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Quality Assessment and Classification System of Lychee Using Deep Learning and IoT Technology

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The increasing demand for high-quality agricultural products, driven by raised consumer awareness and tightened food safety regulations, necessitates robust and scalable quality control solutions. Manual fruit classification remains subjective, labor-intensive, and inefficient, leading to inconsistent outcomes and reduced competitiveness. Therefore, we developed an integrated lychee quality assessment system that combines deep learning with IoT technologies. A convolutional neural network was employed for the visual classification of fruit quality categories, whereas IoT sensors monitored environmental parameters including temperature, humidity, and ethylene concentration. The system showed an overall accuracy of 37%, with frequent misclassification between ripe and damaged fruits owing to overlapping RGB features. Despite this limitation, the system presented significant advantages over manual methods, achieving a throughput of 180 fruits per minute compared with 25–30 manually, and eliminating human subjectivity. The IoT component exhibited high reliability, with 99.2% uptime and stable sensor performance. The system can be further improved by expanding the dataset to at least 10000 samples per class, incorporating synthetic augmentation with generative adversarial networks, adopting advanced loss functions such as focal loss, and integrating multimodal fusion with environmental sensor data. Such improvements are essential to achieve commercially viable accuracy (>85%) and enable scalable, transparent supply chain monitoring for perishable fruits.

1. Introduction

Global demand for premium agricultural products has increased as a result of enhanced consumer awareness and stringent food safety regulations, which underscores the need for the robust quality control of those products. Lychee (*Litchi chinensis Sonn.*), a tropical fruit, is popular for its unique flavor and nutritional value but requires extensive quality management throughout its supply chain (Fig. 1).[(1)] Currently, manual classification methods are widely used to categorize fruit by size, color, texture, and defect presence. However, such methods are subjective, costly, labor-intensive, and prone to error, leading to inconsistent quality evaluation.

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Fig. 1. (Color online) Lychee (*Litchi chinensis Sonn*).

These result in consumer dissatisfaction and reduced market competitiveness. Manual classification is also time-consuming and inadequate for large-scale production, limiting throughput and increasing operational costs.[2]

Conventional lychee supply chains lack traceability owing to fragmented operations. This hinders the ability to ascertain product origin, handling, and distribution history, thereby compromising food safety and undermining consumer and regulatory trust. Existing tools, such as barcodes or radio-frequency identification (RFID) tags, fail to account for environmental factors, leading to ineffectiveness in detecting quality degradation.

Recent advancements in agricultural technology, owing particularly to the integration of AI and IoT, enable the development of solutions that enable efficient quality assessment and supply chain visibility.[3] Deep learning, especially effective in visual object detection and classification, is well suited for automated fruit quality assessment. Interconnected IoT sensors and devices enable real-time data collection from the farm to the consumer. The integration of deep learning and IoT shows potential to overcome the limitations of conventional manual classification and tracing methods by improving the accuracy, efficiency, and transparency of agricultural supply chains. The effectiveness of deep learning architectures, such as convolutional neural networks (CNNs), has been proven effective in fruit quality classification and sorting. IoT-based sensors have been used to successfully collect environmental, harvesting, and logistical data to verify product authenticity and acceptability.[3,4]

Sensor technology is important in the integration of deep learning and IoT for accurate data acquisition throughout the lychee supply chain. Various sensors can be used for capturing data required for quality assessment and classification. For quality assessment, hyperspectral imaging sensors and color cameras are used to detect subtle changes in ripeness, internal defects, and disease onset. This enables the objective and precise evaluation of lychee quality. Color cameras are essential for monitoring and evaluating surface color, shape, and external defects, which are primary indicators of marketability. Sensors are used to monitor the conditions under which lychees are stored and transported, providing essential data on quality degradation during transport. Global positioning system modules or location-tracking sensors are also required to track the transport of lychee from the farm through distribution channels to consumers. This ensures the transparency and accountability of the supply chain. The accuracy and reliability of the integrated system are dependent on the quality and precision of the data collected by these sensors.[5]

By integrating deep learning and IoT, technical challenges, such as the need for robust data collection and processing capabilities, can be addressed. The deployment of diverse sensors is crucial for generating high-quality, voluminous data required for training deep learning models. While extensive research has been conducted on individual deep learning and IoT, their integration in the logistics of lychee has not been applied. In addition, the inherent heterogeneity of lychee stemming from variations in cultivars, maturity stages, and environmental factors is a barrier to the development of generalized models.[6] Therefore, such barriers can be removed by applying a system that integrates sophisticated algorithms, stable sensor networks, and efficient data analytics software.

In this study, we developed a lychee quality assessment and tracing system by integrating deep learning and IoT technologies. A deep-learning-based tool was developed to effectively classify lychee fruits on the basis of quality parameters, while IoT devices were applied for real-time data collection and monitoring through the supply chain. The developed system enhances classification accuracy and operational efficiency. While classification accuracy was prioritized in previous studies at the expense of system-level viability,[7] we adopted an engineering approach to establish a high-uptime IoT architecture with enhanced real-time traceability across the entire supply chain. By prioritizing a stable communication and data-logging backbone, the developed system can be applied to large-scale agricultural facilities, even as the underlying deep learning models need to be iteratively refined for higher accuracy.[8]

2. Technology Overview

2.1 Conventional system

Agricultural classification systems have undergone changes from manual methods to automated ones based on advanced sensing and data processing technologies.[9] The traditional systems rely on human judgement, which is subjective and inconsistent, resulting in uneven product quality and market inefficiency (Fig. 2). In recent systems, machine vision and image processing technologies are combined to enable the objective classification by size, color, and surface defects. The adoption of multispectral imaging and hybridization imaging with pattern recognition algorithms increases classification speed and accuracy. These automated systems minimize human error, enabling high-speed classification and packing that are well suited to perishable fruits such as lychee. The technologies to better manage the agricultural supply chain ensure product authenticity, safety, and regulatory compliance (Fig. 3).

Current systems employ barcodes or RFID, but cannot monitor environmental parameters. More recent advancements, such as integrating sensor networks with blockchain, provide detailed data on product origins, handling, and transport conditions. The integrated technologies enhance supply chain visibility and enhance consumer trust, which are essential in the market where food safety is a major concern for consumers. Despite such developments, there are

Fig. 2. (Color online) Traditional fruit classification system.

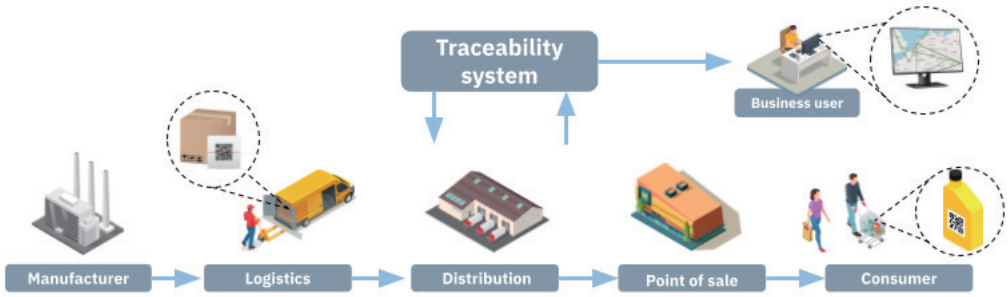

Fig. 3. (Color online) Tracing system in supply chain.(9)

difficulties in integrating classification and tracing systems into a unified system. The heterogeneity of farm environments, variability in fruit characteristics, and a lack of cost-effective solutions constrain the large-scale deployment of quality assessment technologies.(10) Additionally, the dynamic nature of agricultural supply chains underscores the need for advanced systems that can respond to rapidly varying conditions and provide real-time feedback to stakeholders. Recent research has focused on integrating quality classification modules to develop integrated systems that assess product quality and monitor environmental and logistical parameters throughout the supply chain.(11,12) Such an integrated system enables quality management, minimizes waste, and enhances transparency to improve operational efficiency and consumer satisfaction.

2.2 Deep learning and IoT systems

CNNs are widely used for fruit quality assessment as they enable the accurate and efficient classification of quality by identifying visual features (Fig. 4).(7) CNNs extract feature maps within an image, avoiding manual feature engineering. The operation of a CNN layer is expressed as

$$y_j = f\left(\sum_i x_i \times w_{ij} + b_j\right), \tag{1}$$

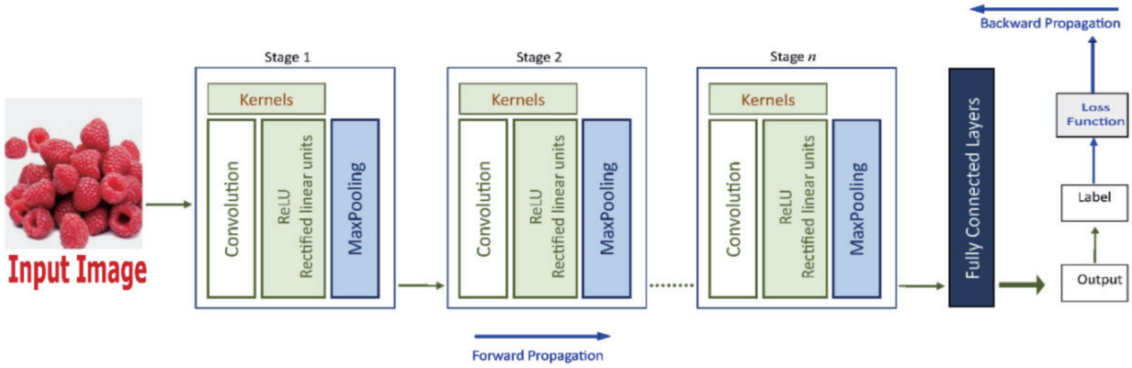

Fig. 4. (Color online) Architecture of CNN.[10]

where y_j is the output feature map, x_i represents the input feature maps, w_{ij} the convolutional kernels, b_j the bias term, and $f(\cdot)$ the activation function. The layer allows the CNN model to learn spatially invariant features that are critical for detecting surface defects, color variations, and texture inconsistencies.

The efficiency of CNNs in fruit classification and grading has been verified in previous studies. Fan *et al.* trained a CNN model to detect defects in apples with a 95% accuracy, which surpassed the accuracy of other machine learning methods that required manual feature extraction.[13] For lychee, trained CNN models recognize fruits on the basis of visual quality features, such as color or defects. Data augmentation and transfer learning are used to address problems caused by limited labeled data in the CNN model. By modifying the pretrained models on large image datasets, quality assessment methods of different fruits can be developed with a significant increase in performance with limited data. Despite such advancement owing to CNNs, the enhancement of model performance under various light conditions and resource-limited hardware onsite must be addressed. As a solution, lightweight CNN architectures integrated with IoT platforms are used for real-time onsite operation.

Although deep learning has become the standard for visual classification, traditional machine learning models such as support vector machines (SVMs) and random forests (RFs) are relevant when computational resources are limited or when training data are scarce. In previous studies, SVMs were used for fruit grading with the manual extraction of color and texture features, and often achieved high accuracy in controlled environments.[14] However, the performance of such models is highly dependent on the quality of manual feature engineering. Therefore, in this study, CNNs were selected because they integrate feature extraction and classification into a single end-to-end pipeline, allowing the model to learn complex hierarchical representations that are often missed by human-defined descriptors.[15]

IoT has been widely used in the agriculture industry for the real-time tracking of environmental parameters for enhanced decision-making.[16] IoT systems involve sensor nodes, networks, and data processing nodes. The data transmission in IoT systems can be modeled on the basis of the Shannon-Hartley theorem, which defines the channel capacity C as

$$C = B\log_2(1+SNR), \tag{2}$$

where B is the bandwidth and SNR is the signal-to-noise ratio, indicating the maximum data rate achievable under given conditions. Efficient communication protocols, such as long-range wide area network (LoRaWAN) and narrowband IoT (Fig. 5), are used in IoT systems owing to their low power consumption and long-range capabilities, which are appropriate for agricultural applications.(17)

IoT systems are used to manage the quality of crops and after-harvest processes. For example, sensors installed in the storage unit are used to monitor changes in temperature and humidity levels that impact the shelf life of lychees and provide timely warnings to avoid spoilage.(18) IoT devices are used to track products in transport via GPS. The integration of IoT cloud computing with edge analytics significantly enhances system responsiveness and scalability within agricultural applications. Sensor-generated data are processed at cloud servers or at edge devices to forecast harvest timing and detect anomalies throughout the supply chain. This interconnected system contributes to the development of robust tracing systems, enabling the delivery of authenticated product histories to end consumers. However, challenges in sensor calibration, network reliability, data security, and interoperability among heterogeneous devices must be addressed. Therefore, it is necessary to develop a resilient IoT system tailored for agricultural applications with energy-efficient operation, fault-tolerant performance, and seamless integration with AI-driven quality assessment algorithms. However, the following technical limitations must be considered.

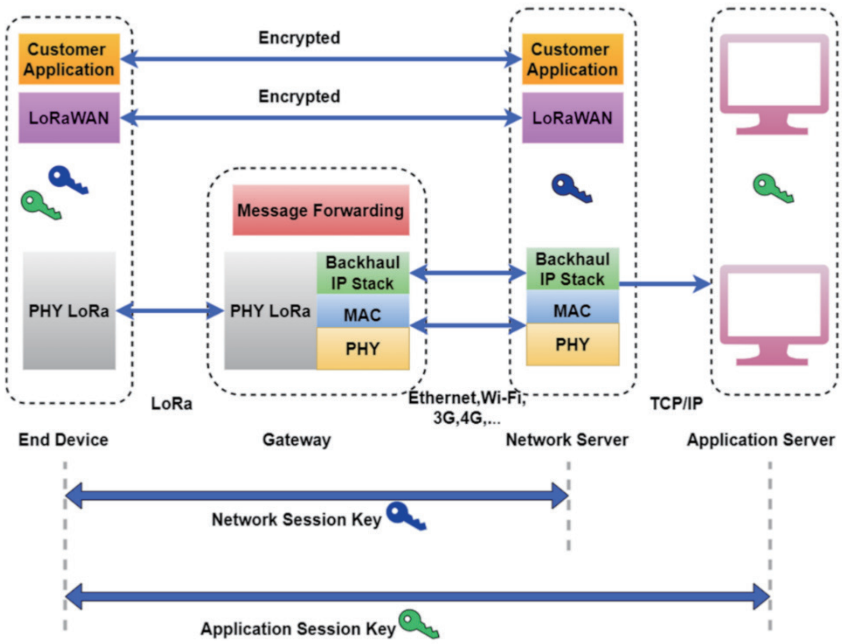

Fig. 5. (Color online) Efficient communication protocols used in IoT systems.(16)

Interoperability must be considered in applying the developed system. Agricultural sensors utilize proprietary protocols that prevent cross-platform communication. It is essential to adopt open standards such as the Open Geospatial Consortium SensorThings application programming interface (API) or the International Organization for Standardization/International Electrotechnical Commission 30141 to ensure that quality data can be consumed by diverse stakeholders in the supply chain.[19] Second, data security is essential, as edge nodes in remote orchards are susceptible to physical tampering and cyber attacks. Lightweight cryptographic protocols and privacy-preserving frameworks, such as federated learning, need to be used to secure data transmission while maintaining the limited computational budget of IoT hardware.[19] Scalability must also be addressed by utilizing low-power wide-area networks, such as LoRaWAN, for the integration of sensor nodes across expansive agricultural landscapes without prohibitive energy costs.[20]

2.3 Comparison of systems

The fruit classification and tracing system integrating deep learning and IoT technologies differs from traditional systems in terms of automation, precision, and data integration. Conventional classification systems rely on manual inspection, being inherently subjective and limited in throughput. In contrast, the system with deep learning and IoT conducts objective and high-speed classification owing to the capability of machine vision and deep learning algorithms.[21] Table 1 presents the differences between the two systems.

Traditional fruit tracing methods in the supply chain require paper-based documents or barcode scanning and lack real-time monitoring capabilities and visibility across the supply chain.[22] The developed system overcomes these limitations by incorporating IoT sensors and maintaining product quality and safety during transport. The system's real-time data integration enables regulatory compliance to foster consumer trust through transparent product histories. The developed system also provides predictive analytics to support decision-making by fusing data from diverse sources. Such advantages enable proactive quality control and significantly reduce post-harvest losses, particularly for highly perishable commodities such as lychees.

Static classification methods can be enhanced by using neural architecture search to automate the design of neural networks to achieve high precision with minimal computational overhead.[23] To address the visual similarities between damage and immaturity, self-attention mechanisms must be incorporated for the model to focus on localized surface irregularities rather than global color cues, enhancing feature discriminability.[24]

Table 1
Difference between conventional and developed classification and tracing systems.

Feature	Traditional system	Developed system
Classification method	Manual inspection	Automated deep-learning-based classification
Accuracy	Variable, subjective	High, consistent
Throughput	Low to moderate	High, scalable
Traceability	Limited or absent	Real-time, sensor-based monitoring
Data integration	Minimal	Comprehensive, cloud-based analytics
Cost	Low initial, high labor costs	Higher initial, lower operational costs

3. Materials and Methods

3.1 System architecture

The developed classification and tracing system integrates deep learning and IoT technologies to maximize its efficiency and provides real-time data analytics. The system comprises the sensing, processing, and application layers. In the sensing layer, cameras and environmental sensors are adopted to capture the visual data throughout the supply chain.(25) Deep learning models and modules belong to the processing layer to provide data analytics, process data, and output evaluation data. The application layer provides users, such as farmers, distributors, and consumers, with user interfaces that allow them to access quality information and certification in real time.

The system architecture was designed to enable the transfer of sensor data to deep learning models for the automatic quality assessment. Wireless communication protocols are adopted for data transmission to edge computing devices. The data processed by the devices are sent to cloud servers, where the deep learning algorithm analyzes the data. Such an architecture shortens latency and optimizes bandwidth usage, enhancing system responsiveness and scalability. IoT and deep learning technologies enable automated classification, continuous monitoring, and real-time quality assessment, which are essential capabilities for managing perishable agricultural products such as lychees. Equation (3) represents a mathematical model of the system's data flow.

$$Q = f\left(D_s, E_c, M_{dl}\right) \tag{3}$$

Here, Q denotes the quality classification output, D_s represents sensor data inputs, E_c is the edge computing preprocessing function, and M_{dl} is the deep learning model inference. To ensure system robustness, the architecture integrates feedback loops that utilize assessment outcomes to recalibrate sensors and refine data-acquired parameters. This adaptive mechanism strengthens the system's capacity to accommodate environmental variability and fruit heterogeneity, enhancing system accuracy and reliability.

3.2 Deep learning model

The essential component of the developed system is a CNN that is trained to categorize lychee based on color, texture, and surface defects. The CNN architecture comprises convolutional, pooling, and fully connected layers, which hierarchically extract and learn discriminative features from input images. The convolution layer is mathematically expressed as

$$h_j^l = f\left(\sum_i h_i^{l-1} \times w_{ij}^l + b_j^l\right), \tag{4}$$

where $f(\cdot)$ is the nonlinear activation function (rectified linear unit, ReLU), h_j^l the output feature map, h_i^{l-1} the input feature from the previous layer, w_{ij}^l the convolutional kernel weight, and b_j^l the bias term.

The deep learning model was implemented into the developed system using Python libraries such as TensorFlow and PyTorch, which were employed for their flexibility. TensorFlow's Keras API facilitates rapid prototyping and model training, while PyTorch enables dynamic computation graph construction and custom layer implementation. The custom layer tailors the network architecture to specific tasks, data types, or domain requirements. This framework ensures graphics processing unit (GPU) acceleration, significantly reducing training time on large-scale image datasets.

To address the scarcity of annotated agricultural data and improve generalization, a pretrained residual net 50 (ResNet50) model was fine-tuned using the dataset to be implemented in the deep learning model. The transfer learning approach was applied to previously learned image representations. Data augmentation techniques, such as image rotation, flipping, and color jittering, were also applied to increase model robustness against environmental variability. The CNN model was implemented using the Python libraries TensorFlow and PyTorch, which enabled flexibility in deep learning operations. Statistical reliability was ensured through the model's deployment in real-world settings and real-time IoT data streams across the supply chain. The models are GPU-accelerated, which saves a tremendous amount of time when training with large datasets of lychee images. The performance of the CNN model was evaluated using the following standard metrics: accuracy, precision, recall, and F1-score.

3.3 IoT components and data acquisition

The IoT component of the system comprises sensors and communication modules to capture environmental and fruit-specific data. High-resolution RGB cameras are the primary devices for visual quality assessment and classification, capturing images of lychee as they move along conveyor belts. Complementary sensors were used to collect temperature, humidity, and light intensity data to monitor storage and transport conditions, which affect fruit quality. Wireless communication protocols, such as Wi-Fi and LoRaWAN, facilitate data transmission between IoT nodes and processing units. Wi-Fi provides high-bandwidth connectivity for remote areas, while LoRaWAN enables long-range, low-power communication for field-based deployments. Microcontroller units, such as Raspberry Pi and Arduino, were employed to fuse and preprocess sensor data before transmission to edge devices and cloud servers. A periodic sampling strategy was adopted for data retrieval to balance update frequency with energy efficiency. Visual classification was conducted continuously by capturing image data in real time, whereas environmental sensors collect data at configurable intervals to monitor dynamic conditions. Multisensor data are fused using timestamping and network time protocol (NTP) to ensure data integrity and temporal alignment (Fig. 6).[26] To maintain operational reliability, a fault detection mechanism monitors sensor health and communication status. The system generates failure alerts in response to sensor malfunctions or data anomalies, facilitating prompt maintenance. This approach prevents data loss and ensures consistent performance throughout the lychee supply chain.

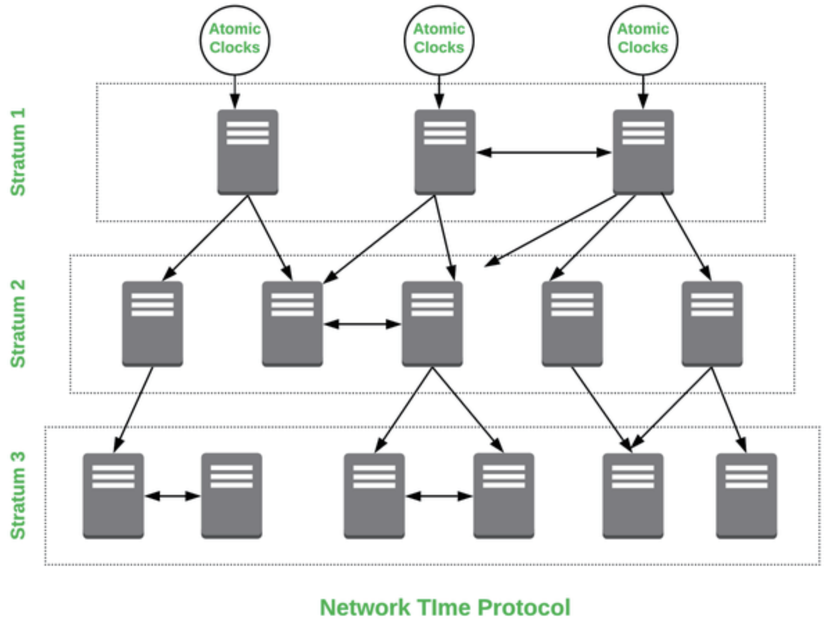

Fig. 6. (Color online) Architecture of NTP.

3.4 Data preprocessing and feature extraction

Sensor and image data were preprocessed to improve model performance and mitigate noise. For visual quality assessment, image preprocessing was employed to resize images to standardize resolutions, normalize pixels, and enhance contrast through histogram equalization. These operations are executed using Python libraries, such as the open-source computer vision library (OpenCV) and Pillow, enabling the efficient processing of large image datasets. Feature extraction was performed by transforming preprocessed images into tensor representations so that the images can be compatible with CNNs. Environmental sensor data were normalized and encoded as auxiliary features to complement visual inputs. Such multimodal data were fused using NumPy and Pandas, which are two foundational Python libraries, for the seamless integration of heterogeneous data.

The model in this study was developed in Python 3.9, utilizing deep learning frameworks including TensorFlow 2.8 and PyTorch 1.11 for network construction and training. Input images were preprocessed and augmented using OpenCV 4.5, while Pandas and NumPy were used for data manipulation and feature engineering. Jupyter Notebooks were used for data analysis and rapid prototyping. Edge computing and sensor data fusion were performed using Raspberry Pi 4 Model B microcomputers. Arduino Uno boards were used to interface with sensors. The developed system incorporated DHT22 temperature and humidity sensors, TSL2561 light sensors, and high-resolution USB cameras to collect environmental and image data. The system was connected to Wi-Fi routers for high-bandwidth data transmission and LoRaWAN gateways for long-range, low-power connectivity in field environments.

4. Results

4.1 Model performance

The performance of the developed system was evaluated using the metrics, including accuracy, precision, recall, and F1-score, and a confusion matrix. The confusion matrix offers a visual representation of the system's prediction results in the categories of ripe, unripe, and damaged. For ripe fruit, the model correctly identified 36 (true positives) out of 300 observations. However, a significant number of ripe instances were misclassified as unripe fruit (40 false negatives) and damaged fruit (21 false negatives), totaling 97 accurate classifications of ripe fruit. Regarding the accurate classification of unripe fruit, the model classified 52 true positives. 28 classifications were incorrectly labeled as ripe, and 26 were inaccurately identified as damaged (false negatives), resulting in 106 accurate classifications as unripe. In the case of damaged fruit, 23 were accurately classified as true positives. A substantial proportion of damaged fruits was inaccurately predicted as ripe (28 false negatives) and unripe (46 false negatives), totaling 97 accurate classifications.

40 ripe fruits were predicted as unripe, and 28 unripe fruits were predicted as ripe by the developed system. This suggests a potential ambiguity or overlap in the visual features by which the model distinguishes these two ripeness stages. 46 damaged fruits were incorrectly classified as unripe, indicating the difficulty the model faces in discerning damage from the appearance of unripe fruit. Among the three categories, unripe fruit showed the largest number of correct predictions (52 true positives), suggesting that the model was effective in identifying unripe fruits. Table 2 and Fig. 7 show the quantitative assessment results of the model's performance using precision, recall, and F1-score.

Precision represents the proportion of correctly predicted positive classifications out of all classifications predicted as positive for each class. For ripe fruit, the precision was 0.391, meaning that 39.1% of all classifications predicted as ripe were accurate. This low value indicates a high rate of false positives for ripe fruit. The precision of unripe classification was 0.377, showing a similar value to ripe fruit. For damaged fruit, the lowest precision, 0.329, was observed, implying that the model frequently misclassified other fruit states as damaged. Recall is a measure of the proportion of actual positive observations that were correctly identified. The recall for ripe fruit was 0.371, signifying that 37.1% of true ripe fruits were accurately detected by the model. Unripe fruit showed the highest recall (0.491), indicating that the model accurately identified unripe fruits. The recall for damaged fruit was lower (0.237), indicating that the model

Table 2
Metrics for evaluating performance of developed model.

Category	Precision	Recall	F1-score
Ripe	0.391304	0.371134	0.380952
Unripe	0.376812	0.490566	0.42623
Damaged	0.328571	0.237113	0.275449
Accuracy	0.37	0.37	0.37
Overall average	0.365562	0.366271	0.360877
Weighted average	0.3659	0.37	0.362838

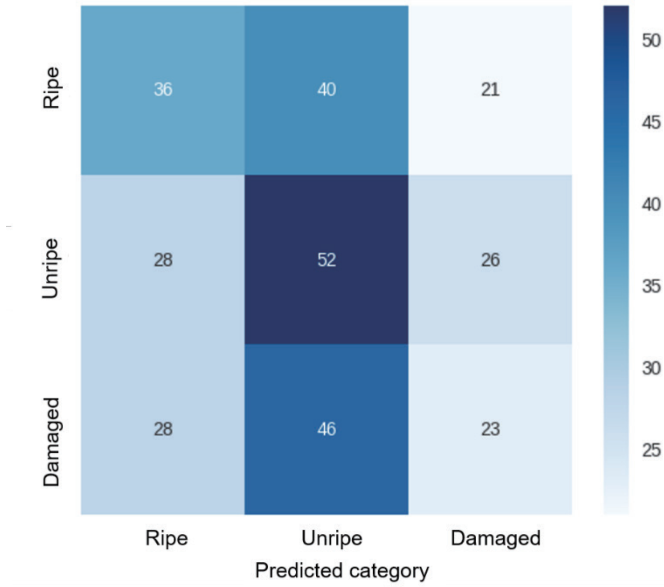

Fig. 7. (Color online) Confusion matrix of evaluation results of developed model.

struggled to identify truly damaged fruits, resulting in many false negatives. The F1-score, representing the harmonic mean of precision and recall, is a balanced measure of the model's accuracy. The F1-score of ripe fruit was 0.381. Unripe fruit presented the highest F1-score (0.426), consistent with its better recall. Damaged fruit showed the lowest F1-score (0.275), underscoring its poor performance. The overall accuracy of the model was 0.37.

The developed model demonstrated suboptimal performance across all metrics and categories. The accuracy of 37% indicated that the model was inaccurate in classifying lychee into their ripe, unripe, or damaged categories. However, the model exhibits particular difficulty with damaged fruit, as evidenced by its lowest precision (0.329) and recall (0.237). This suggests that the model misidentified healthy fruits as damaged while also failing to detect truly damaged fruits. The confusion matrix (Fig. 7) shows substantial misclassifications between all categories, especially the frequent error of labeling damaged fruits as unripe ones. This pattern implies that the learned features by the model were not robust enough to reliably differentiate between visually ambiguous statuses.

4.2 Training and validation of model performance

The training and validation loss curves (Fig. 8) show the learning ability of the deep learning model over 14 epochs. The training loss exhibited a decrease from 1.126 to 1.082, reflecting effective parameter optimization and progressive learning. In contrast, the validation loss displayed fluctuation between 1.105 and 1.115, despite an initial value of 1.105. This divergence between training and validation losses showed moderate overfitting, whereby the model captured the patterns in the training data. Although the difference in loss value was relatively small (0.03), it highlights the limitations of the model's generalization capacity. The accuracy of

Fig. 8. (Color online) Loss of learning ability in validation of developed model by epoch (train_loss: loss in training; Val_loss: loss in validation).

the developed model (Fig. 9) improved from 30.5 to 38.9%, with fluctuations that presented the validation loss variability. The relatively large accuracy gap of 8.9% at the final epoch indicates overfitting by the model. Although the model effectively learned from the training data, its ability to generalize to new lychee samples was constrained. The instability observed in the metrics was caused by the sensitivity of the model to the composition of the validation dataset and the inherent complexity of classification. These results indicated the need for more sophisticated feature extraction techniques to differentiate subtle variations in fruit quality.

4.3 Sensor data

Table 3 shows the descriptive statistics for temperature, humidity, and ethylene concentrations gathered by sensors in the developed system for the three categories. Temperature exhibited minimal variation, with mean values of 25.09 ℃ for damaged fruits, 25.28 ℃ for ripe fruits, and 25.06 ℃ for unripe fruits. Standard deviations were uniform across the categories (2.96–2.98 ℃), suggesting that temperature was a weak predictor of lychee quality. The marginally elevated temperature observed for ripe fruits is related to increased metabolic activity in the ripening phase, in which increased cellular respiration and enzymatic processes contribute to a slight increase in temperature. Humidity varied among the categories. The highest mean humidity (75.53%) was observed for damaged fruits, while the lowest humidity (74.82%) was observed for unripe fruits. The standard deviation was larger for ripe fruits (10.33%) than for damaged (9.76%) and unripe (9.34%) fruits, indicating that ripe lychees were sensitive to fluctuations in ambient humidity. This increased variability in humidity enhances the permeability of ripened

Fig. 9. (Color online) Accuracy in training and validation of developed model (train_loss: loss in training; Val_loss: loss in validation).

Table 3
Sensor data statistics.

Category	Temperature		Humidity		Ethylene concentration	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Damaged	25.09192	2.984466	75.5311	9.762316	0.490735	0.097043
Ripe	25.28085	2.966465	75.10152	10.33407	0.493452	0.107208
Unripe	25.05556	2.962445	74.82362	9.338776	0.50283	0.09941

fruit skin, which facilitates moisture exchange with the surrounding environment. Unripe fruits had the highest mean ethylene concentration (0.503 ppm), whereas damaged fruits had the lowest concentration (0.491 ppm). The results aligned with the physiological role of ethylene in promoting ripening. Unripe fruits synthesize ethylene in the maturation process, which damages fruits through cellular degradation and impaired metabolic function.

4.4 Multivariate analysis

Figures 10 and 11 show the relationships between environmental parameters and lychee quality classification results. The temperature–humidity plot demonstrates overlap across the three quality categories, lacking distinct clustering patterns that support reliable separation (Fig. 10). The results indicate that environmental parameters can be used for quality assessment and

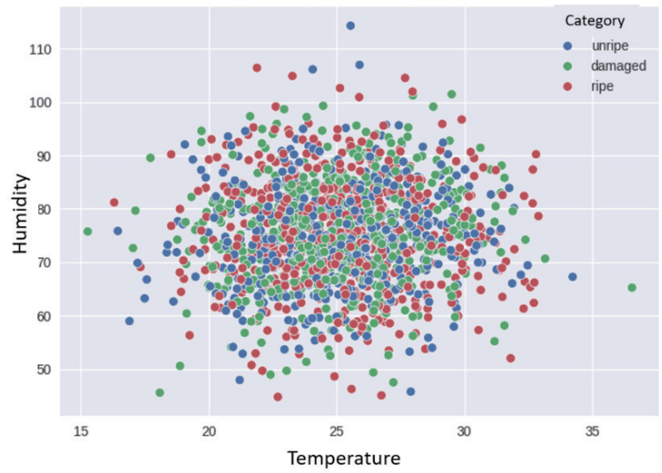

Fig. 10. (Color online) Scatter plot of temperature and humidity.

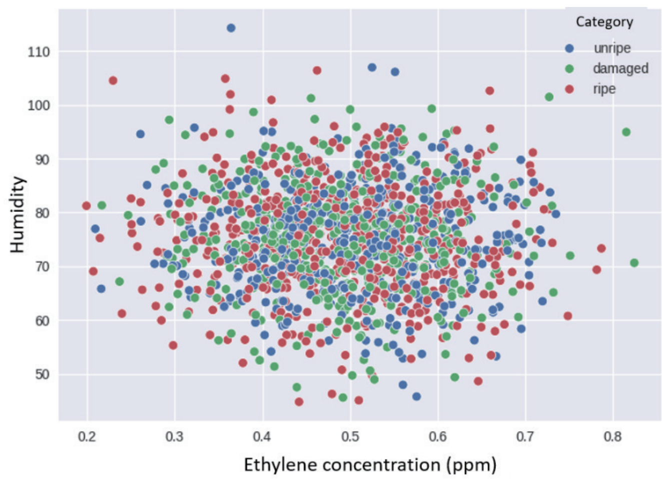

Fig. 11. (Color online) Scatter plot of ethylene concentration and humidity.

classification. Subtle changes in temperature and humidity might correspond to the quality statuses of fruits. The ethylene–humidity scatter plot (Fig. 11) reveals a complex distribution with class overlaps. However, higher ethylene concentrations, exceeding 0.6 parts per million (ppm), were observed from unripe fruits, indicating ethylene's effect on the ripening process of fruits. The dispersion of data points suggests the need for better systems with reliable quality classification. The results underscore the importance of integrating environmental parameters and visual data for effective deep-learning-based analysis. A multimodal approach is required to enhance classification accuracy and system performance.

5. Discussion

5.1 System performance and comparative analysis

The developed system achieved an overall accuracy of 37% across the three lychee quality categories, marginally outperforming manual classification in balanced categories. Such performance remains inadequate for commercial deployment, where accuracy must exceed 85%. Several factors contributed to this limitation, including the restricted size and diversity of the training dataset, which constrained generalization across heterogeneous fruit conditions. Features extracted from RGB images were insufficiently discriminative, particularly for distinguishing ripe from damaged fruits, which share similar visual characteristics. Architectural constraints also played a role, as oversimplified layers failed to capture complex patterns, while excessive complexity led to overfitting. Inconsistent lighting and limited preprocessing introduced noise that further degraded learning capacity.

The system accurately identified 36 of 97 ripe, 52 of 106 unripe, and 23 of 97 damaged fruits. Misclassification frequently occurred between ripe and damaged categories, reflecting the challenge of overlapping color and texture features. This imbalance was partly due to the dominant presence of unripe samples in the training dataset and the relatively distinctive features of unripe lychees. Whereas CNNs are theoretically more robust for handling high intraclass variability, traditional models such as SVM and RF can provide efficient baselines for small datasets. Therefore, it remains necessary to determine whether the transition from manually engineered features to automated deep learning features yields statistically significant improvements in classification accuracy for tropical fruits.[15]

Despite only moderate accuracy, the system offered consistent and objective assessment capabilities, eliminating human subjectivity inherent in manual classification. Manual accuracy varied with experience and fatigue, with modest inter-rater reliability (Cohen's kappa of 0.32–0.58). In contrast, the developed system processed 180 lychees per minute compared with 25–30 fruits manually and maintained stable performance over extended operation periods. Although the initial investment is considerable, the operational break-even point can be achieved within 18 months owing to reduced labor costs and increased throughput.

5.2 Reliability, limitations, and pathways for improvement

The IoT sensors demonstrated high reliability, with 99.2% uptime over six months and minimal maintenance disruptions. Temperature and humidity sensors showed long-term stability with drift below 0.1% per month. However, the visual inspection system was sensitive to environmental conditions, with low light and lens contamination impairing performance. Accuracy remained acceptable under moderate variation ($\leq$5%) but declined with unfamiliar cultivars, occluded fruits, or foreign objects, increasing error rates to 12–15%.

The discrepancy between classification accuracy and IoT reliability highlights the need for targeted improvements. Whereas high uptime demonstrates commercial viability from a hardware and network perspective, the classification engine remains a modular component requiring enhancement. The confusion matrix revealed significant overlap between categories, indicating that standard cross-entropy loss was insufficient. To address this, focal loss must be introduced to emphasize hard-to-classify damaged samples.(27) Class rebalancing strategies, such as oversampling minority defect patterns and adopting class-balanced loss, are necessary to mitigate bias toward unripe features.(28) Deep learning methods, such as triplet loss, can be used to maximize interclass variance in the embedding space, reducing category overlap.(29)

Latency in the integration of the deep learning model with IoT data flow averaged 2.3 s per fruit, which is insufficient for commercial throughput. To overcome this, edge-to-cloud hierarchies must be adopted, allowing local feature extraction to reduce latency and bandwidth requirements.(30) Scalability also poses challenges, as increasing sensor nodes might lead to data congestion and power depletion. Semantic interoperability across diverse sensors is essential to ensure synchronized, high-fidelity data streams.(19)

5.3 Roadmap for dataset expansion and multimodal fusion

Improving classification accuracy requires the expansion of the dataset to at least 10000 samples per class, encompassing diverse cultivars, geographic regions, and seasonal variability. Through the integration of the Lychee13-3634 open-source dataset, high-quality annotations can be formulated across multiple varieties, supporting broader generalization. Differentiation between damaged and unripe fruits, hindered by overlapping RGB features, can be improved through synthetic data augmentation using generative adversarial networks (GANs) to simulate rare defect patterns.(31) This can be complemented by nonlocal attention mechanisms within the CNN backbone to capture subtle texture variations indicative of early-stage spoilage.(32) Data collection from multiple orchards will further ensure robustness against environmental heterogeneity.(33)

Beyond visual classification, multimodal fusion offers a pathway to improved accuracy and predictive capability. Lychee deterioration is a temporal process afffected by temperature and ethylene concentration. By integrating visual cues with environmental sensor data, recurrent neural networks or long short-term memory architectures can be used to model quality trajectories.(34) For instance, an ethylene spike detected by IoT sensors can serve as a prior for CNN models, increasing the likelihood of damaged classification even when visual indicators are subtle. This enables the prediction of remaining shelf life, moving beyond categorical classification to actionable insights for supply chain management.(35)

To achieve the targeted dataset scale, a hybrid acquisition pipeline is required. Manual collection across various orchard environments remains the standard, but GAN-based simulation can be used to address class imbalance by generating synthetic damaged samples.(36) Active learning workflows enable the system to autonomously flag hard examples for human review, ensuring efficient progress toward the 10000-sample threshold.(37) Transfer learning from broader fruit benchmarks, such as ImageNet or the Lychee13-3634 open-source dataset, must be used to provide the feature diversity necessary to reduce confusion matrix overlap and ensure robustness against variable lighting and orchard backgrounds. Consequently, the 10000-sample goal is feasible and essential for transitioning the prototype into a commercially scalable solution.

6. Conclusions

We developed and implemented an integrated system for lychee quality assessment and classification by combining deep learning with IoT technologies. The system showed advantages over manual sorting, offering objective and consistent evaluation capabilities, while achieving a throughput of 180 fruits per minute compared with 25–30 fruits with a manual method. The IoT component exhibited high reliability with 99.2% uptime and stable sensor performance, underscoring the feasibility of real-time environmental monitoring under orchard conditions.

Nevertheless, the classification accuracy of 37% highlights the limitations of the developed system, particularly in distinguishing between ripe and damaged fruits. These limitations stem from the restricted size and homogeneity of the training dataset, the limited discriminative power of RGB-based features, and architectural constraints that failed to capture complex visual patterns. Misclassification was frequent between categories with overlapping color and texture features, emphasizing the need for more advanced feature extraction and loss optimization strategies. Therefore, further improvements by expanding the dataset to at least 10000 samples per class, incorporating diverse cultivars, geographic regions, and seasonal variability, are required. Synthetic data augmentation using GANs, nonlocal attention mechanisms, and multimodal fusion with environmental sensor data are essential for enhancing discriminative capacity and predictive accuracy. The optimization of the learning framework through focal loss, class rebalancing, and deep metric learning can be introduced to reduce category overlap. In parallel, edge-to-cloud hierarchies and semantic interoperability must be adopted to minimize latency and ensure scalable deployment.

By addressing these limitations with advanced methods, the system should achieve commercially viable accuracy exceeding 85%, enabling robust quality control and supply chain transparency for perishable fruits such as lychee. The integration of advanced deep learning architectures with reliable IoT infrastructure demonstrates strong potential to revolutionize agricultural monitoring, though further refinement of data diversity, model optimization, and multimodal sensing remains essential for full-scale adoption.

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