced the exploration-exploitation balance of the optimization process, leading to improved convergence behavior and better model generalization. Additionally, the analysis of ROC characteristics and convergence behavior provided further evidence of the stability and learning efficiency of the proposed framework. The outcomes of this study demonstrate the potential of the proposed approach to support reliable and accurate fruit quality assessment in post-harvest processing environments. Future work will focus on extending the model to other fruit varieties, reducing computational complexity for real-time industrial deployment, and exploring advanced feature selection techniques to further improve detection accuracy and system scalability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Peddireddy Venkateswara Reddy	✓	✓	✓	✓	✓	✓		✓	✓		✓			
Alaguchamy Parivazhagan	✓	✓		✓	✓	✓	✓			✓		✓	✓	✓

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

The author declares that there is no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are not publicly available but can be provided by the corresponding author, [PVR], upon reasonable request. The dataset consists of hyperspectral images of red fuji apples collected from a local market in Kashmir, India, and includes 1,345 samples categorized into five bruise classes (small, medium, large, stem, and calyx). The dataset was divided into training, validation, and testing subsets for model development and evaluation.

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