Convolutional Neural Network–Based Automated Quality Grading of Cinnamon Peel

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I. Introduction

Ceylon cinnamon, endemic to Sri Lanka, holds significant culinary, medicinal, and economic value, reinforcing the country's position as the leading global exporter of authentic cinnamon. However, current processing techniques, particularly manual peeling and quill preparation, are highly labor dependent and introduce quality inconsistencies, limiting scalability. While national efforts increasingly promote value addition and product diversification, maintaining consistent export-grade quality remains challenging. Recent research highlights the potential of technological advancement within the cinnamon value chain, with image processing applied for maturity estimation, and diameter-based grading [1], [2]. Additionally, deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong performance in agricultural applications such as disease diagnosis and adulteration detection [3], [4]. Visual grading of cinnamon based on peel texture, surface defects and residual bark remains subjective and inconsistent. This study addresses this gap by proposing an objective, scalable deep learning–based automated visual inspection framework.

II. Proposed Method

A. *Dataset and Preprocessing*

The automated visual inspection of cinnamon peels was formulated as a binary classification task to distinguish between acceptable and defective samples. Images were captured under controlled illumination using a custom-built light box and categorized into two folders corresponding to the classes (acceptable/ and defective/). The datasets were generated through tf.keras.preprocessing.image_dataset_from directory with an 80/10/10 split for training, validation, and testing. To enhance generalization on the small, mildly imbalanced dataset (720 acceptable and 1050 defective samples), a series of in-graph data augmentation techniques were applied, including random horizontal flipping, ±0.15° rotation, zoom, and contrast adjustments. Inputs were normalized to [0,1], training data were shuffled each epoch, and class weights were employed during optimization.

B. *CNN Configuration and Training Strategy*

The grayscale inspection model uses a compact CNN optimized via Bayesian search for both accuracy and efficiency. As shown in Table I, it comprises two convolutional blocks and a dense head to extract relevant texture features. Feature maps are flattened and fed to a 64-unit dense layer with 0.1 dropout, followed by a sigmoid output for binary classification. The network was trained end-to-end using Adam (learning rate $\approx 3.5\times10^{-3}$) with binary cross-entropy loss. Batch normalization, squeeze–excitation, and focal loss were omitted, as the compact configuration already yielded strong results.

TABLE I. Architecture of the Optimized CNN Model for Gray-Scale Cinnamon Image Classification

Stage	**Layer(s)**	**Filters / Units**	**Kernel / Pool**	**Activati-on**	**Output shape (for 128×128×1)**
Input	Input grayscale patch	-	-	-	128 × 128 × 1
Conv Block 1	Conv2D	16	5 x 5	ReLU	128 × 128 × 16
	Conv2D	16	5 x 5	ReLU	128 × 128 × 16
	MaxPooling2D	-	2 x 2	-	64 × 64 × 16
Conv Block 2	Conv2D	32	5 x 5	ReLU	64 × 64 × 32
	Conv2D	32	5 x 5	ReLU	64 × 64 × 32
	MaxPooling2D	-	2 x 2	-	32 × 32 × 32
Dense head	Flatten	-	-	-	32768
	Dense	64	-	ReLU	64
	Dropout	-	-	-	64
Output layer	Dense	1	-	Sigmoid	1 (probability)

C. *Classical Machine Learning Baseline Evaluation*

In addition to the CNN-based approach, five conventional machine learning models were implemented as baseline classifiers for performance comparison. All models were trained using handcrafted texture and statistical features extracted from the cinnamon images.

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- **Logistic Regression:** Linear probabilistic classifier; used as a lightweight baseline to assess linear feature separability.
- **Linear Support Vector Machine (SVM):** Maximises decision margin using a linear hyperplane; effective in high-dimensional feature spaces.
- **Radial Basis Function (RBF) SVM:** Extends SVM with a Gaussian kernel for non-linear decision boundaries.
- **Random Forest:** Ensemble of decision trees using bootstrap sampling; enhances robustness and reduces overfitting.
- **Histogram-Based Gradient Boosting:** Sequential tree-based model using histogram optimisation; corrects previous errors for efficient and accurate learning.

III. Results and Discussion

A. *CNN Architecture of the Optimized Gray-Scale Model*

The optimized grayscale CNN, selected through Bayesian hyperparameter tuning, demonstrated strong validation performance, as shown in Table II and Fig. 1. The model exhibited high classification reliability between acceptable and defective cinnamon peel samples, confirming that a compact, well-tuned CNN can effectively learn texture information directly from grayscale imagery.

TABLE II. EXPERIMENTAL RESULTS OF GRAYSCALE CNN MODEL

CNN model	Validation Accuracy	Validation F1	Test Accuracy	Test F1
Best model	0.9375	0.90	0.9375	0.90

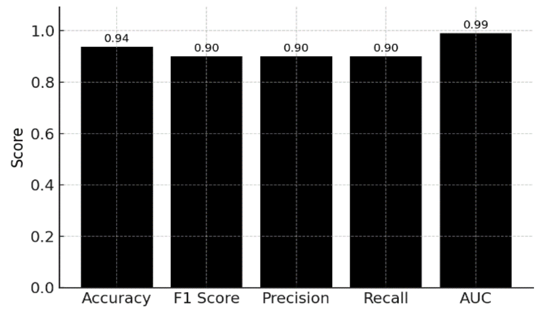

Fig. 1. Validation performance of the optimized grayscale CNN model

B. *CNN Performance Evaluation*

TABLE III. CONFUSION MATRIX FOR BEST-PERFORMING CNN MODEL

True label	Predicted defective	Predicted acceptable
True defective	108(TP)	12(FN)
True acceptable	12(FP)	252(TN)

As shown in Table III, the CNN correctly identified 108 defective and 252 acceptable samples, with only 12 and 12 misclassifications respectively. These results reinforce the preference toward defect sensitivity, which is preferable for industrial quality assurance tasks.

C. *Comparison with Classical Machine Learning Models*

Among classical models (Table IV), Logistic Regression demonstrated the highest performance, followed by RBF SVM. While these approaches offered competitive baselines using handcrafted features, the CNN demonstrated superior generalization by learning texture patterns directly from image data. This trend is further illustrated in the validation comparison of classical models (Fig. 2).

TABLE IV. PERFORMANCE COMPARISON OF CLASSICAL MACHINE LEARNING MODELS

Model	Val Accuracy	Val F1 score	Test Accuracy	Test F1 score
Logistic Regression	0.9062	0.9032	0.9524	0.9524
Linear SVM	0.8438	0.8387	0.8571	0.8421
RBF SVM	0.8125	0.8421	0.9048	0.9167
Random Forest	0.8438	0.8387	0.9048	0.9000
HistGradientBoosting	0.8125	0.8235	0.8095	0.8182

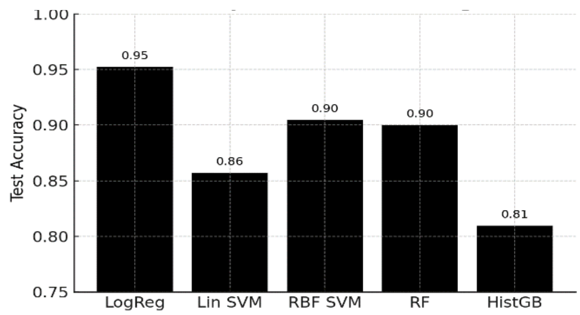

Fig. 2. Validation performance of the Machine learning models

IV. Conclusion

This research confirms the suitability of convolutional neural networks for automated cinnamon bark quality assessment. Classical machine learning models established competitive baselines using handcrafted texture features; however, the CNN-based approach demonstrated superior performance by learning spatial and textural patterns directly from grayscale image data. These findings establish CNNs as the most reliable and scalable solution for industrial inspection tasks. Future work will focus on expanding the dataset and incorporating defect severity ranges to enhance model robustness and support fine-grained quality grading.

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