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Comparative Performance and Cost-Effectiveness Analysis of Scientific Methods for Durian Ripeness Assessment: International Practices, Regional Development and Implications for Thailand

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Abstract- The export supply chain of Thai durian has so far relied heavily on manual fruit inspection for maturity testing, which has 70 to 80% accuracy when conducted at a packinghouse. Manual inspection is no longer valid in terms of the SPS and NTMs of importing countries, labor shortages during harvest time, and it is no longer competitive with new durian-producing countries such as Vietnam and Malaysia. This paper reviews non-destructive techniques for monitoring fruit maturity, such as NIR/Vis, NIR spectroscopy, HSI, AI-based computer vision, acoustic technology, in-field IoT monitoring, and the cost and performance analysis of the techniques under the SPS and NTMs for durian export.
From the literature review, the most promising technique for further development is NIR, with over 94% accuracy, fruit-sorting capacity of 600 to 1,200 pieces per hour, and an initial investment of USD 15,000 to 150,000. In addition, this paper presents step-by-step investment planning for the fruit grading system and discusses future work on establishing a national durian spectral database and conducting a real packing-house test run to make the system ready for deployment of the technology-based fruit grading system for Thai-exported durian.

Keywords: Durian Ripeness Assessment, Non-Destructive Evaluation, NIR Spectroscopy, Cost-Effectiveness, Postharvest Technology, Artificial Intelligence, Quality Control Standards, Agricultural Technology Adoption.

Abbreviations: AI = artificial intelligence; ARDA = Agricultural Research Development Agency (Thailand); CNN = convolutional neural network; CT = computed tomography; DEPA = Digital Economy Promotion Agency (Thailand); ERIA = Economic Research Institute for ASEAN and East Asia; FAO = Food and Agriculture Organization of the United Nations; GAP = Good Agricultural Practices; GC–MS = gas chromatography–mass spectrometry; HPLC = high-performance liquid chromatography; HSI = hyperspectral imaging; IoT = Internet of Things; ISO = International Organization for Standardization; ISO/TC 34/SC 3 = ISO Technical Committee 34, Subcommittee 3 (Fruits, vegetables and their derived products) ; LC–MS/MS = liquid chromatography–tandem mass spectrometry; MARDI = Malaysian Agricultural Research and Development Institute; NIR = near-infrared spectroscopy; NMR = nuclear magnetic resonance; NTM = non-tariff measure; NTMs = non-tariff measures; OTOD = One Tambon One Digital (Thailand); µPAD = microfluidic paper-based analytical device; PCA = principal component analysis; PLS-DA = partial least squares discriminant analysis; SC = subcommittee; SPS = sanitary and phytosanitary measures; SVM = support vector machine ; Vis–NIR = visible–near-infrared spectroscopy; YOLO = “You Only Look Once”

1. Introduction

Durian (Durio zibethinus Murr.) is shifting from traditional fruit to export commodity, with Chinese demand alone projected over US$7 billion by 2024 (South China Morning Post, 2025). Thailand is the primary volume exporter, with both extensive durian plantations and a national digital agriculture strategy (Digital Economy Promotion Agency, 2024), but harvest maturity and quality grading are based almost exclusively on human subjective evaluation. The traditional knocking and tapping approach is knowledge-intensive and thus subjective, leading to inconsistency, inadaptability to large-scale export, and poor timing of harvest (Pornpanomchai, 2024).
This paper distinguishes between ‘maturity’, referring to the physiological stage of fruit development that can be measured through dry matter content, soluble solids content, and peduncle metabolites, and ‘ripeness’, referring to the stage of fruit development suitable for consumption, characterized by ideal texture, sweetness, and aroma, with the two concepts linked but distinct, since durian may achieve commercial maturity before eating ripeness (Kader, 2008). Since eating ripeness determines the sweetness, texture, aroma, shelf life, and likeliness of rejection, inaccurate classification results in postharvest loss and economic injury (Kader, 2008), even as

international trade increasingly requires third-party verifiable maturity metrics (Codex Alimentarius Commission, 2023; International Organization for Standardization (ISO) Technical Committee (TC) 34/Subcommittee (SC) 3 (ISO/TC 34/SC 3), 2024).

Though Thailand has developed automated computerized tomography (CT) scanning for AI-supported grading (Agricultural Research Development Agency, 2025), the technology is underutilized in commercial packinghouses. Non-destructive spectral measurement has been shown effective for predicting key quality attributes such as dry matter and soluble solids content in durian (Ditcharoen et al., 2023) and other tropical fruits such as pomelo (Sarakum & Sukpancharoen, 2025). Metabolomics (Mettakoonpitak et al., 2024) and microfluidics (Chulalongkorn University, 2021) research have further demonstrated that durian ripening can be objectively measured without destroying the fruit. International reviews have identified machine learning-enabled near-infrared (NIR) and visible-near infrared (Vis–NIR) spectroscopy as mature technologies for predicting internal quality attributes in export-oriented fruit (Nicolaï et al., 2007; Walsh et al., 2020; Aline et al., 2023). NIR spectroscopy has been found to outperform computer vision and hyperspectral imaging in terms of the balance of accuracy, speed, and cost achieved in a packinghouse environment (Felix Instruments, 2020b; World Bank, 2021), and is now commonly used for apples, melons, citrus, table grapes, and pomelo (Agriculture and Agri-Food Canada, 2015; Jing et al., 2024; Walsh et al., 2020).

Competitor countries Vietnam and Malaysia have adopted postharvest technologies consistent with international market access requirements (Vietnamese Ministry of Agriculture and Rural Development, 2024; MARDI, 2020), but though Thailand has strong research and development capacity, as well as national strategies to apply both (Ministry of Agriculture and Cooperatives, 2025), the technologies have not yet been adopted in commercial durian packinghouses. Previous reviews have discussed non-destructive measurement technologies for quality evaluation of tropical fruit (Walsh et al., 2020; Aline et al., 2023; Nicolaï et al., 2007), but none have considered cost–performance trade-offs, sanitary and phytosanitary (SPS) and non-tariff measure (NTM) compliance with international trade agreements, competitive dynamics among producing countries, and practical implementation considerations within the specific national context of Thailand's export-oriented durian supply chain. This article fills that knowledge gap by presenting the first structured cost–performance comparison of durian ripeness technologies designed specifically in the context of the Thai export sector's market access needs and policy environment, and positions technology adoption as a national policy issue rather than a technological question.

II. Literature Review

This section discusses the key scientific and technological tools for determining the ripeness of durian, with a focus on non-destructive measurement targets, validation environments, and the practicality of export systems. Scientific testing for durian maturity has moved beyond the subjective toward an objective measurement of quality criteria: dry matter, soluble solids, amino acids, moisture distribution, and density, all detectable by non-destructive techniques. It is a multidisciplinary field combining spectroscopy, imaging, acoustics, and chemical analysis to satisfy the requirements of export-system deployment and international standards for quality.

2.1 Near-Infrared Spectroscopy (NIR) as the Core Technology

The near-infrared region spans from 700 to 2, 500 nm, and non-destructive detection of key water and organic compound absorbance peaks correlates with dry matter and soluble solids, the most reliable maturity index (Walsh et al., 2020; Aline et al., 2023; Fodor et al., 2024). Optimal wavelengths and chemometric models such as principal component analysis (PCA), partial least squares discriminant analysis (PLS-DA), and support vector machine (SVM) have demonstrated a classification accuracy of over 94% for maturity in durian fruit, while biochemical analysis has confirmed that peduncle metabolites are indeed indicative of the actual maturity (Ditcharoen et al., 2023; Pornpanomchai et al., 2024; Chulalongkorn University, 2021). NIR-based classification of the peduncle allows for non-destructive grading, which can be transferred to packinghouse and field grading, according to the postharvest quality standards of the FAO and ISO (Imai et al., 2025; Li et al., 2022; Téllez-García et al., 2024; Walsh et al., 2020; ISO/TC 34/SC 3, 2024).

2.2 Computer Vision and Artificial Intelligence (AI) for External Quality Complement

Computer vision with convolutional neural networks (CNNs) and You Only Look Once (YOLO) architectures has been successful for external quality features, obtaining high accuracy when surface appearance and external quality attributes are correlated to maturity, such as the case with melons (Jing et al., 2024). For durians, the low correlation between the rind features and internal quality attributes renders computer vision unsuitable for maturity prediction but still viable for detecting defects, sizing, and grading surface quality (Pornpanomchai, 2024; Wanthong et al., 2025; Tapway, 2022).

2.3 Acoustic and Density-Based Assessment

The use of acoustic vibration to predict ripeness has demonstrated that changes in density are detectable at different stages of maturity, with the experimental model able to distinguish immature and ripe durians with high accuracy (Kongrattanaprasert et al., 2001). However, the sensitivity of the device to the positioning of the fruit and the device and the relative lack of robustness mean that the technology is best suited to presorting field operations, but not for export documentation.

2.4 Chemical and Laboratory Reference Methods

Analytical techniques, including high-performance liquid chromatography (HPLC), liquid chromatography–tandem mass spectrometry (LC–MS/MS), gas chromatography–mass spectrometry (GC–MS), and nuclear magnetic resonance (NMR), can precisely determine the concentration of sugars, amino acids, and volatiles related to maturity, and have been used to identify key biochemical markers in durians (Chulalongkorn University, 2021). Due to the destructive nature, cost, and low speed, these methods are mostly used as reference methods for calibration of the spectral models rather than as operational tools for quality grading.

2.5 Economic and Trade Context: Why Measurement Can't Be Optional

Tighter SPS conditions and contaminant testing (especially from the PRC) and the demonstration that NTMs have a direct influence on the competitiveness of export goods render a subjective grading system obsolete (South China Morning Post, 2025; Ministry of Agriculture and Cooperatives, 2025; Shepotylo, 2015; Doan et al., 2023; Zhang et al., 2025). Both economic and policy analysis point to the growing need for objective, technology-mediated quality control methods as key to maintaining the competitiveness of Thai durian and thus illustrate postharvest metrology as a technological imperative rather than choice (Bangkok Bank, 2025; Likhitpichitchai et al., 2023; Lippe & Grote,2015; World Bank, 2021; Krungsri Research, 2025).

2.6 Synthesis: The Technological Hierarchy for Durian Systems

All of the above evidence suggests a hierarchy. NIR is the sole technology offering biochemical robustness, practical applicability, economic viability, and legal viability. Computer vision is the technology of choice for appearance grading. Acoustic methods are best suited to in-field screening. And laboratory-based chemical methods are best suited to reference analysis. Together, they comprise the technological hierarchy toward a scientific durian grading system.

III. Methodology

3.1. Search Strategy and Study Selection

This study performs a scoping-oriented narrative review together with a structured case comparison to assess the current state of durian ripeness measurement technologies in the context of export supply chains. We do not perform a statistical meta-analysis, as the studies differ in terms of objectives (classification or prediction of quality attributes), technological settings (instrumentation, measurement protocols), and experimental conditions (validation datasets, laboratory or on-line setup). The systematic search of the literature is done using the main academic databases (Scopus, WoS, PubMed, IEEExplore) and trusted websites for standards and regulations (see below). The search string is composed of (i) terms related to the commodities ("durian", "Durio zibethinus") and (ii) terms related to the measurement technology and context ("ripeness", "NIR", "Vis-NIR", "hyperspectral", "computer vision", "packinghouse", "throughput", "cost"). After screening the titles and abstracts, we select articles that report at least one among the performance metrics of interest here (classification accuracy, R^2, RMSE, throughput, cost). We focus on durian only, as the other Southeast Asian tropical fruits mentioned in the Introduction are not the object of automated measurement technologies for quality attributes in the academic literature.

3.2. Data Extraction and Synthesis

For each article retained, we extract information based on a standardized template including: type of technology, attributes measured, experimental conditions, performance metrics (classification accuracy, R^2, RMSE), throughput, cost. When cost information is reported in different formats across articles, we standardize them into rough estimates to facilitate comparison rather than quoting absolute numbers. The output of the systematic review is synthesized in the form of a cost-performance matrix (Table 1) and an action plan (Section 4.7; Table 2) that relate technological features to SPS/NTM-induced regulatory pressure and feasibility for the Thai packinghouse environment.

IV. Results and Discussion

4.1 Comparative Cost–Performance: Which Technologies Are Economically Transformative

Cost–performance comparison studies of fruit maturity measurement technologies show that, in practical packinghouse use, commercial feasibility is contingent on the technology's throughput, speed and non-destructive nature, rather than biochemical resolution. For instance, HPLC and LC–MS/MS are destructive, time-consuming and capital-intensive laboratory techniques that are not appropriate for on-line fruit grading. HSI provides comprehensive spectral data but is hampered by the need for sophisticated optical equipment, specific lighting environments and substantial computing power, making the technology more suitable for scientific research or ultra-premium fruit producers. Computer vision is not a feasible technology for measuring the maturity of durians, as the outer thorny husk and the relatively low correlation between external attributes and the fruit's internal dry matter content makes accurate maturity predictions challenging [Walsh et al., 2020; Aline et al., 2023; Fodor et al., 2024].

On the other hand, NIRS is an on-line technology capable of measuring rapidly and non-destructively the dry matter and soluble solid content of fruit, with moderate cost and scalability for on-line fruit grading, including in-line conveyor-belt-based sorting, and has been successfully applied in the field for sorting durian and other tropical fruit crops [Ditcharoen et al., 2023; Li et al., 2022; Aline et al., 2023; Imai et al., 2025; Felix Instruments, 2020a]. From a cost–benefit perspective, NIRS is a transformative technology, as it substitutes subjective human decisions with objective measurements, minimizes the cost of misclassified produce and the time required to train graders and provides quantifiable quality data that meets SPS and traceability requirements, thus delivering the largest practical benefit when applied to export-oriented fruit sorting systems [Shepotylo, 2015; Doan et al., 2023].

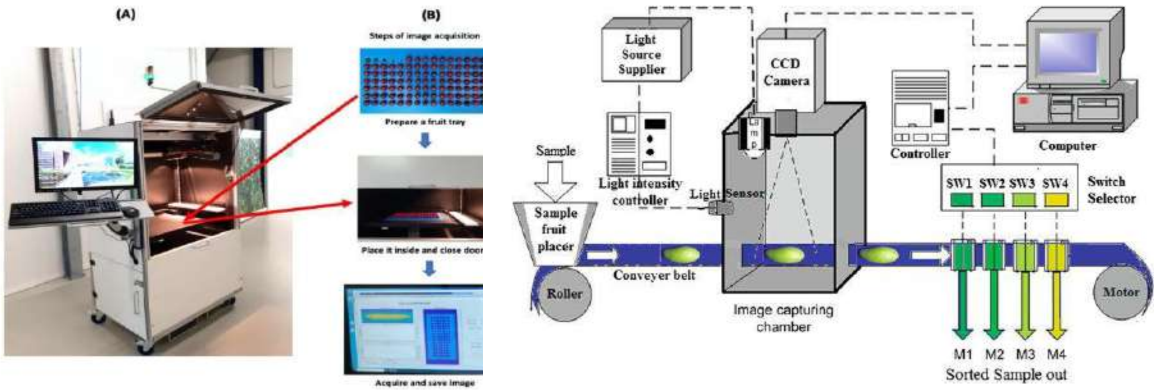

Figure 1. Left: All-in-one spectral imaging laboratory system for standardised automated image acquisition and real-time spectral model deployment. Adapted with permission from Mishra, P., Sytsma, M., Chauhan, A., & Polder, G. (2022). Analytica Chimica Acta, 1192, 339235. https://doi.org/10.1016/j.aca.2021.339235. Right: Proposed model of machine vision-based automated mango fruit sorting and grading. Adapted with permission from Nandi, C.S., Tudu, B., & Koley, C. (2014). In Proceedings of the International Conference on Frontiers of Intelligent Computing: Theory and Applications, pp. 7–15. https://doi.org/10.1007/978-3-319-02315-1_2.

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4.2 Technology is Already Being Used in Other Fruits: Learning from Other Fruits

The general process of adopting NIR and Vis-NIR spectroscopy for fruit quality screening and harvest maturity sorting for export can be found in the apple and kiwifruit industries in New Zealand and Europe. Both fruits utilize both NIR and Vis-NIR spectroscopy to predict harvest maturity for fresh market and storage life, through analysis of the spectral data (Walsh et al., 2020; Li et al., 2022). In the case of citrus fruits, both NIR and hyperspectral spectroscopy are being used to ensure consistent sweetness among exported fruits. In the melon industry, acoustic and spectroscopic methods are being used to replace the tapping technique for internal quality evaluation of the fruit (Aline et al., 2023; Fodor et al., 2024).

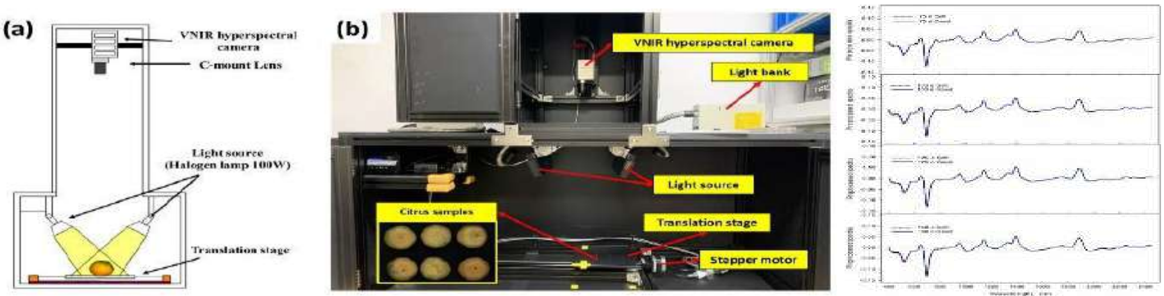

Figure 2. Technology adoption of non-destructive ripeness and maturity assessment methods across selected export-oriented fruit industries. Figure compiled by the authors based on Walsh et al. (2020), Agriculture and Agri-Food Canada (2015), and Jing et al. (2024).

For all of the above fruits, the technology is adopted for export purposes, not because of the availability of the technology but because of the export requirement for consistent fruit quality. When export restrictions are made based on fruit quality, the inconsistency of human judgement can be a risk to the business, while the spectroscopic technology is able to provide consistent, quantitative and traceable information to the customer (Aline et al., 2023; Fodor et al., 2024). Currently, the technology for the application of NIR and Vis-NIR spectroscopy for durian quality screening is already available.

4.3 Regional Strategies: Contrasting Approaches in Vietnam, Malaysia, and Thailand

For Vietnam, the strategy hinges on being close to China and adapting as quickly as possible to SPS and traceability standards, with a focus on certified growing areas, standardised packaging, and documentation, rather than replacing grading with technology (Doan et al., 2023; Likhitpichitchai et al., 2023). For Malaysia, the strategy is based on quality, with a focus on orchard management, post-harvest handling, cold chain, and selective use of NIR technology in a premium quality context, assisted by MARDI. For Thailand, despite a strong research base and early achievements in NIR and durian biochemistry, the strategy remains centred on large-scale human grading, leaving a knowledge gap between research and practice (Ditcharoen et al., 2023; Imai et al., 2025). Accordingly, Vietnam competes on speed and SPS compliance, and Malaysia on quality consistency. Thailand remains in a volume and reputation game, implying future competitive success will need to come from implementing the spectral and smart-farming technologies it already knows about, rather than increasing the area of its durian orchards or the number of people it employs to grade the fruit.

4.4 Thailand's Technological Readiness: Closer to Deployment Than Recognized

The technological readiness of Thailand to implement new tools for durian ripeness assessment is underestimated because it focuses on remaining knowledge gaps rather than the knowledge that already exists. During the last five years alone, research conducted in Thailand has shown that it is possible to predict the dry matter (and hence maturity) of durian non-destructively using peduncle-based Near-Infrared Spectroscopy, backed up with biochemical determination of key maturity-related compounds (Imai et al., 2025; Walsh et al., 2020; Aline et al., 2023). This research is at the advanced validation stage, similar to research in other fruits that has led to subsequent commercial implementation.

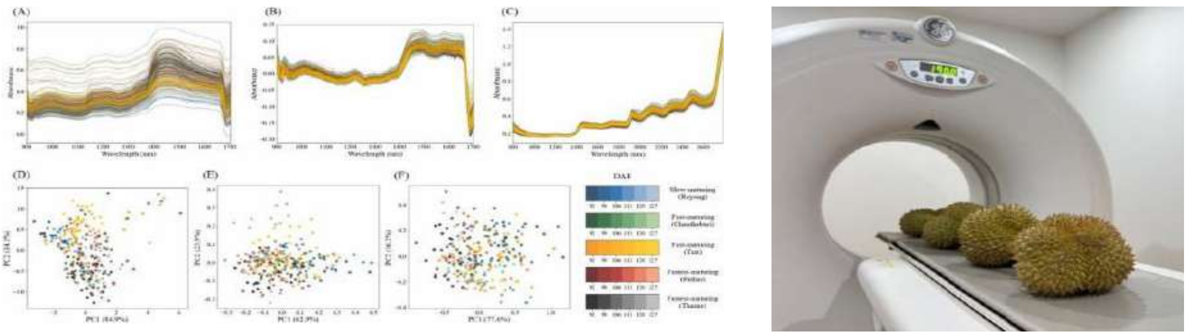

Figure 3. Spectral profiles and principal component analysis (PCA) of durian samples across maturity stages and orchard locations. Adapted from Imai, M., Yatsugi, Y., Tsuchikawa, S., & Inagaki, T. (2025). Postharvest Biology and Technology, 224, 113773. https://doi.org/10.1016/j.postharvbio.2025.113773

Meanwhile, in Thailand, with projects like Digital Durian and various technologies by ARDA, including an AI-enabled CT-scan grading system, we see that the country has already moved past the ideas of grading by sight, skin color, and texture, and embracing instrument-based grading. So, the gap here is not about the knowledge, money, or even infrastructure, but the gap of applying the technology from the lab to the packing houses. In other words, Thailand doesn't need new technology for fruit ripeness, but rather a mechanism for integrating the current spectral and digital technologies into the export grading practice.

4.5 From Ripeness Technology to National Competitiveness Strategy

Ripeness assessment is a strategic lever influenced by labor vulnerability, SPS compliance, market trust, and regional competition. Dependence on seasonal labor exposes the sector to policy and border risks, which NIR-based grading reduces by replacing tacit human skill with measurable data (Richardson & Pettigrew, 2022; Bangkok Post, 2026). Stricter SPS and traceability requirements, especially from China, render subjective grading insufficient, while spectral measurements provide objective, recordable evidence of maturity and improve buyer confidence by reducing variability (Shepotylo, 2015; Doan et al., 2023; Walsh et al., 2020). In this context, while Vietnam competes on logistics and compliance and Malaysia on premium consistency, Thailand's competitiveness depends on delivering scientifically verified quality at scale, positioning ripeness technology as a national competitiveness instrument rather than a technical tool.

4.6 Comparative Performance and Cost–Effectiveness Analysis

Overall, the comparative evidence in Table 1 indicates that manual inspection remains cost-attractive but suffers from low and inconsistent accuracy. At the same time, chemical analysis (HPLC) delivers precision comparable to reference methods but at prohibitively high cost and with minimal throughput, limiting its use to laboratory validation rather than commercial grading (Kader, 2008; Nicolaï et al., 2007). In contrast, non-destructive technologies, particularly NIR spectroscopy and AI-based computer vision, demonstrate the most robust balance between accuracy, scalability, and economic feasibility, with proven capability for high-throughput industrial deployment in fruit quality assessment systems (Walsh et al., 2020; Kamilaris & Prenafeta-Boldú, 2018; Li et al., 2022). Acoustic methods show strong technical potential for durian-specific applications but remain constrained by operational stability and throughput, while microfluidic approaches are best positioned as low-cost experimental or niche solutions (Mizrach, 2008; Pathare et al., 2013; Yetisen et al., 2013).

Table 1. Comparative technology performance and cost characteristics for durian ripeness assessment

Technology	Metric (acc. % or R^2)	**CapEx**	**OpEx/fruit**	**Throughput**	**Setting**	**Readiness**	**Key source(s)**	Evidence Tier †
NIR spectroscopy	94% acc.	\$15k–\$150k	\$0.10–\$0.30	600–1,200 fruit·h^{-1}	Lab; field benchmark	Commercial	Ditcharoen et al., 2023; Imai et al., 2025; Walsh et al., 2020; Felix Instruments, 2020a; Instruments, 2020b; TOMRA, n.d.; World Bank, 2021	T1b
HSI / Vis–NIR inline	R^2 to 0.97 (dry matter)	\$80k–\$500k	NR [a]	1,800–10,800 fruit·h^{-1}‡	Lab; inline benchmark	Pilot–commercial	Sharma et al., 2023; Wieme et al., 2022; Kim et al., 2008	T2
Computer vision (AI)	Up to 97% acc. (external) [b]	NR	\$0.05–\$0.20	600–1,800 fruit·h^{-1}	Pilot/packinghouse	Commercial	Jing et al., 2024; Wanthong et al., 2025; Tapway, 2022; Lu et al., 2023	T2

Acoustic analysis	High (controlled)	$15k–$40k	$0.02–$0.08	300–600 fruit·h⁻¹	Lab	Emerging	Kongrattanaprasert et al., 2001; Mizrach, 2008; Nicolaï et al., 2007	T1b
HPLC / LC–MS/MS	≈99%‡	$200k–$500k	$50–$150	10–20 fruit·day⁻¹	Lab	Research	ISO/TC 34/SC 3, 2024; Kader, 2008	T2
Microfluidic (μPAD)	Est. 85–92%	$10k–$50k	$0.05–$0.50	50–200 fruit·h⁻¹	Lab	Prototype	Mettakoonpitak et al., 2024; Yetisen et al., 2013	T1b
Manual inspection	70–80%	$0	$0.01–$0.05	200–400 fruit·h⁻¹	Field/packinghouse	Traditional	Thai packhouse baseline; see Section 4.6	T1a

† Evidence Tier Classification:
T1a = Durian-specific, field/packinghouse setting
T1b = Durian-specific, laboratory/controlled setting
T2 = Cross-fruit or multi-technology benchmark

a OpEx/fruit for HSI/Vis-NIR inline systems is not reported (NR) because per-unit operating cost depends heavily on system configuration (number of spectral channels, lane count), integration complexity, and facility utilization rate. Published sources report capital cost ranges but do not provide standardized per-fruit cost figures comparable to those available for benchtop NIR systems. Cost estimation for HSI deployment requires site-specific techno-economic modelling.

b Accuracy values for Computer Vision/AI relate primarily to external quality grading (surface defect detection, sizing, colour classification) under controlled conditions. These figures do not represent the accuracy of internal maturity prediction for durian, where the thick rind severely limits the correlation between surface appearance and internal dry matter content. Computer vision is therefore classified as a complementary tool for external grading only, not as a standalone method for assessing internal maturity.

Note: Ranges are approximate and sourced from various references. CapEx estimates for NIR systems are indicative values based on commercial suppliers' data (TOMRA; Felix Instruments) and publicly available technology cost analyses (World Bank, 2021), and should not be taken as the actual purchase price. " 'Key source(s)' column provides a hyperlink to the relevant evidence for each performance and cost metric. 'Tier' labels used are: T1a = on-farm or packinghouse-based durian evidence; T1b = laboratory or controlled-environment durian evidence; T2 = cross-commodity or cross-technology evidence. 'Metric' column states either classification accuracy (%) or coefficient of determination (R 2) for continuous IQMs (e.g., DM). Computer vision costs are mostly for external quality grading rather than dedicated IQMs. Up to denotes laboratory-based estimates that may not translate to on-farm or packinghouse conditions. Throughput may vary by configuration and operating parameters. NR denotes that no directly comparable evidence was found. Commercial suppliers (TOMRA, Felix Instruments) are cited only for indicative cost specifications and may have since updated website content referenced in this paper. The date of access is provided in the reference list.

To facilitate interpretation of the cost–performance matrix in Table 1 in absolute terms, an indicative variable cost envelope (VCE) can be calculated using the product of (cost per fruit) and (throughput). For NIR spectroscopy, a cost of US$0. 10 to 0. 30 fruit −1 and a throughput of 600 to 1200 fruit h −1 yields a VCE of US$60 to 360 h −1. For computer vision/AI, a cost of US$0. 05 to 0. 20 fruit −1 and a throughput of 600 to 1800 fruit h −1 results in a VCE of US$30 to 360 h −1 ; one supplier quotes that their durian grading line grades ~30 fruit min −1 (1800 fruit h −1) under optimal operating conditions (Tapway, 2022). Nonetheless, for durian, computer vision should only be used as a supplemental tool for EQ, not as a dedicated IQM predictor. Acoustic (US$0. 02 to 0. 08 fruit −1 ; 300 to 600 fruit h −1), US$6 to 48 h −1 ; and microfluidic paper-based analytical devices (μPAD) (US$0. 05 to 0. 50 fruit −1 ; 50 to 200 fruit h −1), US$2. 5 to 100 h −1 , the majority of which are still in the prototype phase, round out the IQM modalities. VI (US$0. 01 to 0. 05 fruit −1 ; 200 to 400 fruit h −1 or ~US$2 to 20 h −1) is the cheapest option, but its accuracy is relatively low (70 to 80%) compared with the other modalities, and misclassification may occur, leading to further loss. On the other hand, HPLC is too costly to be used as an IQM technique for routine grading (US$50 to 150 fruit -1 ; 10 to 20 fruit day -1). However, it can serve as a reference method in a laboratory setting for calibration and validation purposes. For in-line HSI/Vis–NIR platforms, the per-fruit cost is highly dependent on the degree of integration and usage. Meanwhile, many laboratory-based durian models have demonstrated high prediction capabilities for DM and TSS. The cost of using in-line HSI/Vis–NIR for routine grading at a packinghouse will depend on the number of lanes, data transfer speed, and maintenance requirements.

Important ⚠: CapEx and OpEx values for NIR and HSI systems are sourced primarily from the commercial suppliers (TOMRA; Felix Instruments) and the World Bank (2021) analysis. These are indicative only and have not been verified under local (Thai) packinghouse conditions. Actual costs may vary widely by supplier, system configuration, facility size, and integration requirements. An independent analysis is recommended before investment decisions are made.

4.7 Investment Scenarios and Policy Pathways

Moving from readiness to competitiveness can be envisioned as a sequence of three consecutive stages, all of which build on existing capabilities in Thailand and thus do not entail a leap in the dark. In the short-run, the emphasis should be placed on proof-of-concept rather than on scaling-up. An on-site pilot NIR testing in a few packinghouses located in the provinces of Chanthaburi, Rayong, and Trat, would provide much needed information on sorting speed, sorting accuracy, labour displacement, and cost per fruit. In the medium-run, Thailand should capitalize on its research capacity at the university level to develop a national durian spectral library that encompasses the main cultivars grown in the country, the main production areas, the main production seasons, and the main stages of maturity. This is a knowledge gap that is critical for the calibration of the NIR technology and for the technology to perform accurately and reliably across different production environments (Walsh et al., 2020; Aline et al., 2023). In the long-run, the emphasis should be placed on measuring the ripeness of durians before they are harvested rather than after they have been harvested. Techniques such as smart irrigation, soil moisture probes and drone monitoring can be used to reduce the dependence on human labour in the field and improve the uniformity of durians at harvest. This set of techniques can be combined with the NIR technology to create a precision agriculture system that encompasses the field and packinghouse (Guebsi et al., 2024; Yuan et al., 2024; Thongnim & Srinil, 2025).

Table 2. Phased strategic roadmap for implementing NIR-based quality grading and smart-orchard technologies in Thailand's eastern durian supply chain

Phase	Focus	Action	Key Supporting Evidence
Short term (1–2 years)	Pilot NIR in packinghouses	Establish shared NIR grading hubs in major eastern provinces	Proven commercial use of NIR for postharvest decision support and grading accuracy in fresh produce (Walsh et al., 2020; Fodor et al., 2024); Evidence of peduncle-based NIR feasibility specifically for durian dry matter prediction (Imai et al., 2025)
Medium term (3–5 years)	Standardization	Develop national spectral database, calibration, and validation protocols	Calibration transferability across cultivars and environments requires multi-season, multi-location spectral data (Aline et al., 2023; Walsh et al., 2020); MARDI's cultivar-specific NIR database demonstrates the feasibility of national-scale spectral standardization (MARDI, 2020); SPS/NTM compliance increasingly requires standardized, auditable quality metrics (Shepotylo, 2015; Doan et al., 2023)
Long term (5+ yrs)	Smart-orchard integration	Integrate Internet of Things (IoT) sensors, drones, and sensor-based orchard management.	Evidence that drones, IoT, and precision irrigation reduce labor dependency and increase resource efficiency (Guebsi et al., 2024; Yuan et al., 2024); a smart farming model demonstrated for durian cultivation in Thailand (Thongnim & Srinil, 2025)

4.8 Critical Research Gaps That Must Be Addressed

Even though non-destructive technologies such as NIR, Vis-NIR, hyperspectral imaging, computer vision, Internet of Things (IoT) and smart farming, have already been shown to outperform human assessment for a wide range of fruits and although they have already been commercialized at the international level (Walsh et al., 2020; Aline et al., 2023; Fodor et al., 2024), very few attempts have been made to test their applicability to durians grown in Thailand.

The first knowledge gap is the absence of a national durian spectral library that covers the main durian cultivars grown in Thailand (Monthong, Chanee, Kanyao), the various stages of maturity, as well as the various conditions faced in the orchard. The absence of such a library restricts the ability to calibrate the NIR technology and the accuracy of the technology in the field (Aline et al., 2023).

The second knowledge gap is the near absence of validation exercises that have been carried out under Thai packinghouse conditions. While some studies have been carried out under laboratory conditions and shown promising results, including the measurement of NIR spectra at the level of the peduncle (Imai et al., 2025), very few validation studies have been carried out on-site in a packinghouse.

The third knowledge gap is the absence of economic analyses that compare the cost of an NIR-based durian grading system with the rising cost of skilled labour. In the absence of such studies, it is not possible to carry out informed policy and investment analyses.

The fourth knowledge gap is the absence of a Smart Orchard model that is dedicated to durians. While IoT and precision technologies have been successfully tested in several other fruit supply chains (Guebsi et al., 2024; Yuan et al., 2024), they have not yet been tested for durians.

The fifth and last knowledge gap is the absence of a resilience framework that is dedicated to the durian supply chain in Thailand. While such a framework has already been successfully applied to other supply chains (Roque Júnior et al., 2023), it has not yet been applied to the durian supply chain in Thailand.

True research should include formal techno-economic evaluation metrics, especially return on investment (ROI), payback period, and net present value (NPV), to compare instrument deployment with labor-based grading under realistic packinghouse conditions. For example, NPV is calculated as:

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} - I_0$$

where CF t is the net cash flow in year t, r is the discount rate, and I_0 is the initial investment. Incorporating an illustrative scenario analysis would improve the practical relevance of the proposed implementation pathway.

4.9 Limitations of This Review

This review has several limitations. ***Firstly***, the results are mainly based on data collected in the eastern part of Thailand (Chanthaburi, Rayong, and Trat provinces), which might not be fully representative of other parts of the country or of other durian-producing countries with a different durian variety profile, climate, or market chain.

Secondly, some of the cost and performance parameters, especially for NIR and HSI technology, were estimated based on information from technology providers (TOMRA, Felix Instruments) and literature data on other fruits, which were not validated through an independent techno-economic analysis in a Thai durian packinghouse; hence, the presented values should be regarded as order-of-magnitude estimates.

Thirdly, this review was not performed as a systematic review according to the PRISMA statement. Although a scoping review of mostly qualitative and narrative evidence seems justified, some relevant articles might have been missed.

Lastly, since this review is based on secondary data only, no field experiments were conducted to test the applicability of the technologies under local conditions; thus, the outlined implementation scenario is still conceptual and requires experimental verification. Future studies should fill these knowledge gaps with field validation experiments, a techno-economic survey of independent cost assessments, and variety-specific spectral data collection.

4.10 Key Findings

Several conclusions can be drawn from the literature. ***First,*** the use of NIRS and other spectroscopic techniques is more accurate and reliable than human grading for fruit quality, and is already widely used in various fruit industries. Though NIRS feasibility studies have been conducted on durian, industrial-scale application is still lacking (Walsh et al., 2020; Li et al., 2022; Imai et al., 2025).

Second, the use of seasonal migrant workers has been highlighted in the literature on agricultural labour as a weak point, which is directly relevant to the dependence of the Thai durian industry on Cambodian workers for harvesting and grading (Richardson & Pettigrew, 2022).

Third, in the literature on SPS and NTM, it has been shown that increased stringency requires science- or evidence-based quality information, not subjective information, making human grading of durian incompatible with the current situation of global trade (Shepotylo, 2015; Doan et al., 2023).

Fourth, smart orchard, drones and IoT have been shown in the smart agriculture literature to help decrease the time and resources and inefficiency of manual labour in the field (Guebsi et al., 2024; Thongnim & Srinil, 2025).

Overall, these results suggest that the problem of the Thai durian industry does not lie in supply or demand, but in its heavy dependence on human expertise for quality and orchard management. Therefore, the Thai durian industry should shift from a labour-intensive system to a knowledge-intensive system by adopting spectral grading and smart orchard management for global trade and competitiveness.

4.11 Recommendations

The next five recommendations specifically target the research and implementation needs outlined in Section **4.8.** Each recommendation is tied to a specific need to clarify the direct link between the identified issue and the proposed solution.

National Durian Spectral Database (Gap in Section **4.8**, Need **1:** Lack of national-level spectral library). A national durian spectral library should be created that covers the three main commercial durian cultivars (Monthong, Chanee, Kanyao) in eastern Thailand, the variation in durians from each season, and the different maturity stages. The library would be necessary for creating the more accurate and generalized NIR calibration model (discussed later). This should be done through a collaborative effort between ARDA, research institutions and local packinghouses. Without this, it is not possible to make a generalized NIR model that can be used across different locations and different harvests.

Packinghouse Pilot Trials (Gap in Section **4.8**, Need **2:** Lack of validation in a packinghouse environment). A controlled pilot study should be conducted in actual packinghouses in Chanthaburi, Rayong, and Trat provinces to test the NIR machine on-site and collect data on the accuracy, capacity, rate of misidentification, and the rate of labor replacement. The pilots should be conducted in a way that is replicable and publishable, in order to supply data for further policy decisions. The pilot studies would help fill in the missing data between the laboratory-scale and full-scale industrial applications.

Techno-Economic Cost-Benefit Analysis (Gap in Section **4.8**, Need **3:** Lack of independent economic analysis). An independent economic analysis should be conducted to compare the cost-benefit of investing in an NIR machine with the cost-benefit of using skilled labor (incorporating the cost of misidentification, frequent retraining, and fluctuating labor costs). The analysis should use standard investment analysis tools (NPV, ROI, payback period) and should include scenario analysis for a range of packinghouse sizes and technology levels. This analysis would be necessary before any government subsidy or co-investment.

Smart Orchard Pilot Model (Gap in Section **4.8**, Need **4:** Lack of Smart Orchard pilot for durians). A pilot Smart Orchard model should be developed and tested that incorporates IoT sensors, precision irrigation, and drone imaging, specifically designed for the growing conditions of durian in eastern Thailand. The pilot should be monitored to measure improvements in yield consistency, precision in harvest timing, and reduction in labor use. A Smart Orchard model has already been demonstrated in other Thai agricultural sectors (Thongnim & Srinil, **2025)**, and could be adapted for durians.

Integrated Supply Chain Resilience Framework (Gap in Section **4.8**, Need **5:** Lack of framework integrating labor, SPS, and technology). A framework should be developed to specifically assess supply chain resilience in the Thai durian sector, which incorporates the three key vulnerabilities facing the industry (seasonal labor shortages, SPS/NTM pressures, and technology adoption rates). This framework would support long-term industry planning by allowing policymakers and industry actors to evaluate the resilience benefits of investments in technology. The literature shows that supply chains incorporating both maturity detection technology and labor-reducing technology are more resilient to external trade disruptions (Roque Júnior et al., 2023)**.**

V. Conclusion

This paper has discussed and compared the scientific techniques in determining the ripeness of durians for the export industry in Thailand. From the scientific literature presented, non-destructive spectroscopic technology for assessing the ripeness of durians is currently the only feasible technique to satisfy the needs of the export packinghouses in terms of biochemical correlation, industrial scale processing, and cost. On the other hand, computer vision and artificial intelligence can be used to support the adoption of NIR by identifying and grading the external quality and defects of durians. Acoustic technology is a sensitive technique with respect to its operating conditions, which may be used as an initial screening process for ripeness detection. Although laboratory analysis is an important technique for reference measurement in the determination of the ripeness of durians, it is still impractical for routine use. Therefore, in order to turn technical readiness into competitive advantage for export packinghouses in Thailand, the following steps are recommended:

(i) actual demonstration of packinghouses with the availability of accurate data on performance and cost;

(ii) creation of a national database on spectral signature and standard calibration procedure to accommodate different varieties and harvest seasons; and

(iii) gradual integration with a smart farming system to reduce labor requirements and enhance SPS/NTM compliance.

Ethical Approval: Not applicable. This study is based on secondary sources and does not involve human participants or animal experiments.

Data Availability: No new datasets were generated or analyzed in this study. All information is derived from publicly available sources cited in the reference list.

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