DEEP LEARNING FOR AGRICULTURE

Selection of the Most Suitable Parameters for Classification of Hazelnut Fruit Using ShuffleNet

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Introduction & Motivation

- AI can classify hazelnuts by quality, size, and color — faster and more accurate than manual sorting.
- Automated sorting improves efficiency and supports quality-control processes in production.
- AI-driven monitoring can also aid early disease detection and reduce labor costs during harvesting and processing.
- This study selects the most suitable training parameters for classifying hazelnut fruit using the ShuffleNet deep learning algorithm.

STUDY AT A GLANCE

15,770 hazelnut images (10 views × 1,577 nuts)

3 classes: good, bad, and inner hazelnuts

3 optimizers compared: SGDM, ADAM, RMSprop

Related Work

1 Khosa & Pasero (2014)

X-ray image feature extraction for hazelnut classification; anomaly detection used to identify damaged nuts among 748 healthy images.

2 Solak & Altınışık (2018)

OpenCV + Weka pipeline classifying hazelnuts by size (small/medium/large) via mean-threshold and K-means clustering; 90–100% similarity between methods.

3 Caner et al. (2020)

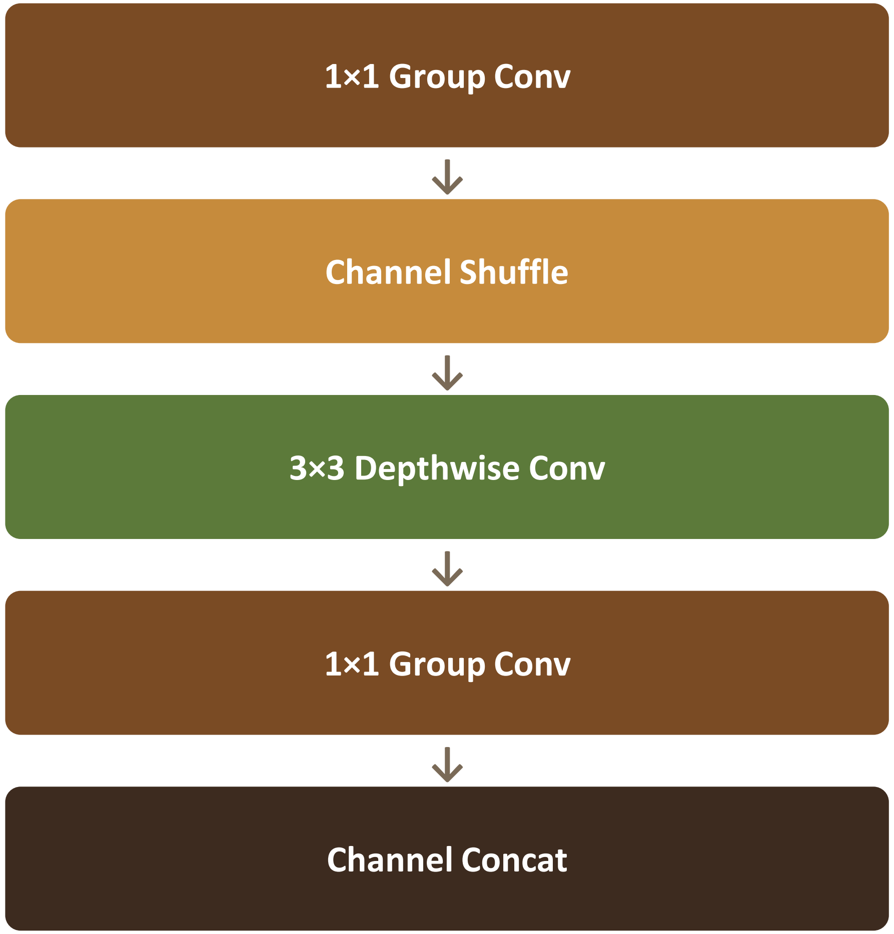
Classified Tombul and sivri/kara hazelnut cultivars using Bagging (Random Forest, 83%) and DL4J deep learning (71%).

4 Gap Addressed

Prior work focused on size/cultivar or shell-based sorting; this study targets fruit-quality classification (good / bad / inner) with a lightweight, mobile-ready CNN.

ShuffleNet Architecture

- A convolutional neural network purpose-built for devices with very limited processing power (e.g., mobile).
- Reduces parameter count and computational load using two key operations: pointwise group convolution and channel shuffle.
- Core building block uses depthwise separable convolutions, processing feature maps at smaller scale for efficiency.
- Channel shuffle mixes information across feature-map groups, improving overall network performance.
- Stride-2 units add 3×3 average pooling on the shortcut path; element-wise addition is replaced by channel concatenation to widen feature maps cheaply.



Reference: Zhang, X., Zhou, X., Lin, M., & Sun, J. (2018). ShuffleNet: An extremely efficient CNN for mobile devices. CVPR.

Dataset & Preprocessing

- Images captured with a 12-megapixel rear camera at 3024×3024 resolution.
- Each image contains a single hazelnut, expert-labeled into one of three classes.
- 519 bad hazelnuts, 535 good hazelnuts, 523 inner hazelnuts.
- 10 images per hazelnut from different angles → 15,770 total images.
- Preprocessing: cropped to 1000×1000 px, then resized to 224×224 px for network input.
- Split: 70% training, 30% testing (randomly shuffled).

Good Hazelnuts

535 nuts

Bad Hazelnuts

519 nuts

Inner Hazelnuts

523 nuts

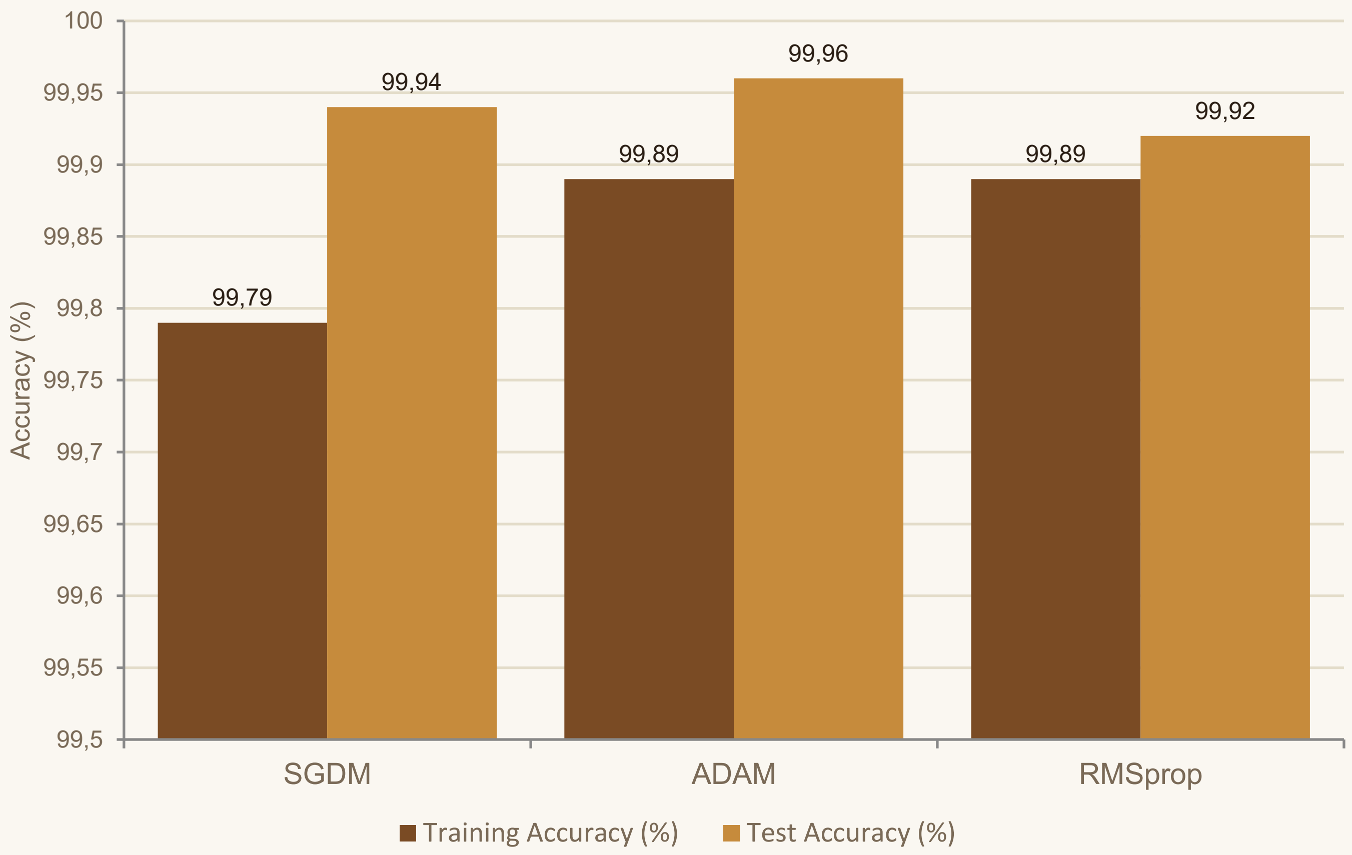
15,770

total images
(10 views each)

Experimental Setup

Environment	MATLAB
Base Network	ShuffleNet (pretrained backbone)
Data Split	70% training / 30% testing (random shuffle)
Metric Suite	Accuracy, Precision (Sensitivity), Specificity, F1-score
Optimizer 1	SGDM — Stochastic Gradient Descent with Momentum
Optimizer 2	ADAM — Adaptive Moment Estimation
Optimizer 3	RMSprop — Root Mean Square Propagation
Goal	Identify which optimizer yields the most suitable training parameters

Results: Training & Test Accuracy



BEST OVERALL

ADAM

99.96%

Test Accuracy

99.89% train / 99.96% test
Highest and most consistent accuracy among the three optimizers tested.

Confusion Matrix Metrics by Optimizer

Optimizer	Precision (Sensitivity)	Specificity	F1-Score
SGDM	0.9997	0.9994	0.9997
ADAM	**0.9997**	**1.0000**	**0.9998**
RMSprop	0.9997	0.9998	0.9997

Table 1 — Complexity-matrix metrics for ShuffleNet with each optimizer.

All three optimizers reach near-perfect scores — the dataset's class separability supports very high, consistent performance across configurations.

WHY ADAM WINS

1.0000

Perfect specificity — zero false positives on the validation set.

F1-score: 0.9998
Highest among all optimizers tested

Discussion

1 ADAM's Adaptive Advantage

Dynamic per-parameter learning rates and momentum tracking let ADAM converge quickly and effectively on this dataset.

2 SGDM Remains Competitive

Momentum-based updates still deliver 99.94% test accuracy — a robust, simpler alternative when tuning resources are limited.

3 RMSprop's Stability

Per-parameter learning-rate adjustment based on gradient variance keeps RMSprop close behind, at 99.92% test accuracy.

4 Practical Impact

Lightweight ShuffleNet + near-perfect accuracy makes automated hazelnut sorting feasible on resource-constrained devices in production lines.

Conclusion

- ShuffleNet achieves near-perfect classification of good, bad, and inner hazelnuts across all three optimizers tested.
- ADAM gives the best overall performance: 99.96% test accuracy, 1.0 specificity, 0.9998 F1-score.
- SGDM (99.94%) and RMSprop (99.92%) remain highly competitive alternatives.
- Sorting out bad and inner hazelnuts before storage prevents yield loss and spoilage — this lightweight model is well suited to on-device deployment in production lines.

99.96%

Best Test Accuracy (ADAM)

15,770
images, 3 classes

3
optimizers compared

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