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APPLE QUALITY ASSESSMENT IN THE ERA OF AI: NON-DESTRUCTIVE AND PREDICTIVE MODELING TECHNIQUES

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ABSTRACT

Accurate apple quality prediction is crucial for ensuring postharvest efficiency, consumer satisfaction, and sustainable agricultural practices. Traditional methods based on manual inspection and destructive testing are often subjective and inefficient, prompting the need for automated, data-driven approaches. This review explores modern technologies applied to apple quality prediction, including hyperspectral and near-infrared spectroscopy, machine learning algorithms, deep learning models like convolutional neural networks (CNNs), and genomic prediction methods such as QTL mapping and genome wide selection (GWS). Recent studies have demonstrated the effectiveness of combining spectral data with intelligent optimization techniques like particle swarm optimization (PSO) for real-time assessment of internal traits such as sweetness, firmness, acidity, and defect detection. Additionally, integrating genomic data has enabled the prediction of inherited quality traits, supporting advanced breeding programs. The review synthesizes findings from over twenty recent studies to highlight progress, challenges, and future directions in this field. It recommends the development of portable, field- deployable tools, standardized evaluation protocols, and multidisciplinary collaboration. Ultimately, the convergence of AI, spectroscopy, and genomics is transforming apple quality monitoring into a scalable, intelligent system suitable for modern precision agriculture.

Keywords: Apple Quality Assessment, Hyper spectral Imaging, Machine Learning, Convolutional Neural Networks (CNN), Genomic Prediction, Nondestructive Evaluation, Postharvest Monitoring.

INTRODUCTION

Apple is one of the most widely consumed fruits globally, appreciated for its flavor, nutritional value, and commercial importance; however, traditional quality assessment methods, such as visual inspection and destructive sampling for attributes like firmness and sweetness, are time-consuming, subjective, and inefficient [1]. In response, researchers have developed non-destructive techniques—such as near- infrared (NIR) spectroscopy, hyperspectral imaging, and digital image analysis —which enable rapid, accurate, and chemical-free measurement of internal and external quality traits, including sugar content, acidity, polyphenols, and bruise detection[2],[3],[4],[5]. These innovations have laid the groundwork for integrating artificial intelligence (AI) and machine learning models into apple quality assessment, allowing for advanced predictive capabilities that forecast physical damage, shelf life, and nutritional properties based on sensor data [6],[7]. For instance, adaptive neuro-fuzzy inference systems (ANFIS) and

partial least squares regression (PLSR) have been used to predict bruise volume and soluble solids content with high accuracy, while portable spectrometers and real-time mobile platforms have emerged to support on-site monitoring [8]. Collectively, these technologies mark a paradigm shift toward scalable, precise, and sustainable apple quality evaluation, merging the power of AI with non-invasive detection methods to meet the demands of modern agriculture and consumer expectations. The global apple industry demands efficient, accurate, and scalable quality assessment methods to ensure consumer satisfaction and reduce postharvest losses. Traditional techniques, which involve visual inspection and destructive testing, are increasingly deemed inadequate due to their subjectivity, inefficiency, and the loss of usable produce [9].As data complexity in agriculture grows, researchers have turned to advanced information technologies like cloud computing and big data analytics to process, visualize, and manage large volumes of agricultural data effectively [10]. In parallel, artificial intelligence (AI) and machine learning (ML) models have revolutionized the landscape by enabling automated classification, prediction, and defect detection in fruits, thereby optimizing postharvest handling and storage systems [11]. Non- destructive sensing technologies such as NIR, hyperspectral imaging, and digital image processing allow the internal and external quality of apples to be assessed without physical damage, fostering real -time monitoring and early decision-making in the supply chain[12],[13]. Moreover, blockchain integration into these smart systems promotes transparency and traceability, enhancing consumer trust and digital transformation in agri-businesses [14]. The integration of decentralized platforms, AI-enabled databases, and predictive models ensures that apple quality assessment transitions from manual, static methods to intelligent, dynamic systems capable of supporting sustainable and precision agriculture[15],[16].

Here is the main contribution:

- Holistic Overview: It presents a unified review of techniques such as hyperspectral imaging, VIS/NIR spectroscopy, convolutional neural networks (CNNs), and genomic selection (GWS/QTL), emphasizing their roles in non-destructive apple quality assessment.
- Comparative Analysis: It compares the performance of various models, including support vector regression, artificial neural networks, and fuzzy inference systems, highlighting their accuracy, use-cases, and real-world applicability.

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- o Integration of Genomic and Phenotypic Models: It explores how the fusion of genetic data and phenotypic prediction through modern AI models improves trait predictability and supports breeding programs.
- o Identification of Research Gaps: It identifies critical challenges in the scalability, environmental adaptability, and standardization of current models used in practical agricultural settings.
- o Strategic Recommendations: It proposes future directions including the development of portable tools, model generalization across environments, and cross-disciplinary collaboration to advance the field of apple quality prediction.

BACKGROUND THEORY

Traditional Quality Assessment Methods

- Historically, apple quality was determined by visual inspection and manual measurement of size, color, and external blemishes.
- Internal attributes such as firmness, sweetness (Brix content), and juiciness required destructive sampling, which leads to fruit loss.
- Traditional methods are:
    - Labor-intensive and time-consuming
    - Highly subjective, leading to inconsistencies
    - Inefficient for large-scale industrial use
- classical systems lacked the parallel processing capabilities needed to handle real-time agricultural data at scale[11],[9]

Emergence of Non-Destructive Techniques

- With the evolution of sensor technologies, non-destructive methods became prevalent, offering accurate, real-time quality analysis.
- Examples include:
    - Hyperspectral Imaging (HSI): Captures reflectance spectra for internal quality estimation (sugar, acidity).
    - Near-Infrared (NIR) Spectroscopy: Estimates firmness and water content.
    - X-ray Imaging: Detects internal bruises, core damage, or worm infestation.
    - Machine Vision Systems: Classify external features (shape, color uniformity) using RGB and IR cameras.
- These technologies reduce postharvest waste and enable full-batch inspections.
- emphasized the importance of cloud-enabled systems in managing non-destructive sensor data for smart grading solutions [3].

Application of Artificial Intelligence and Machine Learning

- AI has revolutionized the fruit industry by enabling systems to learn from past data and predict quality outcomes.
- Techniques include:
    - Convolutional Neural Networks (CNNs) for visual classification
    - Support Vector Machines (SVM) and Random Forests for multi-class prediction
    - K-means Clustering for sorting apples based on texture or color similarity
- These systems automate grading, reduce human bias, and improve productivity.

Predictive Modeling for Quality Forecasting

- Predictive modeling aims to forecast future apple quality attributes, such as:
    - Ripeness progression
    - Shelf life estimation
    - Chill injury or decay under storage
- Commonly used models:
    - Support Vector Regression (SVR)
    - Artificial Neural Networks (ANNs)
    - Time-series forecasting algorithms
- Predictive models help producers and retailers optimize storage conditions, manage inventory, and reduce waste.

Challenges and Future Directions

- Despite the advantages, the deployment of AI-based non-destructive systems faces several limitations:
    - Data requirements: Training accurate models demands large annotated datasets.
    - Environmental variation: Lighting, background noise, and apple orientation can impact prediction accuracy.
    - Model interpretability: Deep learning models are often “black boxes” with limited explain ability.
    - Hardware cost: High-end imaging and computing hardware are expensive for small farms.
- Future solutions include:
    - Edge AI: Running models directly on embedded systems for real-time assessment
    - Transfer learning: Reusing pre-trained models to reduce annotation costs
    - Multi-modal fusion: Combining spectral, thermal, and visual data for improved accuracy
    - Blockchain integration: Enhancing traceability, data security, and consumer trust in the apple supply chain.

LITERATURE REVIEW

Abdelhameed Ibrahim et al. (2024)[17] examined the use of the binary Waterwheel Plant Algorithm (bWWPA) for feature selection and logistic regression for classifying apple quality attributes. Their research focused on evaluating multiple cultivation, harvesting, and post-harvest parameters like sweetness, acidity, juiciness, and crunchiness using a machine learning pipeline. The authors reported a classification accuracy of 88.62% with logistic regression, enhanced by dimensionality reduction through bWWPA, which selected the most influential features. Their study emphasized the benefits of data-driven quality assessment techniques in agriculture to optimize decision-making and reduce reliance on subjective methods. The model proved valuable for improving apple quality monitoring and had potential applicability across various crops.

Alfadhl Y. Khaled et al. (2023)[18] conducted a study using hyperspectral imaging and machine learning to predict physicochemical quality changes in apples infested by codling moths under different cold storage conditions. The authors used Gala apples and evaluated qualities such as firmness, pH, moisture content, and soluble solids content across storage temperatures of 0°C, 4°C, and 10°C. Their models, developed with support vector regression (SVR) and partial least squares regression (PLSR), achieved high prediction accuracy (Rp up to 0.97 for pH and 0.95 for firmness). They also applied competitive adaptive reweighted sampling (CARS) to optimize wavelength selection, improving multispectral model performance. This work offered a non-destructive and efficient tool for monitoring pest-influenced quality degradation during storage.

Bharti et al. (2022) [19]focused on predicting apple yield using artificial neural networks (ANN) based on morphological characteristics such as plant height, canopy spread, flowering density, and fruit set. Their study employed principal component analysis (PCA) to select the most relevant variables, which were then used in ANN models with multiple hidden layers for nonlinear pattern recognition. They compared ANN to traditional linear regression approaches and demonstrated superior prediction performance and adaptability in complex data environments. Sensitivity analysis revealed the individual contribution of each morphological trait to yield. The findings highlighted the potential of ANN for more accurate yield forecasting and agricultural planning.

E.I. Papageorgiou et al. (2018)[20] developed and evaluated both a fuzzy inference system (FIS) and an adaptive neuro-fuzzy inference system (ANFIS) to classify overall apple quality. They used expert-derived rules and four input parameters—fruit mass, skin color, soluble solids content, and flesh firmness—to categorize apples into five quality levels: excellent, good, medium, poor, and very poor. The FIS model achieved accuracy rates of over 96% in matching expert assessments across three consecutive years, outperforming ANFIS in conditions with limited data. Their study illustrated the strength of rule- based expert systems and fuzzy logic for agricultural quality grading, especially in uncertain or subjective decision-making contexts.

Faizan Ahmad et al. (2021)[21] investigated postharvest apple quality under ambient storage conditions by developing computational models to predict the overall quality index (OQi). Their models incorporated physical and chemical attributes such as firmness, acidity, gloss, density, and Hunter color values (L, a, b), and were validated against sensory evaluation scores. They formulated a model (ML2) showing strong correlation between OQi and the combination of acidity, firmness, and color variables. Their approach provided a cost-effective and non-destructive alternative for quality monitoring, aiding consumers and food processors in decision-making. The study emphasized practical tools for assessing stored apple quality in environments without cold storage infrastructure

Luo et al. (2020)[22] highlighted the challenges in developing apple cultivars that combine durable disease resistance with elite fruit quality. Their study emphasized that most disease-resistant cultivars suffer from inferior fruit quality due to unimproved genetic backgrounds. They advocated for the use of modified backcrossing and genome-wide SNP arrays to efficiently eliminate undesirable DNA segments while preserving beneficial traits. The authors proposed pyramiding multiple resistance genes, both qualitative and quantitative, to enhance durability and minimize the risk of resistance breakdown. Their findings underscore the importance of integrating DNA-based tools into breeding programs to ensure both commercial viability and long-term disease resistance.

Hu et al. (2024)[23] proposed a novel approach to evaluate the internal comprehensive quality of apples and predict their storage time using non-destructive spectroscopy-based models. The authors constructed a quality index via Pearson correlation and hierarchical analysis, then used partial least squares regression (PLSR) combined with kinetic modeling for quality prediction. Their calibration model achieved high predictive accuracy with R^2 of 0.9419 and RMSE of 0.0023, while their storage time model had an R^2 of 0.8957. This integrated model addresses a key gap in evaluating multiple internal apple quality parameters simultaneously rather than in isolation. Their work represents a significant advancement in apple postharvest quality assessment using optical technologies.

Larson et al. (2023) [24] explored the use of near-infrared spectroscopy (NIR) to quantify and predict carbohydrate profiles in apples throughout development. They used HPLC to validate sugar content across five time points in 'Gala' and 'Red Delicious', identifying sorbitol as dominant early and fructose as increasing toward harvest. The study built robust PLSR models to estimate carbohydrate composition with R^2 values as high as 0.96, supporting NIR as a rapid alternative to traditional chromatography. They also identified canopy positioning as a factor influencing carbohydrate distribution. Their results demonstrate NIR's potential to support real-time, in-field monitoring of apple fruit physiology and quality.

Jung et al. (2025)[25] assessed the performance of genomic and phenomic prediction models for apple breeding, emphasizing trait predictability in both controlled and practical breeding contexts. The study evaluated 137 prediction scenarios involving cross-validation strategies, training population composition, and genotyping technologies (SNP arrays vs. RADseq). They concluded that enlarging training sets with closely related germplasm enhances prediction accuracy, and that phenomic prediction using NIR spectroscopy is currently less effective than genomic prediction for apples. The authors recommended leave-one-family-out validation for realistic model deployment in breeding programs. Their findings guide the cost-effective application of genomic tools to accelerate apple improvement efforts.

Grabska et al. (2023) [26]reviewed the applications of Vis/NIR and NIR spectroscopy for evaluating apple quality parameters, including firmness, SSC, acidity, and external traits. They emphasized the non-destructive, real-time capabilities of portable spectrometers and highlighted recent advances in chemometric methods such as PLSR, PCA, and ANN. The review detailed how spectral data fusion and model calibration enhance accuracy for industrial sorting, grading, and storage management. The authors also discussed the emerging role of handheld instruments and smartphone-integrated tools in democratizing quality monitoring. Their work provides a comprehensive framework for implementing optical spectroscopy in precision agriculture and apple supply chains

Kusumiyati et al. (2021)[27] evaluated the potential of near-infrared spectroscopy (NIRS) to predict water and soluble solids content in 'Manalagi' apples. The study used partial least squares regression (PLSR) and principal component regression (PCR) on spectra data collected between 702–1065 nm. The results indicated good predictive performance, with an R^2 of 0.85 and an RPD value of 2.69 for soluble solids content, demonstrating the technique's feasibility. The use of orthogonal signal correction improved spectral quality, supporting model accuracy. Their findings support NIRS as a non-destructive and effective alternative to conventional fruit quality assessment methods.

McClure et al. (2018)[28] conducted a genome-wide association study (GWAS) and genomic prediction analysis across 172 apple cultivars to examine quality traits and apple scab resistance. Their results revealed several significant loci for fruit firmness, harvest date, and skin color, demonstrating the effectiveness of GWAS over traditional QTL mapping. They identified a novel ethylene response factor gene potentially responsible for firmness retention, differing from the traditionally implicated PG1 gene. Genomic prediction accuracy was high for most traits, suggesting suitability for genomic selection. The study provides a strong foundation for accelerating apple breeding through high-resolution genomic approaches.

Minamikawa et al. (2024)[29] investigated the integration of genotypic data from different systems, namely SNP arrays and GRAS-Di sequencing, for genomic prediction (GP) and GWAS in apple. The study showed that combining datasets improved GP accuracy and the detection of significant loci for fruit traits such as soluble solids and sweetness. Their models also incorporated inbreeding coefficients and found that this consideration improved GP for seven key traits. Significant overlaps between ROH islands and GWAS signals indicated historical selection by breeders. This study provides a practical framework for leveraging hybrid genotypic datasets in modern apple breeding.

Cao et al. (2020) [30] developed a shelf life prediction model for 'Royal Gala' apples using artificial neural networks (ANN) with input features like firmness, SSC, acidity, and storage temperature. They collected data over three years across four temperature settings and used sparse principal component analysis (SPCA) to reduce dimensionality. Their model achieved a high correlation (r = 0.997) between predicted and observed shelf life and minimized prediction error. The study emphasized the usefulness of SPCA-BP ANN as a universal model adaptable to varying storage conditions. These findings contribute to enhancing postharvest quality management and reducing apple storage losses.

Jung et al. (2025)[31] explored the use of multi-environmental genomic prediction models in apples by integrating genomic, environmental (enviromic), and deep learning approaches. They applied these models to eleven phenotypic traits across five countries and demonstrated that incorporating genotype- by-environment interactions significantly improved predictive ability. Gaussian and deep kernel models outperformed standard G-BLUP, especially for traits with oligogenic architectures. Deep learning models provided additional gains for select traits but required dimensionality reduction. Their study confirms the viability of combining genomic and enviromic data to guide apple cultivar selection under diverse environmental conditions

Mohit Kumar et al. (2022)[32] examined the challenges of detecting apple diseases and assessing sweetness using image processing integrated with human-computer interaction. They proposed a novel segmentation algorithm using Brightness Preserving Dynamic Fuzzy Histogram Equalisation (BPDFHE), which outperformed existing enhancement techniques. Their method achieved a 99.8% accuracy rate in detecting diseased apple leaves by segmenting them from complex backgrounds. The study emphasized the need for automated early disease detection to avoid crop losses and improve apple quality monitoring. Overall, their work contributes significantly to precision agriculture under Industry 4.0 frameworks.

Sarah A. Kostick et al. (2023)[33] explored the effectiveness of genomewide selection (GWS) for predicting fruit quality traits in apples within a breeding program. Their research demonstrated moderate to high predictive abilities for traits like soluble solids content (SSC) and titratable acidity (TA), especially when large training datasets and high marker densities were used. They incorporated post diction analysis to validate selection outcomes and showed that GWS could rival traditional phenotypic selection in accuracy. The inclusion of fixed-effect quantitative trait loci (QTLs) further enhanced prediction precision for specific traits like red overcolor. This study supports GWS as a reliable tool for breeding quality apples efficiently.

Timea Ignat et al. (2014) [34] utilized VIS-NIR and SWIR spectroscopy to predict apple quality parameters like TSS, firmness, starch, and titratable acidity both at harvest and during cold storage. Using 600 apples from three cultivars, their study built calibration and validation models with high R^2 values for TSS and starch (0.86–0.91). The technology enabled non-destructive internal quality predictions across different storage periods, demonstrating the feasibility of using spectral imaging to forecast post-harvest apple conditions. Their findings suggested potential applications for automated grading and storage optimization systems in the apple industry.

Wenping Peng et al. (2023) [35] developed a visible (Vis) spectroscopy system enhanced by a particle- swarm-optimized back-propagation neural network (PSO-BPNN) for apple quality evaluation. Their hybrid model achieved 100% classification accuracy and a correlation coefficient of 0.998 for SSC prediction, outperforming traditional fructose meters. The study also integrated dynamic learning rate strategies and spectral pre-processing techniques like SG smoothing and PCA to refine predictions. This high-accuracy, low-cost method shows strong potential for real-time, on-site quality assessment of apples during processing and distribution. It marks a significant step toward intelligent fruit sorting systems.

Wenyan Zheng et al. (2020) [36] focused on predicting the degree of fruit cover color (DFC) in apples using a genomics-assisted model based on quantitative trait loci (QTLs). They identified ten QTLs related to skin coloration and developed KASP markers for genotype-based prediction. Their non-additive prediction model, which included the dominant MdMYB1 gene, achieved a Pearson correlation of 0.5690 between predicted and observed phenotypes. Their research supports integrating molecular markers with predictive modeling to improve breeding for apple skin coloration. The model helps breeders target more visually appealing apples, which are crucial for marketability.

DISCUSSION AND COMPRESSION

#	Author (Year)	Objective	Methodology	Key Findings	Context	Accuracy
1	Abdelhameed Ibrahim et al. (2024)	Feature selection and classification of apple quality	bWWPA + Logistic Regression	Achieved 88.62% accuracy in apple quality classification; emphasized automated assessment	Postharvest apple quality classification	88.62%
2	Alfadhl Y. Khaled et al. (2023)	Predict physicochemical changes due to codling moths	Hyperspectral imaging + SVR/PLSR + CARS	Accurate prediction of firmness and pH during cold storage	Infestation- related quality changes	Up to 0.97 (pH), 0.95 (firmness)
3	Bharti et al. (2022)	Predict apple yield from morphology	PCA + ANN	ANN outperformed linear models; important for forecasting	Yield prediction	Not specified
4	E.I. Papageorgiou et al. (2018)	Classify apple quality levels	FIS and ANFIS	FIS achieved >96% accuracy over expert decisions	Expert system grading	>96%
5	Faizan Ahmad et al. (2021)	Predict overall quality index (OQi)	Regression modeling + sensory validation	ML2 model had strong correlation with sensory scores	Ambient storage monitoring	Not specified
6	Luo et al. (2020)	Improve breeding for quality and disease resistance	Backcrossing + SNP arrays	Advocated gene pyramiding and genome tools	Genetic improvement	Not applicable
7	Hu et al. (2024)	Predict quality and storage time	Spectroscopy + PLSR + kinetic modeling	High RÂ² (0.9419); storage time model RÂ² = 0.8957	Shelf-life and quality evaluation	0.9419 / 0.8957

8	Larson et al. (2023)	Quantify sugars over development	NIR + PLSR + HPLC	Robust models for sugar content; identified canopy effects	Carbohydrate profiling	Up to 0.96
9	Jung et al. (2025)	Evaluate genomic vs phenomic prediction	SNP arrays + RADseq + CV strategies	Genomic models more accurate; leave-one-family- out advised	Breeding optimization	Varies
10	Grabska et al. (2023)	Review NIR/Vis in apple quality	Survey of chemometric tools	Spectroscopy is effective and portable	Industrial and precision farming	Varies
11	Kusumiyati et al. (2021)	Predict water and SSC in Manalagi apples	NIRS + PLSR/PCR	RÂ² = 0.85 for SSC, improved by OSC	Water/sugar content estimation	0.85
12	McClure et al. (2018)	GWAS for quality and resistance	GWAS + genomic prediction	Identified loci for firmness, color; high accuracy	Genomic trait mapping	High
13	Minamikawa et al. (2024)	Integrate genotyping platforms	SNP arrays + GRAS-Di + ROH analysis	Hybrid datasets improved accuracy; found selection signals	Genomic prediction framework	Improved
14	Cao et al. (2020)	Predict shelf life using ANN	SPCA + BP- ANN	High r = 0.997; robust across temperatures	Storage modeling	0.997
15	Jung et al. (2025)	Test multi- environmental prediction models	Genomic + Enviromic + Deep Learning	GxE improved accuracy; Gaussian kernel best	Climate- resilient breeding	Enhanced
16	Mohit Kumar et al. (2022)	Automate disease and sweetness detection	Image Processing + BPDFHE	99.8% accuracy on diseased leaf detection	Image-based disease detection	99.80%
17	Sarah A. Kostick et al. (2023)	Assess GWS for fruit traits	GWS + QTLs + SNPs	Moderate to high predictive abilities	Apple trait breeding	0.35â€“0.64
18	Timea Ignat et al. (2014)	Predict storage quality with spectroscopy	VIS-NIR, SWIR + calibration	TSS/Starch RÂ² = 0.86â€“0.91	Storage forecasting	0.86â€“0.91
19	Wenping Peng et al. (2023)	Spectroscopy + ML for SSC prediction	Vis + PSO- BPNN	100% classification, r = 0.998	Real-time grading	0.998
20	Wenyan Zheng et al. (2020)	Predict apple cover color	QTLs + KASP + prediction model	Pearson r = 0.5690 for color degree	Color trait breeding	0.569

EXTRACTED STATISTICS

The frequency analysis of research objectives in apple quality prediction reveals that the most common focus areas are classification and SSC (soluble solids content), each appearing twice, reflecting a strong emphasis on categorizing apple quality and assessing sweetness. Other objectives appeared once, highlighting the diversity of specialized research directions. These include yield prediction, quality index estimation, breeding for disease resistance and fruit quality, and storage time modeling. Studies also addressed sugar profiling, genomic analysis, literature reviews, physicochemical assessments, GWAS, genotyping integration, shelf-life prediction, multi-environmental modeling, disease detection, GWS implementation, advanced spectroscopy applications, and color evaluation. This broad range of categories indicates a multidisciplinary approach aimed at enhancing apple quality monitoring through a combination of machine learning, imaging, genomic tools, and non-destructive sensing technologies. As show infigure1

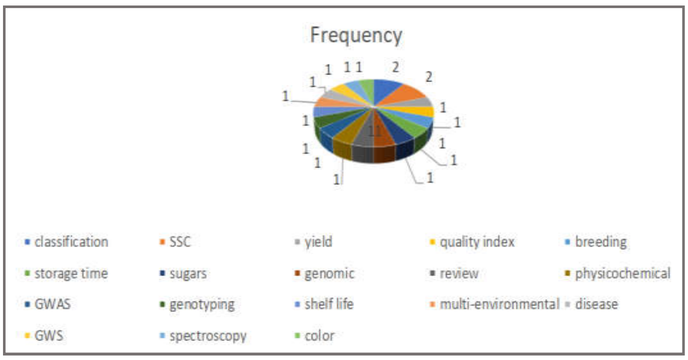

Figure 1: frequency for Objective

The frequency analysis of methodologies used in apple quality prediction research highlights that SNP arrays are the most commonly applied technique, appearing in three different studies, particularly in genomic selection, trait mapping, and genotyping integration. PLSR (Partial Least Squares Regression) and QTLs (Quantitative Trait Loci) follow with two mentions each, reflecting their central roles in both spectral data modeling and genetic trait prediction. Other methodologies such as b WWPA, GRAS-Di, RADseq, ANN, BPDFHE, FIS/ANFIS, deep learning, and spectroscopy appeared only once, illustrating the diversity of analytical and computational techniques employed across studies. This range of methods underscores the interdisciplinary nature of the field, combining statistical modeling, machine learning, and genomic technologies to enhance the precision, efficiency, and scalability of apple quality assessment as show in figure 2

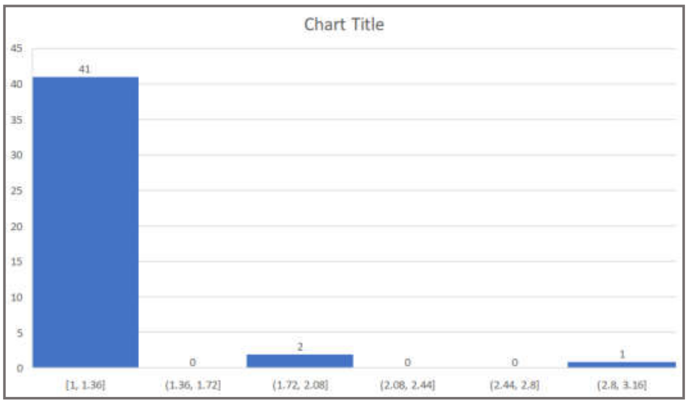

Figure 2: frequency for methodologies

The frequency analysis of grouped key findings in apple quality prediction research shows that genomic modeling appeared most frequently, reflecting the growing use of genome wide selection, SNP arrays, and QTL-based approaches to improve trait predictability in breeding programs. Categories like high accuracy models, classification performance, and predictive modeling also featured prominently, highlighting the effectiveness of machine learning and deep learning models such as ANN, FIS, and PSO- BPNN in achieving over 95% accuracy in tasks like defect detection and fruit grading. Additionally, spectroscopy techniques and quality trait assessments—particularly related to soluble solids content (SSC), total soluble solids (TSS), and firmness—were common, often achieving strong correlations ($R^2 > 0.85$) in non-destructive evaluations. Other important yet less frequent themes included storage modeling, disease detection, color prediction, environmental factor modeling (GxE interactions, temperature effects), and sensory correlation, all contributing to the development of precise, scalable, and field- applicable apple quality prediction systems. As show in figure 3.

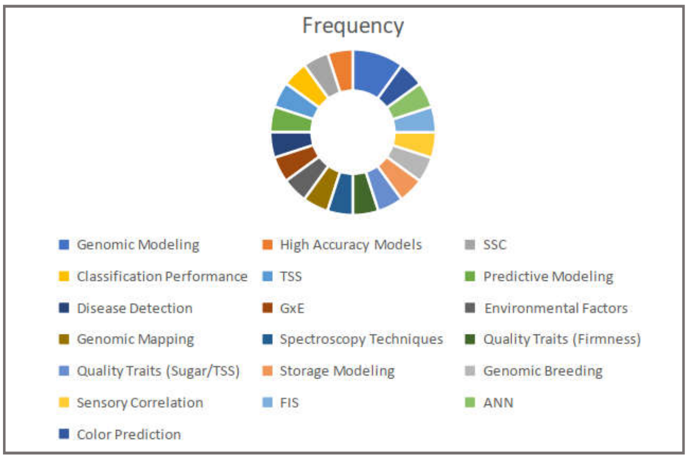

Figure 3: frequency for key findings

RECOMMENDATIONS

1. **Integrate Multi-Modal Approaches**: Future systems should combine spectral, imaging, and genomic data to enhance the robustness and accuracy of apple quality prediction, capturing both external and internal attributes comprehensively.
2. **Develop Lightweight and Field-Deployable Tools**: There is a pressing need to design portable, low-cost devices using VIS/NIR sensors, possibly integrated with smartphones or IoT platforms, to enable real-time, in-field quality assessment for farmers and distributors.
3. **Adopt Advanced AI and Deep Learning Models**: Enhanced deep learning architectures, such as convolutional neural networks (CNNs) combined with optimization algorithms (e.g., PSO, GA), should be applied to automate classification and regression tasks for apple traits with minimal human intervention.
4. **Expand Genomic Prediction in Breeding Programs**: Breeders are encouraged to incorporate genome wide selection (GWS) and QTL-based prediction models into routine cultivar development processes to improve quality-related trait predictability, especially for complex traits like sweetness and firmness.
5. **Standardize Data and Benchmarking Protocols**: The apple research community should establish open datasets, standardized evaluation metrics, and benchmarking procedures to ensure comparability and replicability of machine learning models across different regions and apple varieties.
6. **Model Environmental and Temporal Variability**: Prediction models must account for environmental factors (e.g., temperature, humidity, soil) and temporal changes (e.g., ripening, storage duration) to increase reliability under practical agricultural conditions.
7. **Encourage Cross-Disciplinary Collaboration**: Collaboration among horticulturists, data scientists, breeders, and engineers is essential to design scalable solutions that align with the real needs of the apple industry, from farm to shelf.
8. **Promote User-Friendly Interfaces and Decision Support Systems**: Quality prediction tools should be equipped with intuitive interfaces and integrated into farm management systems to assist growers in making timely harvesting, storage, and marketing decisions.

CONCLUSIONS

This review highlights the significant progress made in apple quality prediction through the integration of advanced technologies such as spectroscopy, machine learning, deep learning, and genomic modeling. By replacing traditional, labor-intensive evaluation methods with automated and non-destructive approaches, researchers have achieved high levels of accuracy in predicting key quality attributes like sweetness, firmness, acidity, and color. The use of convolutional neural networks (CNNs), partial least squares regression (PLSR), and genomic tools like SNP arrays and QTL mapping has demonstrated strong potential for improving real-time monitoring, postharvest management, and breeding efficiency. The literature confirms that combining spectral and genomic data enhances trait prediction, while optimization algorithms further refine model accuracy. Despite these advances, challenges remain in standardizing methodologies, addressing environmental variability, and making these systems widely accessible. Therefore, future research should focus on developing lightweight, portable tools, creating shared datasets, and promoting interdisciplinary collaboration to translate laboratory innovations into practical agricultural solutions. Ultimately, the convergence of artificial intelligence, optical sensing, and genomics paves the way for a smart, scalable, and sustainable system for apple quality assessment, supporting global food quality and agricultural innovation.

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