

Review

Mechanical Damage Control in Korla Fragrant Pear Harvesting and Handling: Biomechanical Evaluation, Detection, and Simulation

Xiangyu Wang and Zhenwei Liang *

School of Agricultural Engineering, Jiangsu University, Zhenjiang 212013, China;
mailto:nuoyan_0713@163.com

* Correspondence: zhenwei_liang@ujs.edu.cn

Abstract

Mechanical damage remains a major constraint in low-damage harvesting and handling of the Korla fragrant pear, owing to its cultivar-specific bruise-sensitive traits (BSTs), namely its thin peel, crisp flesh, smooth epidermis, and high bruise sensitivity. This review synthesizes evidence from the Korla fragrant pear, other pear cultivars, apple, and related fresh produce to clarify damage mechanisms and engineering strategies for damage control. The reviewed studies show that injury is mainly governed by impact energy, compression load, contact stiffness, friction, fruit velocity, spacing, and transfer trajectory. Quasi-static compression and drop-impact tests provide essential thresholds, including elastic modulus, rupture force, absorbed energy, bruise area, and bruise volume, but Korla-specific data remain insufficient. Nondestructive techniques are complementary: RGB machine vision supports rapid surface screening, hyperspectral imaging improves early bruise detection, X-ray computed tomography quantifies internal bruising, and scanning electron microscopy verifies cellular damage mechanisms. FEM and DEM can predict stress distribution, deformation, collision behavior, and equipment-induced injury when calibrated with cultivar-specific parameters. Overall, apple- or general pear-based technologies require recalibration before application to the Korla fragrant pear. Future work should establish Korla-specific damage thresholds and validate detection, simulation, and conveying systems under real orchard and packing-line conditions.

Keywords: Korla fragrant pear; postharvest loss; low-damage harvesting; numerical simulation; fruit bruising; cushioning systems

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1. Introduction

Fruit cultivation constitutes a cornerstone of global agricultural development, with a long history and substantial contributions to human nutrition and rural economies [1,2]. Among the wide range of horticultural crops, pear (*Pyrus* spp.) and apple (*Malus domestica*) are two of the most widely cultivated and economically valuable fruit tree species worldwide [3]. In China, the Korla fragrant pear (*Pyrus sinkiangensis* Yu) is a representative local specialty. This cultivar is mainly produced in the Xinjiang Uygur Autonomous Region and is well known for its distinctive aroma, crisp texture, and excellent quality. At present, the cultivation area of the Korla fragrant pear in Xinjiang is approximately 66,700 ha, equivalent to about 1 million mu, with an annual production approaching 1.8 million

tons and a total output value exceeding CNY 10 billion. The industry has developed into an important pillar of the local rural economy and plays a central role in increasing farmers' income and promoting rural revitalization.

However, with the expansion of production, the Korla fragrant pear industry is facing a critical bottleneck in fruit harvesting. Harvesting fresh fruit is one of the most labor-intensive and time-sensitive operations in horticultural production because fruit must be detached within a short maturity window while avoiding bruising, puncture, and surface abrasion [4]. Despite its considerable economic importance, more than 90% of pear orchards in Xinjiang still adopt the traditional large-canopy, low-density planting system, which is characterized by tall canopies and complex tree architecture. These structural constraints make manual harvesting difficult to replace, requiring workers to climb ladders or trees directly to pick the fruit. Meanwhile, the availability of skilled seasonal agricultural labor has become increasingly constrained by broader demographic and employment changes. National statistics show that China had 299.73 million migrant workers in 2024, including 178.71 million who worked away from their hometowns [5]. Recent rural-labor studies further indicate that younger and able-bodied rural workers increasingly move to urban or other non-agricultural employment, whereas older household members are more likely to remain engaged in farming [6]. Labor-force aging has also been shown to reduce agricultural productivity and weaken the efficiency of technological progress and resource allocation [7]. These national trends are consistent with the seasonal labor pressure observed in Korla fragrant pear orchards. According to local field investigations and grower consultations conducted by the authors in 2024, the cost of manual harvesting for the Korla fragrant pear approached approximately CNY 1 kg⁻¹, accounting for 20–30% of the fruit selling price. This high labor-cost share indicates that traditional manual harvesting is economically burdensome and unsustainable for large-scale production. Consequently, there is an urgent need for efficient, economically viable mechanized harvesting solutions that minimize mechanical damage to the fruit.

Although existing harvesting platforms and robotic systems offer useful references for low-damage fruit handling, their applicability to the Korla fragrant pear remains insufficiently verified. Many reported systems were developed under more structured orchard conditions or for fruits that differ substantially from the Korla fragrant pear in peel strength, flesh firmness, surface friction, and impact tolerance. Compared with many apple cultivars, these BSTs limit the direct adoption of apple-based platform designs. These designs are therefore conditionally transferable, and key conveying and handling parameters must be recalibrated using biomechanical data specific to the Korla fragrant pear. These parameters include belt speed, pipe inclination, inner radius, contact material stiffness, drop height, anti-slip surface design, and bin-filling trajectory.

The transition toward mechanized harvesting and postharvest handling is constrained by the high bruise susceptibility of fresh fruit [8]. Among different injury forms, bruising is particularly important. It can remain partly hidden during early handling, yet later develop into visible browning, tissue softening, decay, and market rejection [9–12]. As shown in Figure 1, the Korla fragrant pear is vulnerable to both impact bruising and friction-induced peel blackening. These symptoms are associated with cell membrane and cell wall rupture, followed by enzymatic browning and tissue degradation [13,14]. In the Korla fragrant pear, bruising during harvesting accounts for 15–20% of total fruit losses, indicating that mechanical injury is a practical production problem rather than a general postharvest-quality concern. Once damaged, fruit becomes more susceptible to pathogenic infection, accelerated decay, and quality deterioration [15–18].



Figure 1. Damage states of fragrant pear: (a) impact bruising; (b) friction-induced peel blackening.

Existing studies provide useful but fragmented evidence for understanding and reducing fruit mechanical damage. Quasi-static compression tests are useful for determining basic load-bearing properties such as elastic modulus, rupture force, and failure energy. Drop tests, by contrast, better reproduce transient impact and energy dissipation during harvesting and conveying. These tests, however, often simplify real handling conditions, in which fruit is exposed to repeated combinations of impact, compression, vibration, rolling friction, and shear. Similarly, machine vision, hyperspectral imaging, X-ray computed tomography, and scanning electron microscopy have improved the detection of surface, internal, and microstructural damage. Their accuracy and field applicability depend strongly on cultivar, maturity, damage stage, imaging condition, and validation dataset. FEM and DEM models are valuable for predicting stress distribution, collision behaviour, and equipment-induced injury, yet their reliability depends on cultivar-specific parameters and experimental validation.

To clarify the logical relationship among the major topics covered in this review, a conceptual workflow was developed (Figure 2). The framework links damage sources, low-damage buffering and conveying, biomechanical characterization, nondestructive detection, and numerical simulation with engineering design and field validation for Korla fragrant pear harvesting and handling.

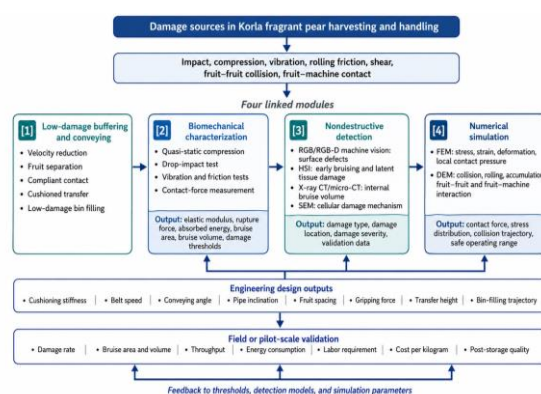


Figure 2. Conceptual workflow for mechanical damage control in Korla fragrant pear harvesting and handling. The workflow links damage sources during harvesting and handling with four core modules: low-damage buffering and conveying, biomechanical characterization, nondestructive detection, and numerical simulation. These modules provide mechanical thresholds, damage information, and simulation outputs for engineering design and optimization. Field and pilot-scale validation provides feedback for recalibrating thresholds, detection models, and simulation parameters. Arrows indicate the directional flow from damage sources to core modules, engineering design/optimization, field validation, and feedback recalibration.

This review aims to provide a crop-specific and engineering-oriented synthesis of mechanical damage control in Korla fragrant pear harvesting and handling. The specific

objectives are to: (1) summarize the main biomechanical parameters and damage thresholds related to impact, compression, vibration, rolling, and friction injury; (2) compare nondestructive detection methods for surface, subsurface, internal, and microstructural damage; (3) evaluate the roles of FEM, DEM, and coupled simulation approaches in predicting fruit–machine and fruit–fruit interactions; and (4) translate findings from apple, pear, and other fresh produce into design implications for low-damage harvesting, conveying, cushioning, and bin-filling systems. The novelty of this review lies in its explicit focus on the Korla fragrant pear as a bruise-sensitive fruit grown mainly in large-canopy orchards and in its integration of biomechanical testing, damage detection, numerical simulation, and equipment design within a unified damage-control framework. Unlike existing reviews that mainly discuss general postharvest fruit bruising, nondestructive detection, or numerical modeling separately, this review evaluates the transferability and limitations of those findings for the Korla fragrant pear according to peel properties, tissue firmness, fruit geometry, maturity stage, contact conditions, and orchard structure. The target audience includes researchers in agricultural engineering and postharvest technology, designers of fruit harvesting and conveying equipment, and practitioners seeking practical guidance for reducing mechanical injury in Korla fragrant pear production.

2. Materials and Methods

A structured literature search was conducted to improve the transparency and reproducibility of this review. The Web of Science Core Collection was used as the primary database, and relevant studies from Scopus and CNKI were supplemented when necessary, especially for studies related to Korla fragrant pear and Chinese pear production. Before defining the search terms, the search strategy was organized around four predefined themes: low-damage harvesting and conveying, biomechanical characterization of fruit mechanical damage, nondestructive damage detection, and numerical simulation using the FEM or DEM. Based on these themes, the main search terms included “fruit”, “pear”, “apple”, “Korla fragrant pear”, “*Pyrus sinkiangensis*”, “mechanical damage”, “bruise”, “impact damage”, “compression damage”, “vibration damage”, “hyperspectral imaging”, “X-ray computed tomography”, “finite element method”, “discrete element method”, “low-damage harvesting”, and “conveying system”. The search covered publications available up to March 2025.

Because direct studies on the Korla fragrant pear remain limited, evidence from related fruits was included but explicitly classified to avoid overgeneralization. All cited studies were assigned to one of five categories according to crop or material type and their relevance to mechanical damage in the Korla fragrant pear. Level I evidence was used as the primary basis for Korla-fragrant-pear-specific conclusions. Level II evidence was considered transferable pear evidence. Level III evidence from apples and other pome fruits was used for comparative engineering interpretation when Korla- or pear-specific evidence was unavailable. Level IV evidence from other fresh fruits and vegetables was used mainly for methodological analogy. Level V studies were retained only when they directly supported mechanical damage detection, numerical simulation, or engineering background.

After classification, 138 publications were included in this review, comprising Korla-fragrant-pear-specific studies ($n = 10$), studies on other pear cultivars ($n = 14$), studies on apple and other pome fruits ($n = 34$), studies on other fresh fruits and vegetables ($n = 28$), and methodological or background studies ($n = 52$). The included studies addressed at least one of the following themes: mechanical damage formation, biomechanical parameters and damage thresholds, nondestructive detection, FEM/DEM-based numerical simulation, or low-damage harvesting and handling systems. The detailed identification, screening, eligibility assessment, and inclusion process is summarized in the PRISMA-

style flowchart shown in Figure 3. This evidence classification was applied throughout the review when interpreting study findings. Direct conclusions about the Korla fragrant pear were drawn primarily from Level I evidence. Findings from Level II–IV studies were used to support transferability analysis, but they were not treated as direct design rules unless their crop properties, loading modes, contact conditions, and validation methods were consistent with the Korla fragrant pear.

PRISMA flow diagram of literature identification, screening, eligibility assessment, and inclusion

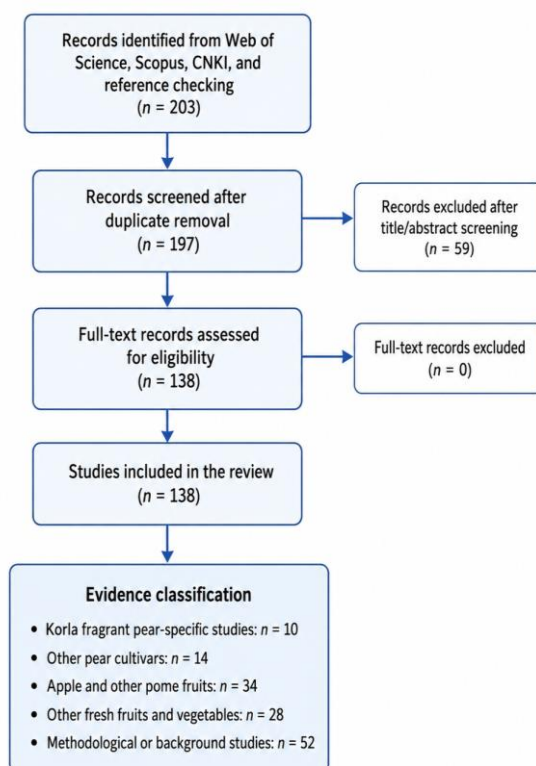


Figure 3. Concise PRISMA-style flowchart of literature identification, screening, eligibility assessment, and inclusion. A total of 203 records were identified, 197 records remained after duplicate removal, 138 full-text records were assessed for eligibility, and 138 publications were finally included in the review.

Studies unrelated to fruit mechanical damage, such as those focusing on pesticide spraying, plant disease diagnosis, crop genetics, rice or tea quality evaluation, or food processing, were excluded. Patents, product manuals, non-peer-reviewed online materials, duplicate publications, and studies without sufficient methodological or quantitative information were also excluded.

To strengthen the critical synthesis, the reviewed methodologies were compared according to four criteria: methodological purpose, main strength, main limitation, and source of inconsistent findings. Because the reviewed studies differed in crop type, cultivar, maturity stage, loading mode, impact surface, contact material, sample size, damage definition, and validation condition, quantitative results from different studies were not treated as directly comparable. Instead, they were interpreted as methodological evidence, transferable references, or cultivar-specific findings according to the evidence classification in Table 1. This approach was used throughout the review when comparing buffering and conveying systems, biomechanical tests, nondestructive detection methods, and FEM/DEM simulation studies.

Table 1. Evidence classification used to evaluate the relevance and transferability of included studies to Korla fragrant pear mechanical damage control.

Evidence Level	Product	Use in This Review	Inclusion Rule
Level I	Korla fragrant pear	Direct evidence	Studies directly addressing mechanical damage, harvesting, detection, biomechanical testing, or simulation of the Korla fragrant pear
Level II	Other pear cultivars	Transferable evidence	Studies on pear cultivars with similar tissue structure, bruising behavior, or post-harvest handling conditions
Level III	Apple and other pome fruits	Comparative evidence	Used when pear-specific data are unavailable; transferability evaluated according to fruit geometry, peel properties, firmness, and loading condition
Level IV	Other fresh fruits and vegetables	Methodological analogy	Used only for detection, simulation, or cushioning methods that may be technically transferable
Level V	Agricultural materials and background studies	Not relevant	Removed unless the method directly supports mechanical damage detection or simulation

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3. Low-Damage Buffering and Conveying Methods for Fruit and Vegetable Harvesting

Mechanical injury during harvesting and conveying is a major source of postharvest loss in fragrant pear production. Reported statistics indicate that mechanical injury can cause annual postharvest losses of fragrant pear exceeding 38% of total production. These losses arise from visible bruising, puncture wounds, epidermal abrasion, tissue cracking, and subsequent physiological deterioration during grading, storage, transportation, and retail distribution. Therefore, low-damage harvesting should be evaluated as an engineering problem involving productivity, impact-energy control, fruit spacing, contact stiffness, and transfer trajectory. For fragrant pear and other pome fruits, damage reduction depends mainly on three controllable factors: reducing fruit velocity before impact, separating individual fruit to reduce fruit-to-fruit collision, and replacing rigid contact with compliant or energy-dissipating interfaces.

Typical manual harvesting scenes in large-canopy Korla fragrant pear orchards are shown in Figure 4a–d. These operations illustrate the height variation, branch interference, and repeated fruit transfer that increase the risk of impact and friction damage during manual or assisted harvesting.



Figure 4. Manual harvesting conditions in large-canopy Korla fragrant pear orchards: (a) branch-climbing picking; (b) ladder-assisted picking; (c) pole-assisted picking; (d) auxiliary-gripping picking.

Four assisted harvesting and conveying systems were compared in terms of machine efficiency, damage-control potential, and cost-effectiveness (Table 2). Mobile elevating platforms reduce ladder climbing and improve worker access to the canopy, but fruit detachment and transfer still rely largely on manual operation. Conveyor-assisted platforms provide continuous fruit transfer from picking stations to collection bins and allow cushioning and bin-filling devices to be integrated into the same system. Pneumatic suction conveying systems can transport fruit continuously, but their high energy demand, structural complexity, and possible pipe-wall impact or friction limit their suitability for the bruise-sensitive Korla fragrant pear. Gravity-driven pipe conveying systems are simple and low-cost, but fruit velocity and collision risk must be controlled by optimizing pipe inclination, curvature, inner diameter, and cushioning materials.

Table 2. Comparison of assisted harvesting and conveying systems for the Korla fragrant pear.

System Type	Main Advantage	Main Limitation	Overall Suitability
Mobile elevating platform	Improves worker access	Fruit transfer remains manual	Moderate
Conveyor-assisted platform	Continuous transfer; easy integration with cushioning and bin filling	Requires parameter calibration	High
Pneumatic suction conveying system	Enclosed continuous transport	High energy use and friction risk	Low to moderate
Gravity-driven pipe conveying system	Simple and low-cost	Velocity control is difficult	Moderate to high

Overall, conveyor-assisted platforms equipped with flexible belts, cushioned transfer points, and low-damage bin-filling devices appear to offer the best balance among harvesting performance, machine efficiency, and cost-effectiveness for the Korla fragrant pear. Gravity-driven pipe conveying systems may serve as a lower-cost auxiliary option, while pneumatic suction systems require further optimization before practical application to bruise-sensitive fruit.

A representative apple harvesting platform with a low-damage packing device is shown in Figure 5. This system is used here as a transferable engineering reference for conveying, cushioning, and bin-filling design. Because it was developed for apple harvesting, key parameters such as belt speed, contact material stiffness, transfer height, and bin-filling trajectory require cultivar-specific recalibration before application to the Korla fragrant pear [19]. Therefore, most apple-based harvesting platforms and cushioning systems reviewed in this section are interpreted as Level III comparative evidence. Level III

evidence suggests useful engineering principles, such as velocity reduction, fruit separation, flexible contact, and low-drop bin filling, but these principles require Level I validation before they can be used as design rules for the Korla fragrant pear.

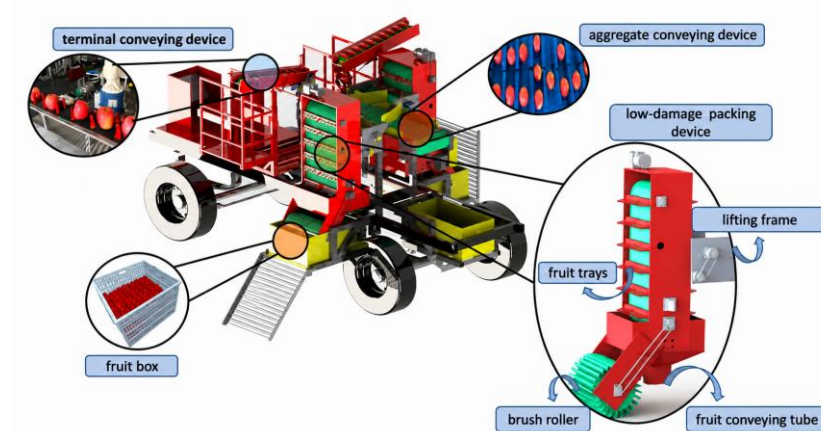


Figure 5. Apple harvesting platform with a low-damage packing device used as a transferable engineering reference for Korla fragrant pear conveying and bin-filling design [19]. Different colors are used only to distinguish structural components in the original schematic and do not represent quantitative variables.

Existing devices can be divided into structural cushioning systems and medium-assisted cushioning systems. Structural cushioning systems include cushioning rods, foam rollers, flexible conveyor belts, soft pads, fabric chutes, fork-array structures, and soft partitions. Their common function is to extend impact duration, enlarge the contact area, reduce local contact pressure, and guide fruit motion. Fu et al. designed two sets of cushioning rods and three rows of cushioning sheets, which provided zonal separation and impact cushioning during apple dropping, rolling, and conveyance [20]. Gao et al. developed a backpack-type manual pear-picking device in which a cable-driven picking head, clamping jaws, cutting blade, cushioned collection tube, and fruit-holding container were integrated into one operation route (Figure 6). The device integrates fruit detachment, cushioned conveying, and collection in one operation route, providing a transferable reference for reducing impact and handling damage in Korla fragrant pear harvesting. Compared with conventional manual picking, this system increased harvesting efficiency by 57.1% [21]. This value should be interpreted as an intra-study improvement rather than a directly comparable benchmark across different harvesting systems. The 57.1% increase was obtained by comparing the backpack-type pear picker with conventional manual picking under the experimental conditions of the original study. However, performance metrics reported in different studies are often affected by crop type, orchard structure, fruit maturity, operator skill, working height, test duration, sample size, damage definition, and whether bruising or only harvesting rate was measured. Therefore, cross-study comparisons of machine efficiency are reliable mainly for identifying general trends, but they are insufficient for ranking devices quantitatively. Future evaluations should use unified indicators, including fruit throughput, bruising rate, puncture rate, contact force, fruit-falling height, energy consumption, labor requirement, and cost per kilogram harvested.



Figure 6. Manually operated backpack-type pear picker used to reduce repeated climbing and manual fruit transfer during pear harvesting [21].

Other structural designs aim to reduce damage during fruit collection and bin filling. Wang et al. used the Explicit Dynamics module in ANSYS Workbench to optimize a three-stage cushioning and collection mechanism composed of a fruit-receiving tray, conveyor belt, and rotary separation unit [22]. Liu et al. developed a collection mechanism for a handheld vibration harvester, using a polyethylene-foam-lined collection frame and a cushioned fabric chute to reduce impact during collection (Figure 7). The cushioned collection frame and fabric chute illustrate structural cushioning principles, but their applicability to the Korla fragrant pear requires validation because branch interference, canopy density, fruit position, and peel sensitivity may change the dominant damage source. However, the same study indicated that fruit detached by vibration remained vulnerable to abrasion and impact caused by contact with trunks, branches, and adjacent fruit [23]. This limitation is important for fragrant pear orchards because branch distribution, canopy density, and fruit position are highly variable under large-canopy planting systems. In this case, the main damage source may shift from the collection device itself to uncontrolled pre-collection collisions.

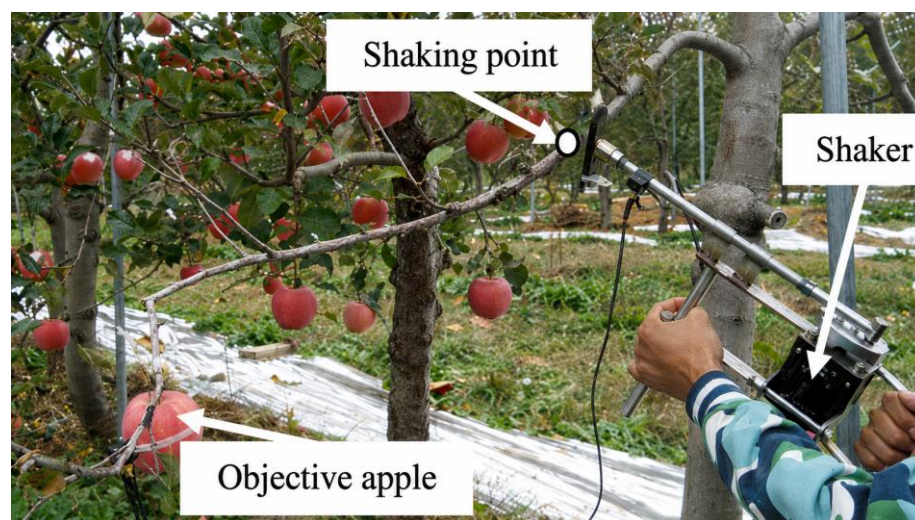


Figure 7. Apple-based picking and collection mechanism used as a transferable reference for low-damage fruit collection design [23].

Bin filling is another critical stage because fruit velocity and discharge trajectory directly determine collision intensity. The Munckhof apple picking platform adopted a three-section flexible conveyor belt to transport apples into storage bins, thereby reducing manual placement and allowing height-adaptive conveying. Zhang et al. optimized a fruit bin filler by installing foam rollers beneath the sorting system and replacing short soft pads on the rotating distribution wheel with nine elongated pads. Foam guiding devices were also added to reduce fruit velocity during the transition from the pads to the fruit

bin. The modified system was reported to reduce fruit damage [24]. However, many studies still describe the outcome using qualitative terms, while specific values for impact velocity, drop height, bruise area, bruise volume, and damage-reduction percentage are often absent. This weakens cross-comparison among devices and limits the development of design standards.

Medium-assisted cushioning systems use air, water, or other media to decelerate fruit and reduce direct rigid contact. As shown in Figure 8, Ma et al. designed an air-flow cushioning collection device for mechanical vibration harvesting. The device used a PVC pipe with bottom vent holes as the collection channel, reducing fruit falling velocity and maintaining spacing between fruit. Experiments showed that this system reduced the damage rate of different apple cultivars by 14.5–36.9% [25]. This is one of the clearer quantitative results among the reviewed cushioning studies. Nevertheless, its direct transfer to the Korla fragrant pear still requires verification because BST-related surface and tissue responses, together with rebound behavior, differ between apples and Korla fragrant pears. Tang et al. used a pesticide aqueous solution as a cushioning medium for harvested apples, while Zhang et al. developed a multi-row fork-array cushioning device to absorb and transform the kinetic energy of falling fruit [26]. Pothula et al. further developed a machine-vision-based apple sorting and collection system in which soft finger-like foam partitions were used on the conveyor belt to isolate individual apples and reduce fruit-to-fruit collisions [27].



Figure 8. Air-flow cushioning collection device for reducing fruit falling velocity and maintaining fruit spacing during mechanical vibration harvesting [25].

Although these devices show promising damage-control principles, their field application remains limited for three main reasons. First, many systems are tested under controlled laboratory or semi-controlled conditions, where fruit height, falling path, impact surface, and fruit spacing can be regulated. Real orchards introduce canopy occlusion, uneven terrain, branch interference, variable fruit maturity, operator differences, and random fruit orientation, which can change the actual impact condition. Second, most available systems are developed for apple or general pear production. Their parameters cannot be directly applied to the Korla fragrant pear without calibration of contact-material stiffness, surface texture, belt speed, conveying angle, pipe inclination, inner radius, fruit spacing, drop height, and anti-slip design. Third, productivity indicators are often incomplete. A device that reduces bruise rate under laboratory conditions may still be unsuitable for commercial harvesting if its throughput is low, its maintenance requirement is high, or its operating cost exceeds the economic benefit gained from damage reduction.

Therefore, the practical outcome of current research is the identification of several engineering principles rather than a ready-to-use mechanized solution for the Korla fragrant pear. Structural cushioning is suitable for compact and mobile devices, but its protection decreases when impact energy exceeds the absorption capacity of the contact material. Medium-assisted cushioning can provide stronger deceleration and fruit separation, but it may increase system complexity, energy demand, cleaning requirements, and field-management cost. For the Korla fragrant pear, future studies should report common quantitative metrics, including fruit damage rate, damage-reduction percentage, fruit throughput, impact velocity, drop height, contact force, bruise area, bruise volume, energy consumption, labor requirement, and cost per kilogram harvested. Field tests should also compare the same device under different maturity stages, canopy positions, orchard structures, and operation speeds. Only with these data can low-damage conveying systems move from laboratory prototypes to practical harvesting equipment adapted to large-canopy fragrant pear orchards.

4. Evaluation and Characterization Methods for Mechanical Damage in Fragrant Pear

The evaluation of mechanical damage provides the quantitative basis for defining safe harvesting, conveying, sorting, storage, and transportation conditions for the Korla fragrant pear. During postharvest handling, fruit is exposed to multiple loading modes, including high-speed impact, repeated vibration, sustained compression, rolling friction, and local shear [28–30]. These loads differ in loading rate, contact duration, force transmission path, and energy dissipation mechanism. Therefore, mechanical damage should be characterized using both material-level parameters and operation-level damage indicators.

At present, two experimental approaches are most frequently used: quasi-static compression tests and drop-impact tests [31–38]. Quasi-static compression tests are suitable for measuring load-bearing capacity under low-speed deformation, while drop-impact tests are more appropriate for evaluating collision-induced bruising during fruit collection and conveying. These two methods should be considered complementary. A single rupture force or firmness value cannot fully explain damage occurring during bin filling, repeated collision, or fruit-to-fruit contact. For engineering design, the most useful indicators include elastic modulus, yield force, rupture force, deformation energy, absorbed energy, critical drop height, rebound height, contact area, surface pressure, bruise area, bruise volume, and energy dissipation ratio.

To clarify why crop-specific thresholds are required, the Korla fragrant pear was compared with other pears and apples in terms of bruise-related biomechanical features and key predictive parameters (Table 3). Because published studies use different cultivars, maturity stages, temperatures, loading directions, impact surfaces, and bruise-evaluation methods, the available thresholds are more suitable for identifying variation trends than for defining universal numerical limits.

Table 3. Comparative biomechanical features and bruise-predictive parameters of Korla fragrant pear, other pears, and apples.

Aspect	Korla Fragrant Pear	Other Pears/Apples	Implication
Peel and surface	Thin peel, smooth surface, sensitive to friction-induced peel blackening	Cultivar-dependent; many apple cultivars have firmer peel or surface structure	Peel strength, friction coefficient, and contact material affect abrasion and local stress concentration

Flesh and bruise sensitivity	Crisp flesh and high bruise sensitivity	Firmness and tissue structure vary widely among cultivars	Flesh firmness, elastic modulus, rupture force, and absorbed energy are important predictors
Direct bruise indicators	Bruise area and bruise volume	Commonly used in pear and apple impact studies	Most direct outputs for judging damage severity
Operating-related predictors	Impact energy, critical drop height, contact force, yield force, rupture force	Widely used for equipment and cushioning evaluation	Useful for setting safe transfer height, belt speed, gripping force, and cushioning stiffness
Threshold variation	Strongly affected by maturity, temperature, loading direction, contact area, and post-impact time	Similar trends occur, but numerical values differ by cultivar and test condition	Thresholds from other fruits should be used only as references and recalibrated for the Korla fragrant pear

4.1. Quasi-Static Compression: Biomechanical Parameters and Engineering Relevance

Quasi-static compression testing is commonly used to characterize the fundamental mechanical properties of agricultural products under low loading rates. In this method, fruit is compressed at a controlled rate, often within the low-speed range reported for agricultural material testing, such as 1–10 mm min⁻¹, and the force–deformation curve is recorded. From this curve, researchers can obtain elastic modulus, yield point, rupture force, stiffness, failure energy, and deformation behavior [28–31]. These parameters are directly relevant to the design of robotic end-effectors, clamping mechanisms, stacking conditions, and low-speed conveying components.

Existing studies have moved from simple rigid-plate compression toward more realistic evaluations of loading direction, tissue anisotropy, and contact-material effects. Shi et al. investigated the coupled effects of loading rate, spatial orientation, and porous cushioning materials on pear yield limit and damage energy [39]. Their work indicates that flexible contact boundaries can redistribute surface stress and increase the load required for visible damage. Pham and Liou et al. compared two pear cultivars and related texture characteristics to elastic modulus and fracture strength; Pham et al. further discussed the nonlinear relationship between internal fibrous texture and macroscopic elastic modulus [40]. These studies are important because they show that mechanical damage resistance is not determined by firmness alone, but by tissue structure, loading direction, and boundary condition.

Temperature and storage conditions further affect compression behavior. Li et al. measured elastic modulus and strength parameters of pear peel and flesh using tensile and compression tests, and established a storage-temperature-related prediction model [41]. As shown in Figure 9, Li et al. also used a universal testing machine to obtain damage volumes under different compression levels and compared different modeling techniques. PLSR, GRNN, and ANFIS performed better than conventional linear models in predicting fruit decay and shelf life [41]. This suggests that mechanical parameters can be linked with post-harvest quality prediction, rather than serving only as isolated physical indices.

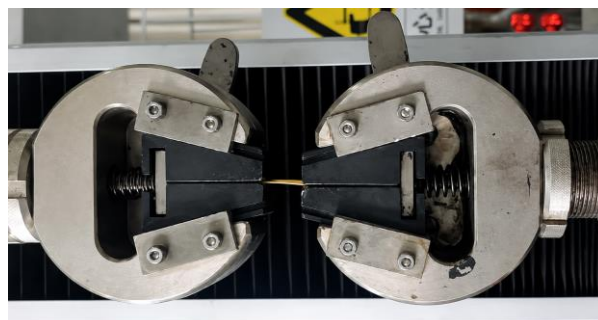


Figure 9. The status of crisp pear peel before tensile test [41].

However, quasi-static compression still has clear limitations. First, the imposed load is usually unidirectional and gradually applied, while fruit in real handling systems often experiences combined compression, impact, rolling, and shear. Second, compression tests are highly sensitive to fruit orientation, contact plate geometry, loading rate, maturity, temperature, and peel condition. Third, many studies report force or deformation values without connecting them to practical design thresholds, such as maximum allowable clamping force, safe stacking height, or minimum cushioning thickness. Therefore, future compression studies on the Korla fragrant pear should report not only elastic modulus and rupture force, but also sample size, maturity stage, loading position, loading rate, contact area, coefficient of variation, and direct engineering implications for gripping, conveying, and storage.

4.2. Drop Tests: Damage Formation and Energy Dissipation

Drop-impact tests are used to simulate transient collision during harvesting, conveying, sorting, and bin filling. Compared with quasi-static compression, they better represent high-rate energy transfer, rebound, and local stress concentration. In a typical test, fruit is released from a known height onto a selected contact surface. The input potential energy can be expressed as $E = mgh$, where m is fruit mass, g is gravitational acceleration, and h is drop height. After impact, part of this energy is returned through rebound, while the remaining energy is dissipated through tissue deformation, friction, heat, and bruise formation. Therefore, drop tests are useful for linking impact energy with bruise area, bruise volume, contact force, and energy absorption.

Rodriguez et al. used free-fall experiments from different heights to analyze the relationship between damage volume and fruit firmness, emphasizing the role of peel properties in impact toughness [42]. Bajema and Hyde et al. quantified “damage energy” by measuring energy absorption during successive rebounds from predetermined heights [43]. As shown in Figure 10, Jiang et al. used a customized fruit drop-damage test bench to examine the effects of impact energy during harvesting and storage. Their results showed a quadratic relationship between kinetic energy and plastic deformation energy [44]. This result is practically important because it indicates that damage may increase nonlinearly once the impact-energy threshold is exceeded.

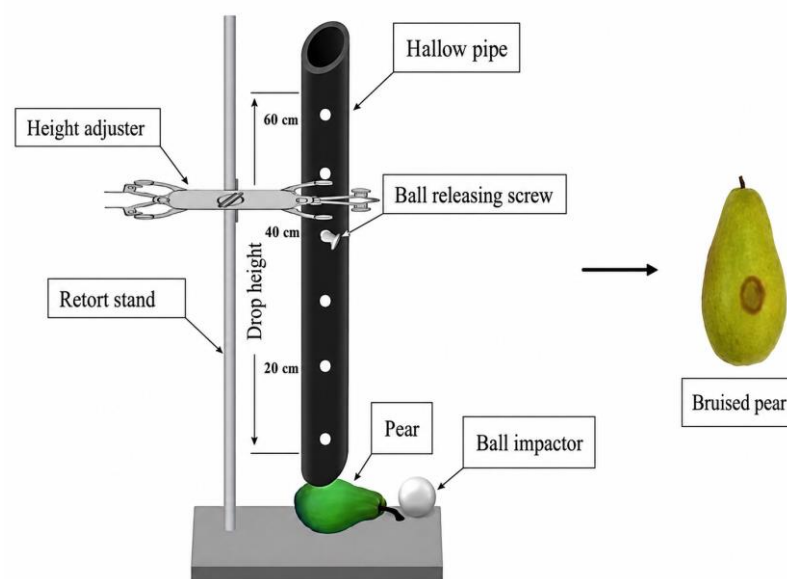


Figure 10. Fruit drop-damage test bench [45].

Several studies have further refined impact-damage indicators. Komarnicki et al. evaluated pear durability using instantaneous force, contact area, and surface pressure, and validated bruise measurements through volumetric image analysis [46]. Komarnicki et al. then expressed bruise volume as a function of drop height and introduced a bruise resistance index based on the relationship between bruise volume and surface pressure [47]. Stropek et al. further applied this index, using mean surface pressure as the primary loading parameter to characterize the impact resistance of pears [48]. These indices are more useful than simple visual grading because they connect external loading with measurable damage response.

More recent studies have considered multifactorial impact conditions. Zhang et al. analyzed impact-damage formation in Huangguan pear and evaluated the effects of drop height, contact-material stiffness, fruit surface curvature, firmness, and ambient temperature [49]. Liu et al. constructed a nonlinear response function between drop height and damage area for pears at different maturity stages [50]. Stropek et al. used high-speed photography to record collision force–displacement behavior and examined the relationship between damage sensitivity and the time lag between peak force and peak displacement [48]. Li et al. used high-speed imaging to track free-fall and rebound heights, showing that the elastic modulus of the contact material affects the proportion of kinetic energy absorbed by fruit [51]. Fu et al. introduced a sliding method to simulate fruit-to-fruit collisions and analyzed the relationships among impact velocity, contact area, kinetic energy loss, and bruise susceptibility [52].

Although these studies provide useful evidence, most drop-impact tests still simplify real handling conditions. Fruit usually falls along a predefined path and impacts a controlled surface, while in field harvesting or bin filling the impact direction, contact angle, fruit orientation, neighboring fruit, branch interference, and conveying speed vary continuously. In addition, drop tests often evaluate a single impact event, whereas commercial handling may expose fruit to repeated low-energy collisions that gradually accumulate damage. Therefore, impact testing for the Korla fragrant pear should include single-impact and repeated-impact conditions, fruit-to-fruit collision, fruit-to-material collision, oblique impact, rolling impact, and post-impact storage assessment.

4.3. Methodological Limitations and Transfer from Laboratory to Field

The main scientific limitation of current mechanical-damage evaluation is that laboratory tests often isolate one loading mode, while real handling systems impose coupled loading. During harvesting and postharvest handling, fruit can experience compression during grasping, impact during dropping, vibration during transport, friction during rolling, and local shear during contact with branches, belts, bins, or other fruit. These processes interact with maturity, temperature, storage duration, moisture status, and tissue heterogeneity. Therefore, mechanical parameters obtained under one controlled condition cannot be directly used as universal design limits [53–59].

Quasi-static compression is useful for material characterization, but it cannot fully capture high-speed energy transfer, rebound, or instantaneous stress concentration during collision [53]. It also has difficulty representing fruit shape irregularity, internal tissue heterogeneity, and local stress concentration caused by curvature or peel defects ([54,60]). Drop tests are closer to impact events, but they are affected by fruit mass, geometry, maturity, contact angle, drop height accuracy, camera alignment, focal length, and pixel-to-length calibration [55,61]. These factors may lead to variation in bruise area and bruise volume estimation.

The transfer from laboratory research to field application is limited by four major gaps. First, testing protocols are not sufficiently standardized. Studies differ in loading rate, impact surface, drop height, maturity stage, storage interval after impact, and bruise-

measurement method, which makes comparison difficult. Second, many studies report mechanical indices without linking them to equipment parameters. For example, rupture force should be translated into maximum safe gripping force; critical drop height should guide the design of conveyor transfer height; bruise volume should be connected with acceptable commercial quality; and contact-material stiffness should be used to select cushioning materials. Third, most experiments are conducted on limited cultivars or small sample sets, so cross-cultivar transfer to the Korla fragrant pear remains uncertain. Fourth, field conditions introduce canopy structure, uneven ground, operator behavior, fruit position, temperature fluctuation, dust, vibration, and random collision pathways, which are rarely reproduced in laboratory tests.

For the Korla fragrant pear, future research should establish standardized mechanical damage thresholds across maturity stages and handling scenarios. Priority parameters include critical compression deformation, rupture force, yield force, elastic modulus, impact-energy threshold, critical drop height, restitution coefficient, friction coefficient, bruise area, bruise volume, and post-impact decay rate. These parameters should be measured under conditions that correspond to real operations: robotic grasping, assisted picking, chute conveying, belt transfer, fruit-to-fruit collision, bin filling, storage stacking, and transportation vibration. The practical outcome should be a set of safe operating ranges for harvesting and handling equipment rather than only laboratory mechanical curves.

4.4. Comparative Synthesis

Quasi-static compression and drop-impact tests provide different but complementary information. Compression tests are stronger for determining material parameters and static failure limits, while drop tests are stronger for evaluating dynamic damage initiation and energy dissipation. However, neither method alone can fully represent the coupled mechanical environment of commercial harvesting and postharvest handling. Therefore, future studies should combine controlled mechanical testing, high-speed imaging, bruise-volume measurement, post-impact quality evaluation, and numerical simulation.

A more outcome-oriented evaluation framework is needed for the Korla fragrant pear. First, laboratory tests should identify threshold values for safe compression and impact. Second, these thresholds should be translated into equipment parameters, including allowable gripping force, maximum transfer height, conveyor speed, cushioning stiffness, pipe inclination, bin-filling trajectory, and storage stacking limit. Third, the proposed parameters should be validated through field or pilot-scale tests using measurable outputs such as damage rate, bruise volume, fruit throughput, operating cost, and postharvest quality retention. This approach would convert biomechanical characterization from descriptive testing into a practical design tool for low-damage mechanized harvesting and handling systems.

To clarify the positioning of these two methods within the broader research field, Table 4 provides a comparative summary of their key characteristics, loading parameters, and target evaluation indices.

Table 4. Comparative summary of quasi-static compression and drop tests, including methodological strengths, limitations, and sources of variation in fruit mechanical damage evaluation.

Feature	Quasi-Static Compression	Drop Test (Dynamic Impact)
Loading rate	Low/constant, e.g., 1–10 mm min ^{−1}	High/transient, variable velocity
Simulated scenario	Storage and slow conveying compression	Harvesting, dropping, and vibration
Key parameters	Elastic modulus, yield strength, stiffness	Peak acceleration, impact energy, rebound
Damage/loss evaluation	Static damage area, failure energy	Bruise volume, energy dissipation rate
Main advantage	Precise biomechanical characterization	High-fidelity simulation of operational impacts
Main limitation	Dynamic energy transfer is ignored	Highly sensitive to sample mass and geometry

5. Detection Methods for Spatial Information on Mechanical Damage Regions in Fruits and Vegetables

Accurate detection of mechanical damage is essential for converting biomechanical testing results into practical grading, handling, and equipment-control decisions. For the Korla fragrant pear, the key detection target is not limited to visible surface defects, but also includes early bruising, peel blackening, subsurface tissue failure, internal cracks, and three-dimensional bruise volume. Traditional manual slicing and visual estimation can provide direct evidence of damaged tissue, yet they are destructive, subjective, low-throughput, and difficult to reproduce. Therefore, recent research has shifted toward instrumental detection methods, including machine vision, hyperspectral imaging (HSI), scanning electron microscopy (SEM), and X-ray CT/micro-CT. These methods differ in detection depth, spatial resolution, throughput, cost, invasiveness, and suitability for laboratory or field use. A critical issue is that many published models report promising accuracy under controlled conditions, while their robustness under real orchard or packing-line conditions remains insufficiently validated.

5.1. Machine Vision for Surface Damage Detection and Online Grading

Machine vision is the most practical method for rapid and nondestructive surface inspection because it can be integrated with conveyor-based grading and sorting systems. Its typical workflow includes image acquisition, preprocessing, feature extraction, classification, and damage-region segmentation. For the Korla fragrant pear, Mei et al. developed a low-cost visible-LED structured-illumination reflectance imaging system for early bruise detection. The system demodulated structured-light images into DC, AC, and ratio images, extracted GLCM-based texture features, and established classification models for different bruising degrees (Figure 11) [62]. Liang et al. developed an RGB image-processing method for extracting the edge of apple impact-damage regions, which enabled automatic measurement of damaged areas after calibration [63]. These studies show that machine vision can quantify external bruise morphology and provide measurable outputs such as defect contour, surface area, and location.

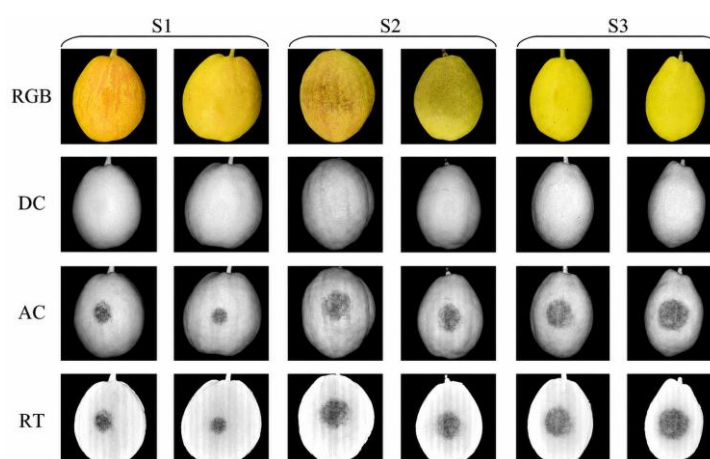


Figure 11. Representative RGB, DC, AC, and RT images of ‘Korla’ pears with different bruising degrees [62]. RGB images show visible appearance, whereas DC, AC, and RT images show structured-illumination-derived grayscale features.

Deep learning has further improved fruit detection under complex visual conditions. Ji et al. improved YOLOv4 by introducing the lightweight EfficientNet-B0 backbone, reducing model parameters by 87.8% while maintaining apple localization ability in complex scenes [64]. Sun et al. combined ResNet-50 with K-means clustering to optimize

Faster R-CNN and improve model adaptability under different environmental conditions (Figure 12) [65]. Tang et al. proposed an improved SOLOv2 model with a lightweight spatial attention module for occluded fruit recognition [66]. These studies are valuable for harvesting robots because fruit localization, occlusion handling, and segmentation accuracy directly influence grasping decisions and collision avoidance.



Figure 12. Examples of model detection [65].

Nevertheless, machine vision still faces clear limitations when used for mechanical-damage assessment. First, conventional RGB images mainly capture surface color, texture, edge, and shape. Internal bruising without surface discoloration can be missed, especially during the early post-impact period. Second, model performance is highly sensitive to illumination, shadows, fruit overlap, reflective surfaces, background complexity, and irregular bruise morphology [67–69]. Third, many image-processing methods are based on two-dimensional information, while bruises, dents, cracks, and cuts have three-dimensional geometry and variable depth. RGB-D imaging partly addresses this limitation. Hu et al. and Tang et al. fused two-dimensional pixel coordinates with depth data and achieved localization errors below 7 mm in the X, Y, and Z directions [70]. Yang et al. proposed the YOLO-GS model based on Ghost convolution, achieving an accuracy of 95.7% under complex environmental conditions [71]. These data indicate that depth and lightweight feature fusion can improve practical robustness, but the reported performance is mainly related to recognition and localization rather than internal damage quantification.

For field application, the main gap is the lack of Korla-fragrant-pear-specific online datasets that cover different maturity stages, lighting conditions, bruise severities, post-impact storage times, fruit orientations, and peel-color variation. Future studies should report not only accuracy, but also precision, recall, F1-score, mAP, detection speed, false-negative rate for early bruises, and fruit throughput. Without these indicators, it is difficult to determine whether a machine-vision system can be transferred from laboratory imaging to commercial grading lines or harvesting platforms.

5.2. Hyperspectral Imaging Technology

HSI combines imaging and spectroscopy and can detect spectral changes associated with tissue injury before obvious surface symptoms appear [72–75]. Compared with RGB machine vision, HSI provides spatial and spectral information across a wider wavelength range, making it more suitable for early bruising, latent tissue damage, and biochemical changes caused by mechanical stress. The main advantage of HSI over conventional

machine vision is its ability to capture damage-related spectral responses before visible symptoms become obvious. Conventional RGB machine vision mainly detects changes in surface color, texture, edge, and shape and is therefore more suitable for visible bruises, peel defects, and external damage-region segmentation. However, early mechanical injury often begins with subsurface cell rupture, moisture redistribution, enzymatic browning, and changes in light absorption or scattering that may not immediately produce visible surface discoloration. HSI can record both spatial location and wavelength-dependent reflectance information, allowing early bruises, latent tissue damage, and biochemical changes to be detected with higher sensitivity. In addition, characteristic wavelength selection and dimensionality reduction can reduce redundant spectral data and support the development of faster multispectral or simplified HSI systems for grading lines. Therefore, HSI is particularly valuable as a second-layer detection method after rapid RGB screening, especially for high-value fruit sorting, early bruise classification, and calibration of lower-cost machine-vision models. Nevertheless, its industrial application still requires improvement in acquisition speed, model simplification, illumination stability, and Korla-fragrant-pear-specific validation under real conveyor conditions.

For the Korla fragrant pear, Fang et al. selected high-quality images at 863 nm to construct mask images and combined dimensionality reduction, adaptive threshold segmentation, and morphological operations. The method achieved a damage recognition accuracy of 93.75% [76]. This is one of the most relevant direct pieces of evidence for the Korla fragrant pear. Because this study directly examined Korla fragrant pear damage detection, it was treated as Level I evidence. By contrast, HSI studies on apple or other fruits were treated as Level III or Level IV evidence and were used mainly to support methodological transferability rather than direct performance expectations for the Korla fragrant pear. The general HSI workflow includes spectral image acquisition, hypercube construction, preprocessing, dimensionality reduction, feature extraction, and classification or segmentation (Figure 13) [77]. Li et al. combined HSI with mechanical parameters to predict the impact-damaged area in the Gong pear using a PLSR model. The prediction set correlation coefficient was $RP = 0.895$, and RMSEP was 54.411 mm^2 [78]. These data show that HSI can provide quantitative estimates of damage severity, rather than simple binary classification.

Evidence from apples and other fruits also supports the value of HSI as a transferable detection method. Zhu et al. acquired spectral scattering images of 300 ‘Golden Delicious’ apples in the 500–1000 nm range and calculated bruise volume using spectral scattering characteristics and an image-based model [79]. Zhang et al. analyzed the relationship between reflectance and mechanical impact energy and found that the fruit damage index increased with drop height [80]. Representative classification maps show that visible/near-infrared HSI can visualize hidden or early-stage apple bruising that is difficult to distinguish with RGB imaging (Figure 14) [81]. HSI has also been applied to sulfur adulteration detection in goji berries [82] and green tea variety identification [83], demonstrating its broader ability to detect subtle spectral differences in agricultural products.

HSI also supports visualization of spatial distribution. Dai et al. applied a CARS-SVR model to each pixel of hyperspectral images to generate pseudocolor maps of lycopene distribution in tomatoes at different maturity stages (Figure 15) [84]. A similar visualization has been used for moisture distribution in lettuce leaves [85]. These examples are methodologically relevant because bruise formation is linked to spatially heterogeneous changes in moisture, pigment, cell integrity, and optical scattering.

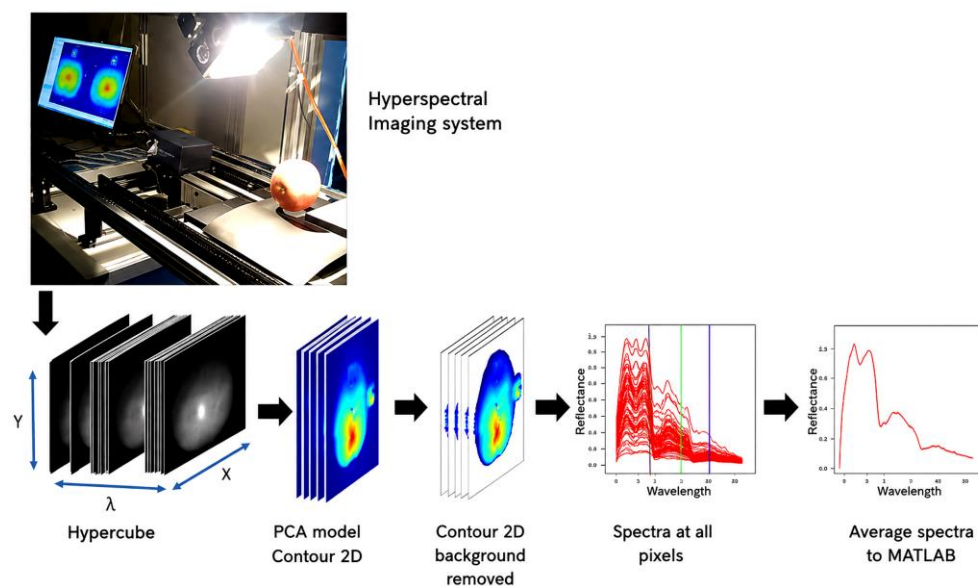


Figure 13. Hyperspectral imaging acquisition and analysis workflow for fruit bruise detection [77]. Pseudo-color maps and colored spectra represent hyperspectral intensity/features at different processing stages, and arrows indicate the analysis workflow.

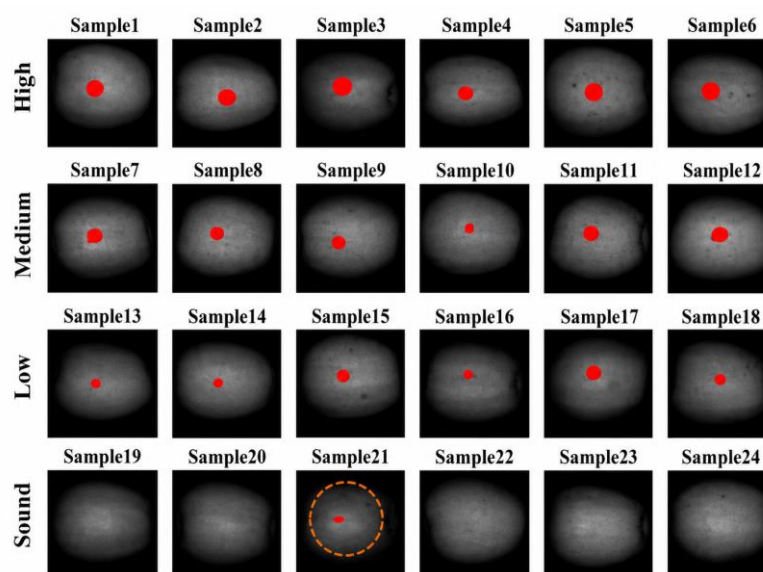


Figure 14. Visualization of apple bruise classification results using visible/near-infrared multispectral images. Red pixels indicate bruise-region pixels identified by the LDA classification model and overlaid on the 553.9 nm band image. The dashed circle highlights the false-positive region/sample generated by the model [81].

The main limitation of HSI is the gap between laboratory detection and operational use. HSI instruments are more expensive and data-intensive than RGB cameras. Image acquisition and spectral calibration are sensitive to illumination, scanning speed, fruit curvature, surface reflection, and temperature. Many studies still rely on threshold segmentation or morphological filtering, which provides limited three-dimensional information. HSI can identify early bruise-related spectral changes, but it cannot directly reconstruct internal bruise volume in the same way as CT. Yang et al. emphasized the need for lightweight models and stronger cross-cultivar generalization; integration with physical damage-evolution models may help shift HSI from static detection toward analysis of bruise formation and development [86]. For the Korla fragrant pear, future work should test

whether HSI models trained under controlled impact conditions remain accurate after storage, vibration, real conveying, and mixed maturity conditions.

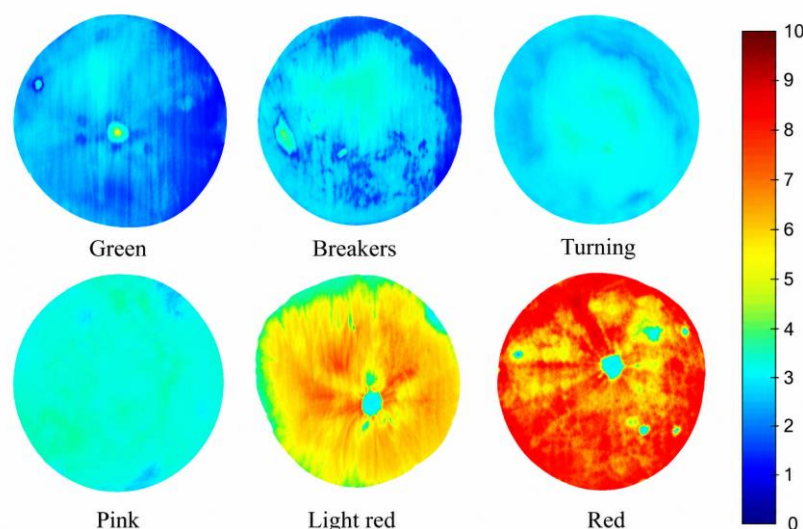


Figure 15. Visualization of lycopene distribution at different maturity stages using hyperspectral imaging [84].

5.3. SEM for Microstructural Verification of Damage Mechanisms

SEM is mainly a mechanism-verification method. It provides high-resolution images of tissue microstructure after mechanical, thermal, or chemical loading [87,88]. Mechanical injury begins at the cellular and intercellular levels: stress concentration, cell wall rupture, middle lamella failure, enlarged intercellular spaces, and cell collapse eventually appear as macroscopic bruising or softening. Therefore, SEM is useful for linking external loading with microscopic tissue failure.

Liu et al. and Li et al. used SEM to compare the micromorphology of the Korla fragrant pear under compression and impact with that of undamaged samples [50,89]. Their observations showed changes in cellular geometry, intercellular spacing, and cell wall integrity. Qu et al. used SEM in tomato peeling research and showed that flame-catalytic infrared peeling caused less structural damage than conventional methods [90]. Although this example does not focus on fruit bruising, it demonstrates how SEM can verify whether a treatment preserves cellulose- and pectin-related tissue structures.

SEM has also been used to provide quantitative information. Nikara et al. and Chavoshi et al. measured the depth and area of damaged regions in potato and ‘Golden Delicious’ apple using SEM images and estimated damage volume through empirical equations [91,92]. These studies indicate that SEM can detect early tissue disruption at the micrometer scale. SEM has also been used to study pathogen infection and physical cell damage. Apaliya et al. evaluated the inhibition of fungal growth in grapes by trehalose-pretreated yeast [93], while Wahia et al. used SEM to observe membrane perforation caused by pulsed multifrequency ultrasound, revealing the mechanism of mechanical cavitation [94].

For the Korla fragrant pear, SEM should be used as supporting evidence for the damage mechanism rather than as a grading tool. Figure 16 illustrates cellular structural features associated with damage. Wu et al. linked microstructural differences in peel and flesh of Huangguan pear with macroscopic load-bearing capacity [95], showing that cellular structure affects mechanical resistance. The limitation is clear: SEM sample preparation is complex, destructive, time-consuming, and unsuitable for online detection. It also provides only local surface or fractured-surface information, so it cannot reconstruct the

full three-dimensional bruise volume. Future SEM studies should be combined with compression or impact tests, CT-derived internal bruise volume, and postharvest quality measurements. This would make SEM evidence more useful for explaining why the same external load may produce different bruise outcomes under different maturity or storage conditions.

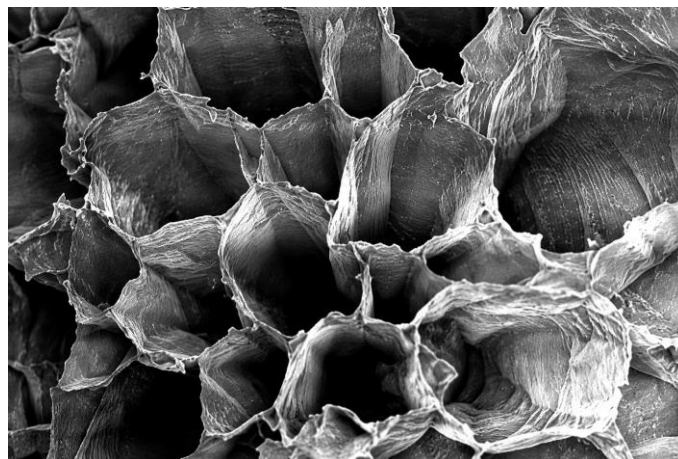


Figure 16. SEM images of fruit cell structure [58].

Although SEM is valuable for revealing cellular-level damage mechanisms, it is not suitable for large-scale fruit damage detection or online grading. Its main limitations include destructive sampling, complex sample preparation, dehydration or coating artifacts, high equipment cost, small observation area, low throughput, and limited representativeness of whole-fruit damage. SEM mainly provides micro-surface or section-level information and cannot directly reconstruct three-dimensional bruise volume or screen large fruit batches in real time. Therefore, SEM should be used as a mechanism-verification tool to confirm cell wall rupture, enlarged intercellular spaces, cell collapse, and tissue structural failure under selected impact, compression, or friction conditions, rather than as a routine detection method for industrial grading lines.

5.4. X-Ray CT and Micro-CT for Internal Damage Reconstruction

X-ray CT and micro-CT provide nondestructive visualization of internal three-dimensional structures. CT can penetrate opaque fruit tissues, obtain two-dimensional slices, and reconstruct internal morphology in three dimensions. This makes it suitable for localizing and quantifying internal bruises, cracks, cavities, voids, and physiological disorders. Figures 17 and 18 show representative X-ray-based visualization examples for internal defects in pome fruit and pear tissues [96,97].



Figure 17. Image of a pear after X-ray image data enhancement [96].

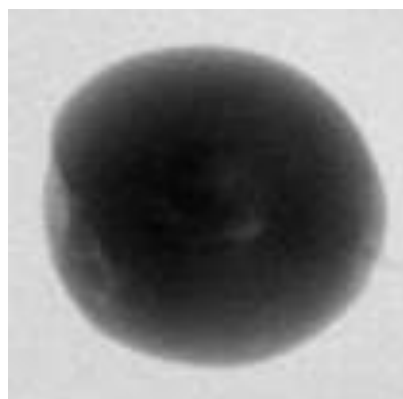


Figure 18. Representative X-ray images for nondestructive detection of internal defects in pears [97].

Diels et al. applied multilevel Otsu thresholding to CT images to separate bruised regions from normal tissues based on density differences, providing an objective method for bruise-volume characterization [98]. Sun et al. used CT to analyze puffing disorder in satsuma mandarin and found that the disorder increased flesh-layer porosity ([99]). Nie et al. combined X-ray imaging with GLCM, gray-gradient co-occurrence matrix features, and a random forest algorithm, achieving 93.10% accuracy in detecting pomegranate heart rot, an internal defect without obvious external symptoms [100]. These studies show that X-ray-based methods are useful when external appearance does not reliably indicate internal condition.

CT-based analysis can also link biological structure with mechanical modeling. Kumi et al. quantified the porosity of tomato seedling growth substrates, ranging from 11.3% to 52.8%, and combined CT with FEA to analyze stress distribution [101]. Although this study concerns growth substrates rather than fruit bruising, it demonstrates that CT-derived structural data can support numerical simulation. Van de Looverbosch et al. proposed a DNN-based semantic segmentation method to quantify internal disorders in ‘Conference’ pears ([102]). This direction is important because manual CT segmentation is time-consuming and sensitive to threshold selection, image noise, and artifacts.

For Korla fragrant pear, CT and micro-CT have strong value as reference methods for internal damage quantification. They can provide ground-truth bruise volume for validating machine vision, HSI, and FEM/DEM models. Their main constraints are high equipment cost, low throughput, radiation-safety requirements, data-processing burden, and limited compatibility with commercial sorting lines. Therefore, CT should be positioned as a laboratory validation and model-calibration tool rather than a routine online grading method. Future studies should use CT to establish internal bruise-volume datasets under known impact energy, drop height, contact surface, fruit maturity, and storage time. These datasets can then support lower-cost online detection systems.

5.5. Comparative Evaluation, Research Gaps, and Practical Outcomes

The reviewed detection methods provide complementary information. Machine vision is suitable for high-throughput surface screening, but it is weak for invisible internal bruising. HSI is more sensitive to early or latent damage, but it is limited by cost, calibration complexity, and lack of direct three-dimensional reconstruction. SEM provides cellular-level evidence of damage mechanisms, but it is destructive and low-throughput. X-ray CT/micro-CT enables three-dimensional internal damage quantification, but it is expensive and currently unsuitable for routine online grading. Therefore, detection systems for Korla fragrant pear should be designed according to purpose: RGB or RGB-D imaging for rapid surface inspection and robotic localization, HSI for early bruise classification, SEM for mechanism verification, and CT/micro-CT for internal bruise-volume ground truth.

This method-specific positioning provides the basis for the comparative evaluation summarized in Table 5.

Table 5. Comparative evaluation of machine vision, HSI, SEM, and X-ray micro-CT for fruit damage detection, including detection depth, throughput, limitations, and practical applicability.

Feature	Detection Depth	Throughput	Invasiveness	Key Limitation
Machine Vision	Surface only	High (Online)	Nondestructive	Sensitive to lighting
SEM	Micro-surface	Low	Destructive	Complex prep
HSI	Subsurface (early)	Moderate	Nondestructive	Challenging 3D
X-ray Micro-CT	Full 3D Internal	Low	Nondestructive	High equipment cost

The main research gap is the lack of an integrated detection framework for the Korla fragrant pear. Most studies focus on single methods and report accuracy under controlled conditions. Fewer studies evaluate cross-season robustness, mixed maturity, real conveying vibration, post-impact storage evolution, fruit overlap, dust, variable lighting, or field-to-packing-line transfer. In addition, detection accuracy alone is insufficient for practical application. Future studies should report detection speed, throughput, false-negative rate for internal damage, model size, computational cost, external validation performance, equipment cost, and compatibility with grading lines.

For practical application, this review recommends a hierarchical detection pathway rather than a single machine-vision model. In this pathway, RGB or RGB-D machine vision is used as the first screening layer for high-speed surface-defect detection and fruit localization on conveyor-based grading lines. HSI is then used as a second layer for early bruising or latent tissue damage in high-value sorting or model calibration. CT-derived bruise volume can provide ground-truth data for validating lower-cost imaging models, while SEM can be used selectively to confirm cellular damage mechanisms. Compared with conventional single RGB-based detection, this pathway may improve detection accuracy by combining surface, spectral, depth, and internal-reference information; improve processing speed by reserving rapid machine vision for online screening and using HSI or CT only for selected samples or calibration; and improve robustness by requiring Korla-fragrant-pear-specific datasets covering different maturity stages, bruise severities, post-impact storage times, fruit orientations, peel-color variation, dust, vibration, and variable lighting. However, these advantages should be regarded as design expectations that require validation under real packing-line conditions. Future studies should report precision, recall, F1-score, mAP, false-negative rate for early bruises, detection speed, fruit throughput, model size, computational cost, and external validation performance under industrial operating conditions.

6. Numerical Simulation of Fruit Mechanical Damage Based on DEM and FEM

6.1. Role of Numerical Simulation in Damage Prediction and Engineering Design

Numerical simulation provides a bridge between controlled biomechanical tests and the design of low-damage harvesting and handling equipment. Physical experiments are indispensable for obtaining material parameters and validating damage thresholds, but they are difficult to use alone for all possible combinations of fruit maturity, impact angle, contact material, conveying speed, bin-filling height, and fruit-to-fruit collision. This limitation is especially relevant during harvesting, conveying, and transportation, where fruit is exposed to coupled compression, impact, rolling, sliding, vibration, and repeated contact. Therefore, the practical value of numerical simulation should be judged by whether it can produce engineering outputs, such as predicted contact force, deformation, stress

distribution, absorbed energy, bruise area, bruise volume, collision trajectory, and safe operating ranges.

Two methods dominate current fruit-damage simulation: the FEM and the DEM. FEM treats fruit tissue as a continuous medium and is therefore suitable for analyzing internal stress–strain distributions, local deformation, compression injury, and tissue-layer response. DEM represents fruit or tissue as assemblies of discrete particles or bonded elements, making it more suitable for multibody contact, rolling, sliding, accumulation, particle separation, and dynamic collision. These methods are complementary. FEM is stronger for single-fruit internal mechanical response, while DEM is stronger for fruit–fruit and fruit–machine interaction during conveying and bin filling.

For the Korla fragrant pear, numerical models should not only reproduce mechanical curves observed in the laboratory. They should also support equipment design decisions, including maximum allowable gripping force, safe transfer height, suitable cushioning stiffness, conveying angle, fruit spacing, pipe inclination, bin-filling trajectory, and vibration-control strategy. At present, most available models are derived from apple, potato, tomato, pepper, or other agricultural materials. These studies provide useful modeling frameworks, but their parameters and predicted thresholds require cultivar-specific validation before application to the Korla fragrant pear.

6.2. Geometry Representation and Material-Parameter Requirements for Fruit-Damage Simulation

For the Korla fragrant pear, geometry and tissue structure should be modelled according to the simulation objective. For DEM analysis of conveying, rolling, collision, and bin filling, the fruit geometry can be simplified as a multi-sphere, ellipsoidal, or scanned irregular model, but the selected shape should reproduce the main contact curvature and mass distribution affecting collision force, rebound, and accumulation behavior. For FEM analysis of compression, gripping, impact stress, and local bruising, a more realistic three-dimensional geometry obtained from 3D scanning or CT reconstruction is preferable. Because the Korla fragrant pear has a thin peel and crisp flesh, a homogeneous single-material model may underestimate local stress concentration near the contact surface. Therefore, peel–flesh layered modeling is recommended when the objective is to predict peel rupture, friction-induced peel blackening, local indentation, or internal bruise initiation. The peel layer should be assigned independent thickness, elastic modulus, strength, and frictional properties, while the flesh should be described using cultivar-specific elastic, viscoelastic, or hyperelastic parameters. Moisture content should also be included in parameter calibration because it affects density, elastic modulus, firmness, damping, restitution coefficient, friction coefficient, and energy dissipation. Changes in moisture during maturation or storage may alter bruise susceptibility and should therefore be reported together with maturity stage, storage temperature, loading direction, and contact material. These requirements would improve the reliability of FEM, DEM, and coupled FEM–DEM models for predicting Korla-fragrant-pear damage under practical harvesting and handling conditions.

6.3. DEM-Based Simulation of Fruit Mechanical Damage

6.3.1. Geometry Representation and Contact Modeling

DEM describes fruit as a collection of interacting particles. The movement of each particle is calculated independently, while contact force, friction, damping, and bond breakage are determined by contact-mechanics laws. Early DEM models simplified fruit as single spheres, but this treatment cannot capture asymmetric shape, local curvature, rolling path, or realistic contact area. More recent models use multi-sphere clusters, polyhedral particles, bonded particle models (BPMs), and multi-ring models (MRMs) to approximate irregular

fruit geometry. MRMs, for example, can describe non-arrayed and asymmetric apple shapes and improve the simulation of contact dynamics (Figure 19) [103].



Figure 19. A representative apple (asymmetric) modelled by MRM [103].

For fruit tissues with heterogeneous structures, DEM models increasingly assign different mechanical properties to particle groups representing peel, flesh, and core. BPMs allow interparticle bonds to fail when stress or strain exceeds a threshold, so they can be used to describe local tissue rupture, crack initiation, and damage evolution. Liu et al. developed a miniature potato model based on material properties and combined physical testing with simulation to calibrate DEM parameters [104]. This type of calibration strategy is relevant for the Korla fragrant pear because model parameters such as particle stiffness, damping, bond strength, friction coefficient, and restitution coefficient cannot be transferred directly from other fruits.

The main advantage of DEM is its ability to describe discontinuous behavior. Fruit rolling on a conveyor, collision between adjacent fruit, accumulation in bins, and particle-level fracture can be represented more naturally with DEM than with continuum-based FEM. However, a higher number of particles improves geometric fidelity while increasing contact-detection calculations. This creates a trade-off between accuracy and computational time. For practical equipment design, DEM models should therefore balance anatomical realism with simulation efficiency.

6.3.2. Parameter Calibration and Quantitative Evidence

The reliability of DEM depends on calibrated microscopic parameters, including normal stiffness, tangential stiffness, friction coefficient, rolling resistance, damping coefficient, restitution coefficient, and bond strength. These parameters are usually obtained through inverse calibration because they cannot be measured directly by standard compression or drop tests. Common calibration methods include direct shear tests, ring shear tests, slope tests, drop tests, response surface methodology (RSM), Box–Behnken design, three-dimensional scanning, and sensitivity analysis.

Several studies provide useful quantitative evidence for calibration accuracy. Du et al. combined three-dimensional scanning with RSM to determine the static and rolling friction coefficients of complex-shaped pepper, obtaining values of 0.21 and 0.10, respectively, with a validation error within 3.35% [105]. Chen et al. used a Box–Behnken design for eight-factor, three-level calibration of pepper seeds and validated the results using a t-test [106]. For microscale materials, Shi et al. introduced the Johnson–Kendall–Roberts contact model and atomic force microscopy to calibrate Young’s modulus and surface energy of tomato pollen, with an error of 1.01% [107]. Zhang et al. also calibrated pepper seeds using three-dimensional scanning and RSM, with an error within 3.35% [108]. Liang

et al. calibrated the contact parameters of Red Fuji, Huaniu, and Golden Delicious apples using EDEM, controlling the relative error of the angle of repose within 5.95–8.67%; for auxiliary materials such as cotton stalks, particle-cluster modeling, and RSM were used to identify the main parameters affecting the angle of repose [109].

These studies show that DEM calibration can reach acceptable errors under controlled conditions. However, their transferability to the Korla fragrant pear remains limited for three reasons. First, several calibration targets, such as angle of repose or seed flow behavior, are not directly related to fruit bruising. Second, the calibrated materials differ greatly from the fragrant pear in geometry, surface texture, tissue structure, and moisture state. Third, many models validate macroscopic movement or accumulation behavior but do not validate bruise area, bruise volume, or post-impact quality. Therefore, DEM calibration for the Korla fragrant pear should use damage-related validation targets, including collision force, rebound height, contact duration, bruise area, bruise volume, rolling distance, and fruit-to-fruit collision frequency.

6.3.3. Applications in Damage Simulation

DEM has been applied to quasi-static compression, free-fall impact, fruit-to-fruit collision, rolling, accumulation, and conveying analysis. In quasi-static simulations, it can reveal force-chain transmission and estimate damage thresholds. Studies on maize kernels reported uniaxial compression simulation errors as low as 3.25–3.90%, indicating that DEM can reproduce compression responses when particle properties are properly calibrated. For drop and impact conditions, DEM has also been used to simulate dynamic responses during free fall. Studies on ‘Jonagold’ apples showed that a 50-sphere model could predict landing position with low error, while contact-force prediction error remained within 11%.

More complex DEM models attempt to describe bruise formation directly. Scheffler et al. developed a clustered-particle apple model and a viscoelastic–plastic model in PFC3D. The reported calculation errors for bruise volume, bruise area, and bruise depth were 47%, 35%, and 30%, respectively [110]. These errors are relatively large, but they are informative because they show that predicting bruise morphology is more difficult than predicting fruit trajectory or contact force. Kafashan et al. used a viscoelastic nonlinear contact model to calculate the normal force between colliding particles and highlighted the importance of realistic shape modeling. Numerical visualization of stress propagation in pear fruit under impact loading also shows that DEM can identify high-risk bruising regions (Figure 20) [111,112]. Yang et al. improved damage prediction by establishing a tissue-scale apple model with a parallel bond model in PFC3D and validating it against micro-CT-derived damage volume and resistance indices. The relative error of the bruise resistance index was only 3.27% [113].

Taken together, these data indicate that DEM prediction accuracy varies strongly with model scale, fruit geometry, damage criterion, and validation method. Errors ranging from 3.27% to 47% suggest that DEM should not be considered universally reliable without case-specific validation. For the Korla fragrant pear, DEM is most suitable for simulating fruit movement and contact behavior in conveying systems, including fruit spacing, rolling trajectory, belt speed, pipe inclination, accumulation pattern, and bin-filling behavior. To make DEM practically useful, future studies should connect simulation outputs with measurable engineering variables: maximum contact force, collision frequency per fruit, impact velocity, residence time in the conveying path, predicted bruise probability, and throughput under different operating speeds.

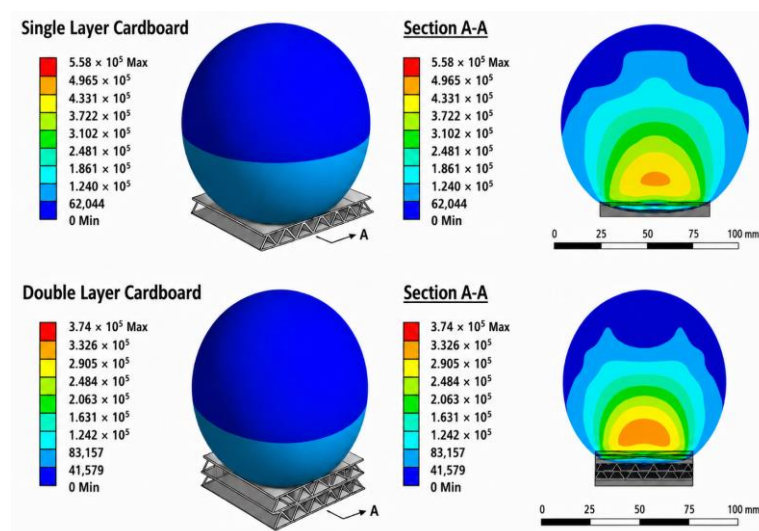


Figure 20. Stress comparison of single- and double-layer cardboard packages under a 1 m drop height [112]. The left panels show the overall simulation models, and the right panels show the Section A–A views. Section A–A represents the half-side sectional view cut along the x-axis, which visualizes the distribution and propagation of maximum von Mises stress inside the pear at the peak stress-concentration stage.

6.3.4. Barriers to Practical Use of DEM

The major barrier to applying DEM in real harvesting systems is the gap between calibrated laboratory models and uncontrolled field conditions. Laboratory DEM models usually assume stable fruit size, uniform maturity, simple contact surfaces, fixed initial position, and controlled impact angle. In orchards and packing lines, fruit mass, surface moisture, maturity, stem orientation, local curvature, dust, branch contact, belt vibration, and neighboring fruit all change the contact state. A model calibrated for a single fruit or a small group of fruit may fail when scaled to hundreds of fruit moving through a conveyor or filling a bin.

Another limitation is computational cost. Multi-sphere or bonded-particle models improve geometry and damage representation, but large-scale simulations require many contact-detection cycles. Simplified single-sphere models reduce computation time, yet they cannot capture asymmetric rolling, local curvature, multiple contact points, or realistic bruise location. In PFC3D, cluster structures may introduce contact-force errors when local curvature is calculated from constituent sphere radii. In EDEM, using bond-breakage counts to quantify damage may oversimplify tissue injury because cell collapse, water movement, and enzymatic browning are not represented. Therefore, DEM should be used with clear boundaries: it is powerful for dynamic contact and motion analysis, while direct prediction of tissue-level bruise formation requires stronger validation and possibly coupling with FEM or CT-based damage measurement.

6.4. FEM-Based Simulation of Fruit Mechanical Damage

6.4.1. Model Construction and Parameter Acquisition

FEM discretizes fruit geometry into finite elements and calculates continuous displacement, strain, and stress fields under defined loading and boundary conditions. A typical FEM workflow includes fruit geometry acquisition, mesh generation, material-property assignment, definition of contact pairs, boundary-condition setting, solution, and validation. Geometry can be obtained from idealized ellipsoids, three-dimensional scanning, MRI, CT, or sliced images. Meshes generally consist of tetrahedral or hexahedral elements. Material properties are obtained from compression tests, tensile tests, shear tests,

nanoindentation, or inverse analysis. FEM models of fresh fruit tissues often distinguish peel, flesh, core, and contact material layers when sufficient data are available [114–122].

FEM is especially useful for visualizing internal stress concentration. For example, it can identify whether high stress appears near the peel, under the contact point, around the core, or along the stem–calyx axis. This is important because fruit may exhibit internal bruising even when surface deformation is small. FEM can also compare different cushioning materials and loading conditions by predicting peak stress, maximum strain, plastic deformation, and energy absorption. Figure 21 illustrates FEM modeling of fresh fruit tissue [119].



Figure 21. FEM modeling of fresh fruit tissue [119].

However, FEM model quality depends on material assumptions. Many studies simplify fruit tissue as isotropic, homogeneous, and linear elastic. These assumptions reduce computational complexity, but fruit tissues are layered, anisotropic, viscoelastic, and maturity dependent. For the Korla fragrant pear, reliable FEM modeling requires separate measurement of peel and flesh properties, including elastic modulus, Poisson's ratio, yield stress, rupture stress, failure strain, density, and viscoelastic parameters. Contact properties such as friction coefficient and restitution coefficient should also be measured for relevant materials, including belts, foam pads, plastic tubes, bin surfaces, and fruit surfaces.

6.4.2. Applications in Damage Simulation and Engineering Design

FEM has been applied to storage compression, impact, packaging optimization, and dynamic collision. Elastoplastic models are commonly used to simulate permanent deformation, while the von Mises criterion is used to identify the transition from elastic to plastic deformation [123,124]. In tomato, finite element results showed that yield cells were concentrated near the peel and along the stem–floral axis, indicating that tissue geometry and anatomical direction affect damage-prone regions. Deng et al. combined three-dimensional scanning with LS-DYNA to simulate a transient collision between a potato and different contact materials. The average error was 3.95–5.04% [125]. Celik et al. simulated pear drop impacts at different heights and angles and established a bruise susceptibility prediction model with a maximum relative error of 7.03% [126]. FEM has also been used for packaging optimization; simulations of ventilated cardboard packaging showed that maximum stress occurred at corners, supporting structural optimization to reduce fruit damage [114,115].

These results demonstrate that FEM can provide practical design information. For example, if FEM identifies stress concentration at a conveyor transfer point, the design can be adjusted by lowering transfer height, increasing cushioning thickness, reducing material stiffness, changing contact curvature, or modifying fruit trajectory. If FEM predicts excessive stress during gripping, the end-effector can be redesigned using a larger contact

area, lower clamping force, softer material, or adaptive pressure control. Therefore, FEM should be evaluated by its contribution to design choices rather than by visual stress nephograms alone.

FEM is effective for predicting fruit damage when the dominant process involves continuous deformation, local contact pressure, internal stress concentration, compression injury, or single-fruit impact response. It can identify damage-prone regions, compare cushioning materials, and provide engineering outputs such as contact force, deformation, stress distribution, absorbed energy, and safe loading ranges. Previous FEM studies have reported relatively small prediction errors under controlled impact or collision conditions, indicating that FEM can support equipment design and parameter optimization. However, its predictive reliability depends strongly on accurate material properties, fruit geometry, boundary conditions, contact parameters, and damage criteria. FEM is less reliable when tissue rupture, crack propagation, repeated collision, fruit-to-fruit contact, vibration, or post-impact biological deterioration dominate. For the Korla fragrant pear, FEM predictions should therefore be validated using cultivar-specific data, including peel and flesh properties, bruise area, bruise volume, rebound behavior, firmness loss, and post-storage browning or decay.

At the same time, existing FEM studies still lack several elements needed for field application. Many models validate only force–deformation curves or peak acceleration, while bruise area, bruise volume, internal tissue failure, and post-impact decay are less frequently validated. Damage criteria are often borrowed from other fruit or fitted from small experimental datasets. Repeated impacts, vibration, temperature changes, storage duration, and fruit-to-fruit contact are also difficult to include in a single FEM model. Therefore, FEM models for the Korla fragrant pear should be validated using both mechanical outputs and biological damage outputs: contact force, deformation, rebound height, bruise area, bruise volume, browning development, firmness loss, and decay incidence after storage.

6.4.3. Limitations of FEM

The main limitation of FEM is its dependence on continuum assumptions. FEM performs well when deformation is continuous, but it becomes less stable when tissue rupture, crack propagation, fragmentation, or large discontinuous deformation occurs. In such cases, cohesive elements, extended finite element methods, remeshing, or element-deletion strategies are required, increasing model complexity and computational cost. Multiscale modeling that links cellular structure with whole-fruit deformation is also difficult because tissue geometry, cell size, water distribution, and cell-wall failure are not easily incorporated into large-scale fruit models [91].

Another limitation concerns the estimation of damage volume. FEM often predicts stress, strain, or plastic deformation, and bruise volume is then inferred using empirical relationships from physical tests. If these empirical equations are cultivar-specific or sensitive to maturity and storage time, their uncertainty is transferred into the simulation result. This is one reason why FEM models developed for pear, apple, potato, or tomato should be treated as methodological references for the Korla fragrant pear rather than direct predictive tools.

6.5. FEM–DEM Comparison and Coupled Modeling

FEM and DEM should be selected according to the dominant mechanical process. FEM is appropriate for continuous deformation, internal stress analysis, tissue-layer response, local contact pressure, and damage-prone region identification. DEM is appropriate for fruit movement, rolling, sliding, fruit-to-fruit collision, accumulation, and bulk conveying. Their main differences are summarized in Table 6.

Table 6. Comparative characteristics, strengths, limitations, applicable scenarios, and key parameters of FEM and DEM for fruit mechanical damage simulation.

Comparative Dimension	DEM	FEM
Fundamental principle	A collection of discrete and independent particles; governed by Newton's second law	Discretization of a continuum into finite elements; governed by constitutive equations
Constitutive/contact model	Hertz–Mindlin model, BPM, parallel bond model	Linear elastic, viscoelastic, hyperelastic
Tissue representation	Multi-sphere models, clusters, or polyhedral particles	Three-dimensional meshes, including hexahedral/tetrahedral elements,
Damage mechanism	Breakage of interparticle bonds; separation of elements	Stress/strain thresholds; von Mises yield criterion; cohesive elements/extended FEM
Applicable damage types	Tissue fracture, particle separation, multibody collision, and bulk conveying	Internal bruising, stress distribution, sustained deformation, and vibration
Parameter calibration	Macroscopic calibration of stiffness, friction, and related parameters through inverse identification	Material property testing, including compression/tensile tests and nanoindentation
Computational efficiency	Relatively low, owing to the extremely high number of contact-detection cycles	Moderate to relatively high, depending on mesh density and nonlinearity

Recent research is moving toward FEM–DEM coupling because single-method models cannot fully describe the whole harvesting and handling process. FEM can analyze stress distribution inside an individual fruit, while DEM can describe contact and movement among multiple fruits and machine components. Coupled models have been used in agricultural materials and related mechanical systems [127–139]. For example, accurate acquisition of potato mechanical properties is necessary for constructing reliable discrete element models [140], while kinematic processes such as soil separation may require hybrid modeling strategies [141]. This logic is also applicable to the Korla fragrant pear: FEM can determine safe stress or strain thresholds for individual fruit, and DEM can apply those thresholds to simulate large-scale conveying and bin filling.

6.6. Research Gaps and Practical Outcomes for Korla Fragrant Pear

The reviewed numerical studies provide useful methods, but several gaps prevent direct transfer to real Korla fragrant pear harvesting and handling. Accordingly, most available FEM/DEM studies are classified as Level III or Level IV evidence for the Korla fragrant pear. They provide useful modeling frameworks and parameter-calibration strategies, but their predicted stress thresholds, collision responses, and damage criteria should be regarded as methodological references until validated with Level I Korla-fragrant-pear-specific data.

First, cultivar-specific parameters are insufficient. DEM and FEM require elastic modulus, Poisson's ratio, peel strength, flesh strength, density, friction coefficient, restitution coefficient, damping coefficient, and viscoelastic constants. These parameters vary with maturity, moisture status, storage temperature, loading direction, and contact material. Without Korla-specific datasets, models calibrated for apple, potato, pepper, or other pear cultivars cannot reliably predict fragrant pear bruising.

Second, validation targets are incomplete. Many studies validate only contact force, landing position, angle of repose, or deformation. For engineering design, validation should include bruise area, bruise volume, internal damage depth, browning development, firmness loss, decay rate, and commercial grading outcome. CT or micro-CT-derived bruise volume can serve as a reference for validating internal damage, while high-speed imaging can validate rebound, impact duration, and collision trajectory.

Third, laboratory models rarely reproduce field loading conditions. Actual harvesting and conveying involve repeated impact, oblique collision, rolling friction, branch contact, fruit-to-fruit collision, vibration, and variable orientation. A model validated under a single drop height or compression speed may fail when applied to chute conveying, belt transfer, bin filling, or transport vibration. Therefore, future models should include repeated-impact conditions, multiple contact materials, different fruit orientations, mixed maturity stages, and realistic equipment geometries.

Fourth, productivity and economic indicators are seldom linked with simulation outputs. A model may predict lower contact force after adding cushioning, but the same design may reduce throughput, increase energy consumption, or complicate cleaning and maintenance. To support practical adoption, simulations should report equipment-level outcomes such as predicted damage rate, fruit throughput, collision frequency, safe operating speed, power demand, and cost-related design implications.

For the Korla fragrant pear, the practical outcome of numerical simulation should be a parameterized design framework. FEM should define safe limits for gripping force, contact pressure, transfer impact, and tissue stress. DEM should optimize fruit spacing, conveying speed, pipe inclination, bin-filling path, and collision reduction. Coupled FEM–DEM models should connect internal stress thresholds with multi-fruit handling behavior. When validated against experimental bruise area, bruise volume, collision force, deformation behavior, rebound response, and post-impact quality, numerical simulation can become a decision-support tool for low-damage harvesting, conveying, and bin-filling systems rather than a descriptive modeling exercise.

6.7. Modeling Challenges for Korla Fragrant Pear Damage Prediction

Several modeling challenges limit the direct application of existing FEM and DEM models to the Korla fragrant pear. First, geometry representation remains difficult. Simplified spherical or ellipsoidal models are useful for DEM simulations of rolling, conveying, and bin filling, but they may not capture the asymmetric shape, local curvature, and mass distribution that influence contact force, rebound, and collision behavior. For FEM-based stress analysis, 3D scanning or CT-reconstructed geometry is preferable when predicting local indentation, contact stress, and bruise initiation.

Second, the peel–flesh structure should be considered according to the simulation objective. Owing to BSTs, homogeneous single-material models may underestimate stress concentration near the contact surface. Layered peel–flesh modeling is therefore recommended when simulating peel rupture, friction-induced peel blackening, local indentation, or internal bruise initiation. The peel and flesh should be assigned separate thickness, elastic modulus, strength, frictional, and viscoelastic properties.

Third, material parameters are strongly affected by moisture content, maturity, storage temperature, loading direction, and contact material. Moisture content influences density, firmness, elastic modulus, damping, restitution coefficient, friction coefficient, and energy dissipation. Therefore, simulation parameters should be calibrated under clearly reported fruit conditions. At present, many models are validated only against force–deformation curves or qualitative damage observations. For the Korla fragrant pear, future FEM/DEM models should be validated using bruise area, bruise volume, collision force, deformation, rebound response, and post-storage quality changes.

7. Future Research Priorities

Future research should focus on four priorities. First, standardized Korla-fragrant-pear-specific mechanical thresholds should be established under different maturity stages, temperatures, loading directions, and contact materials. Key parameters should

include rupture force, yield force, critical drop height, impact energy, contact force, absorbed energy, bruise area, and bruise volume.

Second, low-damage harvesting and conveying systems should be evaluated under real orchard and packing-line conditions. Future studies should report common engineering indicators, including damage rate, fruit throughput, transfer height, belt speed, cushioning stiffness, energy consumption, labor requirement, operating cost, and post-storage quality.

Third, nondestructive detection models should be developed using Korla-specific datasets that include visible bruises, early bruises, internal damage, peel blackening, different maturity stages, fruit orientations, lighting conditions, and post-impact storage intervals. Detection performance should be evaluated using accuracy, precision, recall, F1-score, detection speed, throughput, and external validation results.

Fourth, FEM, DEM, and coupled FEM–DEM models should be calibrated with measured peel and flesh properties and validated against physical damage indicators. Future modeling should connect internal stress thresholds with multi-fruit conveying behavior and equipment design parameters, such as gripping force, conveying angle, pipe inclination, fruit spacing, transfer height, and bin-filling trajectory.

8. Conclusions

This review indicates that the central challenge in low-damage harvesting and handling of the Korla fragrant pear is the lack of crop-specific damage thresholds that can be directly translated into equipment design. Although studies on apple, pear, and other fresh fruits provide useful principles for reducing impact, compression, friction, and collision damage, these findings cannot be directly applied to the Korla fragrant pear because of its BSTs and large-canopy orchard structure. Low-damage mechanization for Korla fragrant pear should therefore shift from isolated device development and descriptive damage evaluation toward a threshold-driven engineering design framework. This conclusion is based primarily on Level I Korla-fragrant-pear-specific evidence and supported by Level II–IV transferable evidence, which provides methodological and engineering references but requires cultivar-specific validation.

Future work should prioritize the validation of these thresholds under real harvesting, conveying, grading, and bin-filling conditions. Pilot-scale studies should link damage reduction with fruit throughput, energy consumption, labor requirement, operating cost, and post-storage quality. These efforts will support practical, economical, and cultivar-adapted low-damage mechanization for Korla fragrant pear production.

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